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An Efficient Gaussian, Impulse and Mixed Noise Detection and Reduction Filtering Techniques for MR Brain Imaging

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Abstract:

This Paper is focused on the noise detection and reduction filtering technique of Image Enhancement. The Proposed filter combined approach of proposed Gaussian and Impulse noise removal filters. This proposed work reduces the Gaussian, Impulse, Mixed noises from MR Images. ELM noise detection technique is applied for this filter. Training and testing phases also discussed in ELM technique. The performance of the proposed filter is evaluated by some parameters. They are PSNR, MSE, SSIM, IEF and SC. The experimental result shows that the proposed filtering technique gives the best result.

Keywords — **Filters, Enhancement, PSNR, MSE, SSIM.**

I. INTRODUCTION

Denoising is the one of the preprocessing techniques in digital image processing. Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age. But, the main drawback in digital images is inheritance of noise while their acquisition or transmission. Removing noise from digital images is a big challenge for researchers.

Choice of denoising algorithm is application dependent and depends upon the type of noise present in the image. Every algorithm has its own assumptions, advantages and limitations. This Paper presents the proposed noise removal technique to deal Mixed Gaussian and Impulsive Noise.

There are two stages for noise detection. Training and testing phases are using Extreme Learning Machine [ELM][1]. ELM training algorithm is applied to calculate the center gradient for Impulse noise level. An improved decision-based algorithm is applied to remove the highly corrupted by Impulse noise, An Efficient Impulse Noise Removal Image Denoising Technique is applied to remove the Impulse noise. Otherwise, to remove the Gaussian noise using proposed Gaussian noise Image Enhancement Technique. The proposed algorithm is faster and also produces better result than existing technique. The performance metrics such as Peak-Signal-to Noise Ratio (PSNR), Mean Square Error (MSE), Average Difference (AD), Time, and Structure Similarity Index Measure (SSIM) are applied on the techniques and analyzed.

This paper is organized as follows: Section 7.3 presents noise detection technique is discussed. Section 7.4 presents proposed gaussian and impulse denoising technique is applied with section 7.5. Section 4 presents the result and analysis of the denoising technique. Section 5 includes the conclusion of this paper.

II. NOISE DETECTION AND REDUCTION ARCHITECTURE:

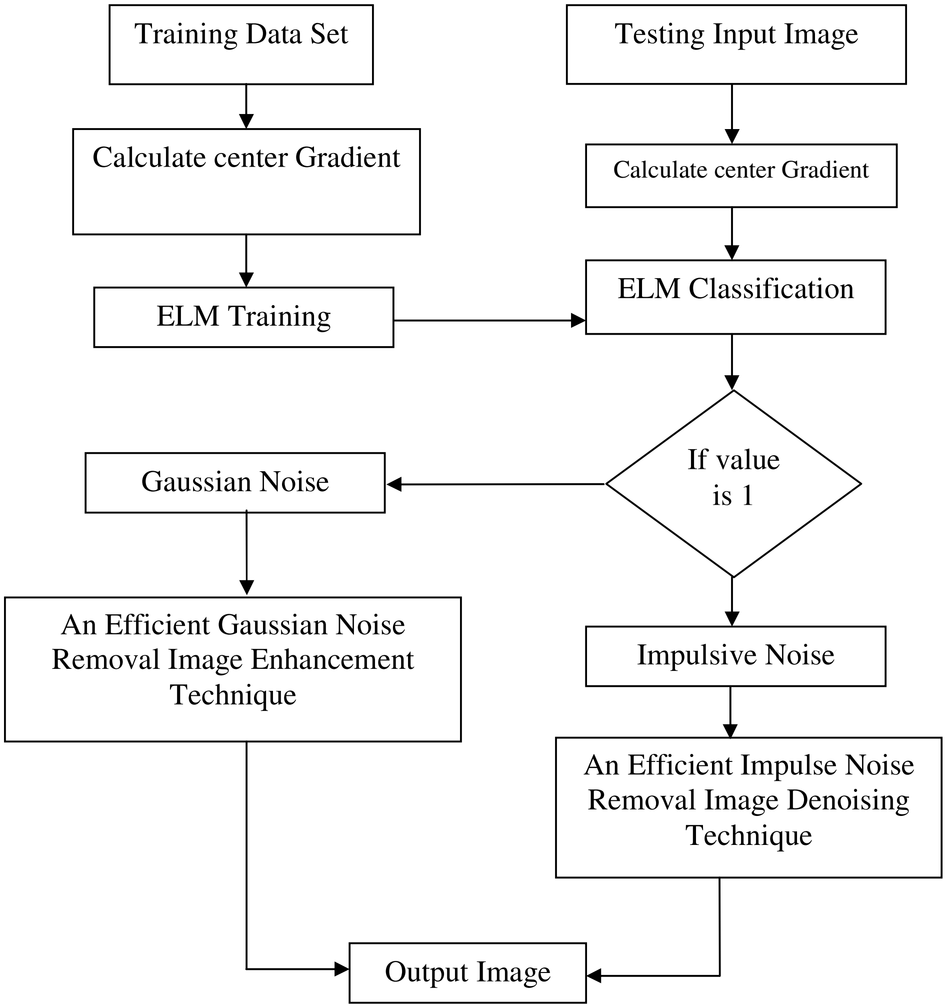


Fig.1.1 Noise detection and reduction architecture

Algorithm

1. There are two stages such as training and testing.
2. In training take input images (Both normal and impulsive noise images).
3. Find center gradient. i.e consider the center pixel and find the difference with neighbor pixel of 8 direction.
4. These center gradient values are considered as a feature for detecting the impulsive noise pixels. These values are given to Extreme Learning Machine (ELM) training for making decision.
5. In testing take test image.
6. Find center gradient. i.e consider the center pixel and find the difference with neighbour pixel of 8 direction.
7. These center gradient values are considered as a feature for detecting the impulsive noise pixels. These values are given to ELM Classification for detecting the input pixel is impulsive noise pixels or not.
8. If the output of the ELM classification is 1 it is considered as the impulsive noise then apply the proposed impulsive noise filter [2] to remove the noise and then go to step 10.

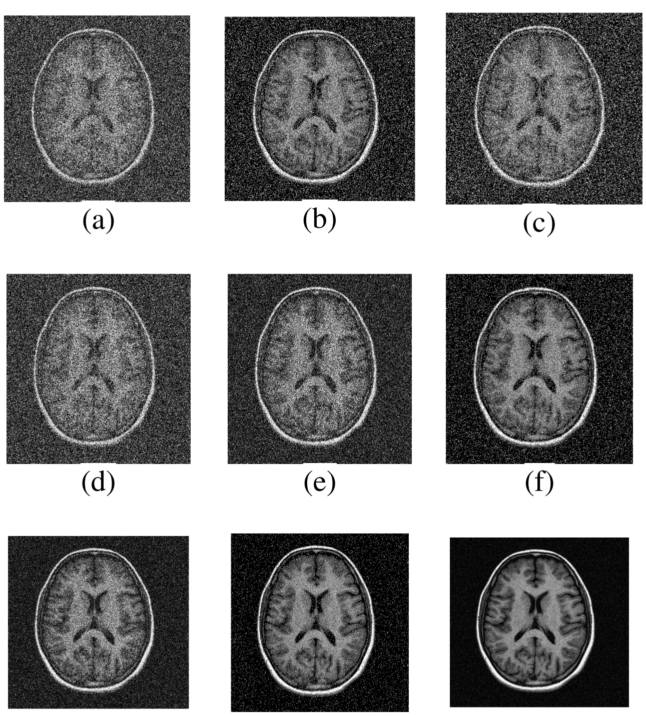
9. If the output of the ELM classification is 0 it is considered as the Gaussian noise pixel then go to step 10.

10. Apply the proposed Gaussian noise filter [3] to remove the Gaussian Noise Image and get the denoised image.

III. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

The performance of the proposed filter is analyzed by fifty different MRI brain images with varying noise level ranging from 10% to 90%. The capability and potential of the proposed filter is compared with various filters with respect to several performance metrics. Comparison is done between proposed filter, mean filter [4], bilateral filter [5], non-local mean filter [6], vector median filter [7], Wiener filter [8], Unsymmetrical Trimmed Mean Filter (UTMF) [9], Modified Decision based Mean-Median Filter (MDBMMF) [10] , Mid-Point Median Filter (MMF) [11] and Enhanced fuzzy peer group filter (EFPGF) [12]. For performance evaluation, this Paper uses the following metrics.

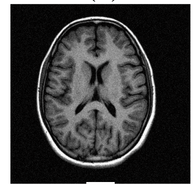
The below Images are filtered with various filters with the noise ratio of 10% for Gaussian noises



(a) (b) (c)

(d) (e) (f)

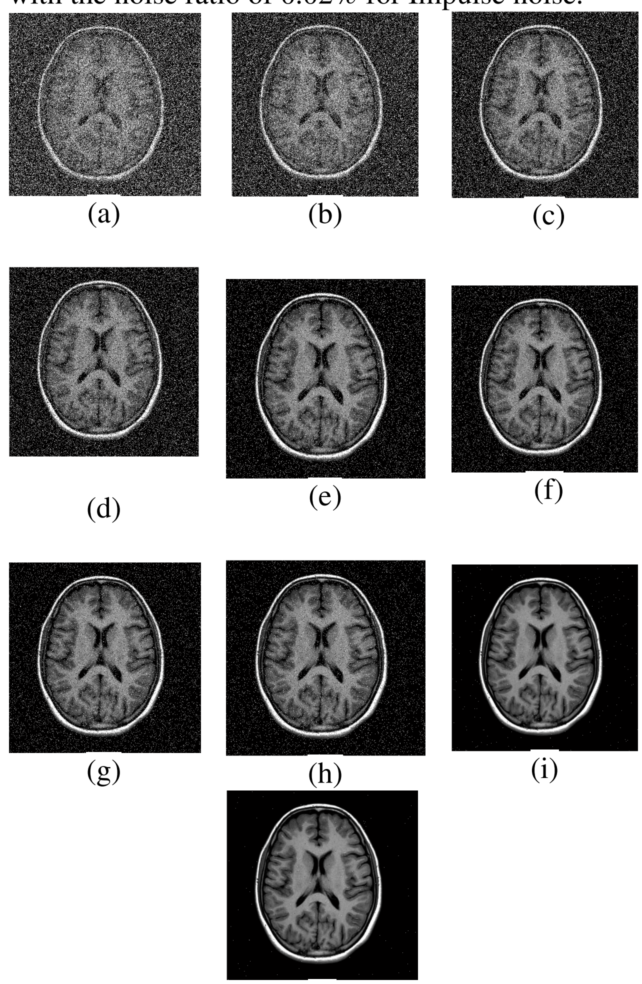
(g) (h) (i)



(j)

Fig.1.2 The various filter are (a) Mean filter, (b) Bilateral filter, (c) Non-local mean filter, (d) Vector median filter, (e) Wiener filter, (f) Unsymmetrical trimmed mean filter, (g) Modified decision based mean median filter, (h) Midpoint median filter (i) EFPGF (j) Proposed filter

The below Images are filtered with various filters with the noise ratio of 0.02% for Impulse noise.



(a) (b) (c)

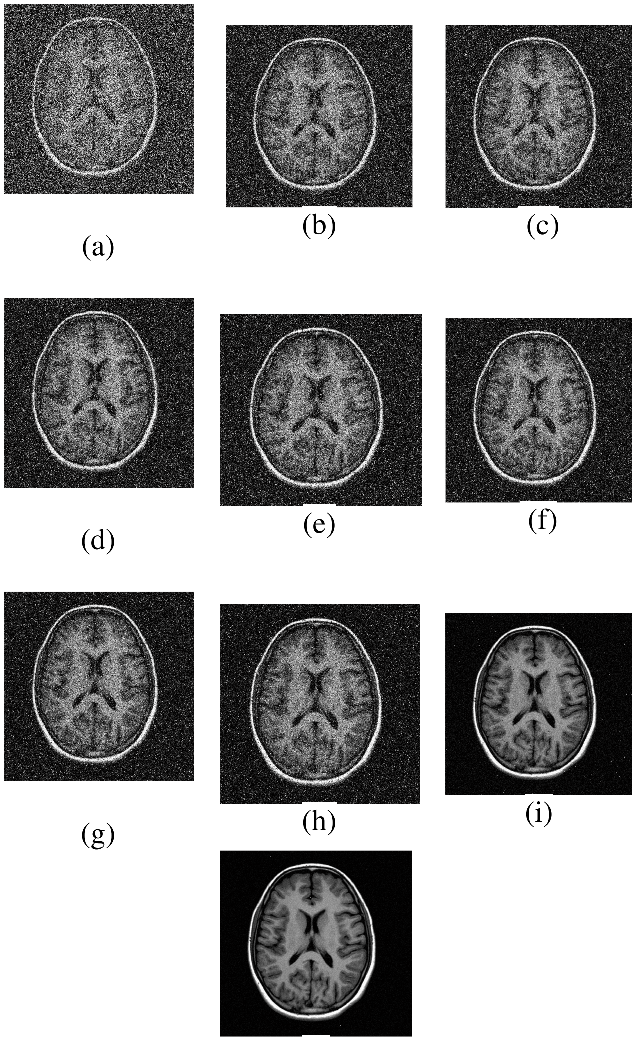
(d) (e) (f)

(g) (h) (i)

(j)

Fig.1.3 The various filter are (a) Mean filter, (b) Bilateral filter, (c) Non-local mean filter, (d) Vector median filter, (e) Wiener filter, (f) Unsymmetrical trimmed mean filter, (g) Modified decision based mean median filter, (h) Midpoint median filter (i) EFPGF (j) Proposed filter

The below images are filtered with various filters with the noise ratio of 10% gaussian noise and 0.02% impulse noise, which is mentioned as mixed noise.



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Fig.1.4 The various filter are (a) Mean filter, (b) Bilateral filter, (c) Non-local mean filter, (d) Vector median filter, (e) Wiener filter, (f) Unsymmetrical trimmed mean filter, (g) Modified decision based mean median filter, (h) Midpoint median filter (i) EFPGF (j) Proposed filter

The Table 1.1 shows that the performance analysis of gaussian noise removal for proposed and existing filters. The Table 1.2 shows that the performance analysis of Impulse noise removal for proposed and existing filters. The Table 1.3 shows that the performance analysis of mixed noise removal for proposed and existing filters. The Table 1.1, 1.2 and 1.3 shows that the proposed technique gives the best result compared with existing techniques.

Table 1.1 proposed filter comparison of existing filters for gaussian noise removal

Filters	Metrics	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
Mean Filter	PSNR	28.6734	28.382	28.951	28.9837	27.676	27.474	27.969	27.5235	27.081	27.015
	MSE	35.3498	35.028	35.771	35.5032	36.215	36.926	36.271	36.7700	36.900	35.788
	SSIM	1.9175	1.9163	1.9141	1.9119	1.9097	2.9085	2.9070	2.9053	1.9034	0.9017
	IEF	10.17	13.46	14.32	15.51	17.80	18.18	19.015	20.835	22.65	23.92
	SC	7.87	10.12	11.09	12.54	15.34	17.8	18.24	19.37	20.15	22.5
Bilateral Filter	PSNR	37.620	37.001	37.789	37.8241	37.197	37.813	37.382	37.582	37.903	37.004
	MSE	21.481	21.513	21.559	19.0237	19.672	20.218	20.340	20.829	21.540	21.926
	SSIM	2.9175	2.9163	2.9141	0.9119	0.9097	1.9085	1.9070	1.9053	2.9034	2.9017
	IEF	12.87	15.34	17.87	19.22	20.91	21.88	25.824	26.01	29.05	30.425
	SC	11.0	13.65	15.23	17.121	19.92	20.22	23.40	25.485	27.23	29.825
Non-Local Mean Filter	PSNR	36.620	36.001	36.789	36.8241	36.197	36.813	36.382	37.582	37.903	37.004
	MSE	19.481	19.513	21.559	19.0237	19.672	20.218	20.340	20.829	21.540	21.926
	SSIM	2.9175	2.9163	2.9141	0.9119	0.9097	1.9085	1.9070	1.9053	2.9034	2.9017
	IEF	24.13	24.56	28.145	29.54	30.124	32.14	34.128	36.789	38.90	38.97
	SC	22.90	23.5	27.82	28.267	29.234	30.348	33.00	34.56	37.90	38.19
Vector Median Filter	PSNR	35.620	35.001	34.789	33.8241	33.197	32.813	32.382	31.582	30.903	35.620
	MSE	18.481	18.513	18.55	19.0237	19.672	20.218	20.340	20.829	21.540	18.481
	SSIM	0.9175	0.9163	0.9141	0.9119	0.9097	0.9085	0.9070	0.9053	0.9034	0.9175
	IEF	33.34	33.892	34.80	35.192	36.74	37.89	38.03	38.91	39.56	40.545
	SC	29.72	30.24	33.73	34.82	36.15	36.78	37.947	38.24	38.34	39.48
Wiener Filter	PSNR	33.542	33.382	32.951	31.9837	31.676	31.474	30.969	29.523	29.081	29.015
	MSE	21.349	25.028	28.771	31.5032	34.215	36.926	39.271	41.770	43.900	45.788
	SSIM	0.9175	0.9163	0.9141	0.9119	0.9097	0.9085	0.9070	0.9053	0.9034	0.9017
	IEF	32.24	34.844	35.123	36.90	37.29	38.10	3 8.93	39.672	39.187	40.943
	SC	29.654	32.675	34.26	35.372	36.54	38.03	37.65	38.496	38.56	39.456
UTMF	PSNR	34.192	33.098	33.309	32.2019	32.092	31.542	31.874	30.213	30.089	29.120
	MSE	21.349	25.028	28.771	31.5032	34.215	36.926	39.271	41.770	43.900	45.788
	SSIM	0.9175	0.9163	0.9141	0.9119	0.9097	0.9085	0.9070	0.9053	0.9034	0.9017
	IEF	33.67	33.93	34.87	33.174	29.85	28.680	27.15	26.62	24.56	23.94
	SC	32.15	32.19	33.98	29.59	27.90	27.563	23.729	25.469	23.692	20.53

Table 1.1 (Cont'd)

MDBMMF	PSNR	38.1734	38.382	37.951	37.9837	37.676	37.474	37.969	37.5235	37.081	37.015
	MSE	37.3498	35.028	35.771	35.5032	36.215	36.926	36.271	36.7700	36.900	35.788
	SSIM	1.3275	1.9163	1.9141	1.9119	1.9097	2.9085	2.9070	2.9053	1.9034	0.9017
	IEF	21.59	22.369	24.567	26.369	27.564	28.259	31.235	31.567	32.353	33.257
	SC	20.80	21.54	23.92	25.47	25.82	27.43	29.76	30.45	31.54	32.23
MMF	PSNR	37.9810	37.123	36.951	36.9837	35.676	35.474	34.969	34.5235	33.981	33.015
	MSE	38.3498	38.028	38.771	38.5032	38.215	38.926	39.271	39.7700	39.900	39.788
	SSIM	1.3275	1.9163	1.9141	1.9119	1.9097	2.9085	2.9070	2.9053	1.9034	0.9017
	IEF	36.59	35.369	34.567	33.398	32.564	31.259	29.235	29.134	29.096	29.049
	SC	34.77	34.23	34.128	32.75	31.24	30.323	29.185	29.025	29.056	29.023
EFPGF	PSNR	38.6734	38.382	38.951	38.9837	37.676	37.474	37.969	37.5235	37.081	37.015
	MSE	35.3498	35.028	35.771	35.5032	36.215	36.926	36.271	36.7700	36.900	35.788
	SSIM	1.9175	1.9163	1.9141	1.9119	1.9097	2.9085	2.9070	2.9053	1.9034	0.9017
	IEF	33.59	33.839	34.567	35.369	36.564	36.672	37.18	37.954	38.24	38.434
	SC	32.22	31.34	32.17	33.980	35.24	35.923	35.12	35.024	36.35	38.093
Proposed	PSNR	40.3655	39.122	38.352	37.0893	38.644	38.363	38.610	38.257	37.234	37.465
	MSE	19,356	19.365	19.108	20.591	20.567	21.788	20.541	20.5671	19.572	19,672
	SSIM	2.4676	1.588	2.6891	2.0034	2.904	2.671	1.753	1.672	1.692	1.6892
	IEF	29.465	29.462	28.004	27.861	27.561	27.468	26.032	25.691	25.356	24.599
	SC	26.34	25.98	27.12	26.56	27.2	27.22	25.44	25.543	24.43	23.45

Table 1.2 proposed filter comparison of existing filters for Impulse noise removal

		Noise Levels									
Filters	**Metrics**	**0.01**	**0.02**	**0.03**	**0.04**	**0.05**	**0.06**	**0.07**	**0.08**	**0.09**	**0.1**
Mean Filter	PSNR	34.053	34.053	34.053	34.052	34.047	34.046	34.048	34.047	34.046	34.04
	MSE	14.991	14.991	14.991	15.992	16.001	14.004	14.000	16.002	15.003	15.00
	SSIM	2.9189	2.9187	0.9185	3.9181	2.9186	3.9184	2.9183	1.9180	3.9178	2.917
	IEF	29.097	30.011	31.921	31.986	32.763	33.409	33.654	34.453	34.894	32.58
	SC	19.87	28.23	29.34	30.763	31.03	32.65	32.75	33.56	33.12	31.56
Bilateral Filter	PSNR	36.4	37.729	36.028	38.921	38.569	37.007	34.770	36.337	38.457	39.89
	MSE	16.402	17.457	17.496	18.539	14.587	13.627	15.683	13.761	14.829	13.87
	SSIM	3.234	3.896	3.346	3.10	2.9027	3.9012	4.8990	2.8988	1.8984	2.891
	IEF	34.1234	34.535	35.123	35.645	36.68	36.413	37.39	37.334	38.88	39.1
	SC	19.145	19.343	23.19	24.19	33.90	33.14	34.09	36.19	37.96	38.13
Non-Local Mean Filter	PSNR	36.620	36.001	35.789	37.8241	36.197	36.813	36.382	36.582	36.903	37.004
	MSE	16..481	16.513	15.559	17.0237	16.672	18.218	16.340	14.829	16.540	16.926
	SSIM	3.9175	3.9163	2.9141	2.9119	3.9097	2.9085	1.9070	3.9053	2.9034	2.9017
	IEF	28.013	26.331	28..526	29.3882	30.412	31.604	32.64	33.335	34.254	35.565
	SC	19.43	23.99	26.41	28.15	29.074	30.464	31.342	32.14	33.084	34.42
Vector Median Filter	PSNR	37.620	37.001	38.789	37.8241	37.197	36.813	37.382	38.582	36.903	38.620
	MSE	17.481	17.513	18.55	17.0237	17.672	16.218	37.340	18.829	16.540	18.481
	SSIM	2.9175	3.9163	1.9141	1.9119	2.9097	0.9085	2.9070	2.9053	3.9034	0.9175
	IEF	22.013	23.331	24.526	25.3882	26.412	23.604	29.954	30.324	32.821	33.013
	SC	19.34	22.14	23.976	24.134	25.767	22.12	28.45	29.231	31.23	32.453
Wiener Filter	PSNR	37.542	38.382	37.951	38.9837	38.676	38.474	36.969	37.523	38.081	38.015
	MSE	17.349	18.028	17.771	18.5032	18.215	18.926	16.271	17.770	46.900	47.788
	SSIM	1.565	1.7879	0.9141	2.9119	2.9097	2.9085	2.9070	2.9053	1.9034	1.9017
	IEF	32.568	33.369	34.567	35.3698	35.564	36.259	38.235	35.6547	34.235	37.125
	SC	29.243	32.123	33.24	34.91	34.12	35.13	37.23	34.243	33.08	36.24
UTMF	PSNR	31.329	31.158	31.003	30.196	29.932	29.707	29.634	28.992	27.752	26.552
	MSE	21.302	21.131	22.553	22.385	23.912	24.501	26.120	28.129	30.162	32.784
	SSIM	0.9189	0.9187	0.9071	0.9027	0.9012	0.8990	0.8993	0.8988	0.8984	0.8819
	IEF	27.238	27.378	28.448	29.548	30.556	31.601	32.101	32.823	32.891	33.891
	SC	25.46	26.94	25.14	27.03	29.234	30.923	31.434	29.34	31.43	32.15

Table 1.2 (Cont'd)

		Noise Levels									
Filters	**Metrics**	**0.01**	**0.02**	**0.03**	**0.04**	**0.05**	**0.06**	**0.07**	**0.08**	**0.09**	**0.1**
MDBMMF	PSNR	26.128	25.773	25.352	24.850	24.123	24.456	23.198	23.125	22.871	22.081
	MSE	28.183	28.735	28.639	29.084	29.126	30.908	30.828	31.141	32.607	34.998
	SSIM	0.8901	0.8896	0.8885	0.8879	0.8861	0.8851	0.8751	0.8662	0.8081	0.6020
	IEF	21.588	22.618	23.624	23.639	24.665	25.671	26.703	27.757	28.796	25.859
	SC	19.434	22.34	21.943	22.01	21.45	24.53	25.123	26.232	27.13	24.01
MMF	PSNR	33.8	33.101	33.003	32.916	32.129	31.461	31.994	30.9822	30.732	29.034
	MSE	29.302	29.131	29.553	29.282	29.932	28.464	28.209	28.3410	27.109	27.5
	SSIM	0.9181	0.9182	0.9073	0.9024	0.9015	0.8999	0.8998	0.8987	0.8986	0.8815
	IEF	27.231	27.379	27.428	27.5284	28.553	29.600	30.614	31.723	32.850	32.896
	SC	19.34	23.084	25.15	23.10	25.0745	28.934	29.055	29.534	31.532	31.832
EFPGF	PSNR	36.4	37.729	36.028	38.921	38.569	37.007	34.770	36.337	38.457	39.89
	MSE	16.402	17.457	17.496	18.539	14.587	13.627	15.683	13.761	14.829	13.87
	SSIM	3.234	3.896	3.346	3.10	2.9027	3.9012	4.8990	2.8988	1.8984	2.891
	IEF	24.1234	24.535	25.123	23.645	25.68	28.413	29.39	29.334	30.88	31.10
	SC	23.13	22.106	24.132	22.01	22.96	27.342	28.143	28.434	29.343	29.231
Proposed	PSNR	43.3655	44.122	42.352	43.0893	45.644	41.363	43.610	40.257	42.234	42.465
	MSE	23.234	23.577	2.579	20.591	21.567	22.788	23.541	23.5671	24.572	21,672
	SSIM	5.4676	4.588	3.6891	1.0034	2.904	2.671	2.753	2.672	3.692	5.6892
	IEF	28.465	28.462	29.0043	29.861	30.561	23.468	28.0732	28.691	29.3456	30.5899
	SC	25.43	27.34	28.93	28.0123	29.02	22.54	27.89	28.023	28.042	29.0543

Table 1.3 Proposed filter comparisons of existing filters for mixed noise removal

		Noise Levels									
Filters	**Metrics**	**G=0.01 I=0.01**	**G=0.02 I=0.02**	**G=0.03 I=0.03**	**G=0.04 I=0.04**	**G=0.05 I=0.05**	**G=0.06 I=0.06**	**G=0.07 I=0.07**	**G=0.08 I=0.08**	**G=0.09 I=0.09**	**G=0.1 I=0.1**
Mean Filter	PSNR	29.6734	29.382	28.951	29.9837	27.676	28.474	27.969	27.5235	26.081	25.015
	MSE	33.3498	33.028	33.771	32.5032	32.215	31.926	31.271	30.7700	30.900	30.788
	SSIM	2.9175	2.9163	2.9141	2.9119	2.9097	2.9085	2.9070	2.9053	1..9034	0.9017
	IEF	25.59	26.369	27.567	28.3698	29.564	30.259	31.235	31.6547	32.09	32.943
	SC	23.12	25.85	26.756	27.904	28.13	29.195	30.24	29.234	31.453	31.090
Bilateral Filter	PSNR	38.620	38.001	38.789	38.8241	37.197	37.813	38.382	38.582	38.903	37.004
	MSE	18.481	18.513	18.559	19.0237	19.672	18.218	18.340	18.829	18.540	18.926
	SSIM	2.9175	2.9163	1.9141	1.9119	1.9097	1.9085	1.9070	2.9053	2.9034	2.9017
	IEF	25.013	25.331	26.526	27.3882	31.412	32.604	34.954	35.324	36.821	38.231
	SC	19.54	23.23	24.12	25.78	29.123	31.343	33.12	34.86	35.656	37.123
Non-Local Mean Filter	PSNR	36.577	36.246	36.454	36.4557	36.689	36.22	37.382	37.582	37.903	37.004
	MSE	16..481	16.513	16.559	16.0237	19.672	16.218	16.340	16.829	16.540	16.926
	SSIM	2.9175	2.9163	2.9141	1.9119	1.9097	1.9085	2.9070	1.9053	1.9034	2.9017
	IEF	24.013	25.331	26.526	27.3882	28.412	29.604	30.64	31.335	32.255	32.56
	SC	22.34	21.89	25.93	26.73	28.90	28.08	29.124	30.084	31.042	31.978
Vector Median Filter	PSNR	37.620	37.001	37.789	37.8241	38.197	38.813	37.382	38.582	36.903	38.620
	MSE	17.481	17.513	17.55	17.0237	17.672	17.218	17.340	17.829	16.540	16.481
	SSIM	1.9175	1.9163	1.9141	1.9119	1.9097	1.9085	1.9070	1.9053	1.9034	1.9175
	IEF	32.013	32.331	24.526	27.3882	28.412	29.604	30.954	31.324	32.821	34.013
	SC	32.867	32.06	22.97	26.545	27.54	28.43	29.43	30.232	31.454	33.232
Wiener Filter	PSNR	33.542	35.382	37.951	36.9837	38.676	37.474	37.969	37.523	37.081	37.015
	MSE	15.349	15.028	18.771	16.5032	14.215	16.926	15.271	13.770	13.900	15.788
	SSIM	2.9175	2.9163	1.9141	1.9119	2.9097	0.9085	1.9070	1.9053	2.9034	0.9017
	IEF	32.568	33.369	33.567	33.3698	34.564	36.259	38.235	32.6547	33.235	35.125
	SC	29.998	23.53	32.24	31.08	33.123	34.103	37.934	31.989	32.92	34.762

Table 1.3 (Cont'd)

		Noise Levels									
Filters	**Metrics**	**G=0.01 I=0.01**	**G=0.02 I=0.02**	**G=0.03 I=0.03**	**G=0.04 I=0.04**	**G=0.05 I=0.05**	**G=0.06 I=0.06**	**G=0.07 I=0.07**	**G=0.08 I=0.08**	**G=0.09 I=0.09**	**G=0.1 I=0.1**
UTMF	PSNR	38.356	38.122	38.243	38.578	39.788	38.135	39.610	39.257	39.234	39.465
	MSE	20,356	20.365	20.108	20.591	20.567	21.788	20.541	20.5671	19.356	19,672
	SSIM	2.4676	1.588	2.6891	2.0034	2.904	2.671	1.753	1.672	1.692	1.6892
	IEF	30.465	31.462	32.0043	33.861	34.561	35.468	36.0732	37.691	38.3456	39.5899
	SC	26.232	29.-98	31.042	32.080	33.153	34.76	35.869	36.797	38.123	38.790
MDBM MF	PSNR	25.918	25.861	25.629	25.3293	25.106	24.828	23.621	22.9215	21.316	20.658
	MSE	21.921	21.671	21.553	22.9025	23.992	24.469	25.780	26.127	27.138	29.006
	SSIM	0.8120	0.8373	0.8571	0.8697	0.8476	0.8078	0.7831	0.7618	0.7297	0.6771
	IEF	21.817	21.828	21.943	22.1424	23.107	24.617	25.872	26.2012	27.387	28.445
	SC	19.34	18.5	20.54	21.867	22.342	23.978	23.13	25.12	26.184	27.12
MMF	PSNR	34.324	34.152	33.903	33.195	32.432	32.267	31.894	31.1822	30.732	29.034
	MSE	30.302	31.131	33.553	33.2825	34.912	34.461	35.282	35.1209	35.162	36.12
	SSIM	0.9189	0.9187	0.9071	0.9027	0.9012	0.8990	0.8993	0.8988	0.8984	0.8819
	IEF	28.238	28.378	28.486	29.528	30.576	31.609	32.611	33.713	33.801	34.898
	SC	26.878	27.34	27.35	28.08	29.78	30.78	31.06	32.767	32.67	33.134
EFPGF	PSNR	35.620	35.001	34.789	33.8241	33.197	32.813	32.382	31.5825	30.903	30.004
	MSE	18.481	18.513	18.559	19.0237	19.672	20.218	20.340	20.8293	21.540	21.926
	SSIM	0.9175	0.9163	0.9141	0.9119	0.9097	0.9085	0.9070	0.9053	0.9034	0.9017
	IEF	25.013	25.331	26.526	27.3882	28.412	29.604	30.954	31.3244	32.8210	33.2310
	SC	23.809	24.878	25.70	26.897	27.709	28.89	29.789	30.97	31.79	32.78
Proposed	PSNR	40.356	38.122	38.243	38.578	39.788	38.135	39.610	39.257	39.234	39.465
	MSE	20,356	20.365	20.108	20.591	20.567	21.788	20.541	20.5671	19.356	19,672
	SSIM	2.4676	1.588	2.6891	2.0034	2.904	2.671	1.753	1.672	1.692	1.6892
	IEF	36.465	26.462	25.043	24.861	25.561	27.468	28.032	29.691	30.346	31.899
	SC	32.790	24.89	23.076	23.07	24.68	26.12	27.67	28.69	29.97	30.02

IV. CONCLUSION

In this Paper we have discussed noise detection and reduction techniques for Gaussian, Impulse and Mixed noises. The ELM noise detection method also discussed. Training and testing phases also discussed in ELM technique. The performance of the proposed filter is evaluated by some parameters. They are PSNR, MSE, SSIM, IEF and SC. The experimental result shows that the proposed filtering technique gives the best result compared with existing filters.

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