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REMOVAL OF IMPULSIVE NOISE USING WEIGHTED FUZZY MEAN FILTER BASED ON CLOUD MODEL

K. Kannan[1] and S. Ramesh[2]

[1]*Department of Mechanical Engineering, Kamaraj College of Engineering and Technology, India*
E-mail: kannan_kcet@yahoo.co.in
[2]*Department of Computer Science and Engineering, Anna University Regional Centre, Madurai, India*
E-mail: rameshcse@autmdu.ac.in

Abstract
This paper proposes a weighted fuzzy mean filter based on cloud model and reports its performance in removing the impulsive noise from the digital image. In addition, the performance of the proposed weighted fuzzy mean filter is compared with already existing variants of median and switching filters using root mean square error, peak signal to noise ratio and quality index. Even though the image is corrupted by 90%, this weighted fuzzy mean filter is capable of recovering the original image with good detail preservation.

Keywords:
Weighted Fuzzy Mean Filter, Cloud Model, Median Filters, Switching Filters

1. INTRODUCTION

Image Denoising is the process of removing the noise from the digital images using some prior knowledge about the noise while retaining as much as possible important image features. Basically, there are two approaches to image denoising based on the domain in which the denoising taken place. These approaches are named as spatial domain and transform domain filtering approaches. Spatial Filtering approaches remove the noise by manipulating the image in the spatial domain itself, whereas Transform Filtering approaches manipulate the image in transform domain. Spatial filtering of images is an important aspect of image processing as it provides means for removing noise and sharpening blurred images. There are many types of spatial filters which can be classified into linear and non-linear filters. The simplest linear spatial filter is the averaging filter, which works by passing a mask over the image calculating the mean intensity and setting the central pixel to this value. They tend to remove the fine details in the image and fail to remove high level noise effectively. Among spatial filters, the famous non-linear filter is the median filter and its varieties. Standard Median Filter (SMF) was implemented by moving a finite length of window throughout the image that replaces the centre pixel of the window with the median value of the pixels in that window [1]. This implementation modifies both noisy and noise-free pixels. Thus, they tend to remove the lines and corners in the image while suppressing the noise. To overcome this difficulty, several variations of the median filters have been proposed. The weighted median filter (WMF) is one of the extensions to median filter which assigns more weights to some pixels in the window [2, 3]. This WMF provides some degree of control to the smoothing behavior through the weights assigned. These weights introduce additional complexity in the design and implementation of WMF. One variation of WMF is the Centre Weighted Median Filter (CWMF), which gives more weights to the central value of the window only, thereby reduces the complexity in the design [19]. The CWMF filter performs well for low noise level and fails when the noise level is high. To overcome this, Adaptive Median Filters (AMF) with variable window size was introduced. This AMF is robust in removing the impulse noise while preserving the image details even though the probability of occurrence of impulse noise is high [5]. Relaxed Median Filter (RMF), whose filtering operation is controlled by its parameter l and u, provides ability to tradeoff between noise suppression and detail preservation [22]. When $l = 1$, the output of the relaxed median filter is simply the identity filter. When $l = u = N + 1$, the output of the relaxed median filter is the median filter. The filters discussed above uses only the randomness associated with impulse noise. They unconditionally replace each pixel with median value of the window without checking whether the pixel is “bad” or not. As a result, since the uncorrupted pixels are altered, they damage many image details in the high noise levels. With development of Fuzzy, the use of switching filters in removal of impulse noise has attracted more research recently. These filters employ an impulse detector to determine the presence of pixels corrupted by impulses in the image. Only these noisy pixels will be filtered by these switching filters. The Progressive Switching Median Filter (PSMF) is one of the switching filters in which both impulse detector and noise filter are applied progressively in iterative manner to obtain the best results [6]. These progressive iteration increases the time complexity of the filter. To minimize the time complexity, Fast Median Filter (FMF) was proposed in which the corrupted pixels are replaced by either the median pixel or neighborhood pixel in contrast to other existing algorithms that use only median values for replacement of corrupted pixels [7]. Since, the median value may also be a noisy pixel at higher noise level, neighborhood pixels are used for noisy pixel replacement in FMF. Even though switching filters performs better than median and its variant filters, they are not able to recover the original image at high noise level because of not understanding the randomness and fuzziness completely. To avoid this problem, this paper proposes and implements a Weighted Fuzzy Mean Filter (WFMF) based on cloud model which combines randomness, fuzziness and their membership degrees. The experimental results shows that the proposed filter has better performance than SMF, RMF, PSMF and FMF in terms of Root Mean Square Error, Peak Signal to Noise Ratio (PSNR) and Quality Index (QI) [17] across a wide range of noise level from 10% to 90%. The remainder of the paper is organized as follows. In section 2, a review of the cloud model which is necessary to effectively implement our algorithm is presented. The proposed algorithm is described in section 3. Section 4

presents the evaluation criteria used in this paper to evaluate the results. After that, results of the proposed algorithm are presented in section 5. Last section presents the conclusion.

2. CLOUD MODEL

Fuzzy provides a method to transact the fuzziness and randomness. The commonly used method of uncertainty reasoning is based on fuzzy set theory. The basis of fuzzy set theory is the membership function. The membership function is a one-point to one-point mapping from a space U to the unit interval [0, 1]. After the mapping, the uncertainty of an element belonging to the fuzzy concept becomes certain to the degree represented by a precise number. The uncertain characteristics of the original concept are not passed on to the next step of processing at all. This is the intrinsic shortcoming of the fuzzy set theory. In order to overcome this shortcoming, Jianhua Fan and Deyi Li present a new mathematical representation of qualitative concepts—Cloud Model (CM). With this CM models, mapping between quantities and qualities becomes much easier and interchangeable. CM is a model of the uncertainty transformation between quantitative representation and qualitative concept based on normal distribution and bell shaped membership function. CM has been successfully applied to data mining [10, 12], image classification [11], image segmentation [13, 14] and optimization [15].

Let U is a quantity domain expressed with accurate numbers and C is a quality concept in U. If the quantity value, $x \in U$ and x is a random realization of the quality concept C, then $\mu(x)$ is the membership degree of x which lies between [0,1]. It is the random number which has the steady tendency,

$$\mu : U \rightarrow [0,1], \forall x \in U, x \rightarrow \mu(x) \qquad (1)$$

The distribution of x is called cloud and each x is called a cloud drop. The cloud can be characterized by three parameters, i.e., the expected value E_x, entropy E_n and hyperentropy H_e [10-15, 20-21]. E_x is the expectation of the cloud drops' distribution. It points out which drops can best represent the concept and reflects the distinguished feature of the concept. E_n is the uncertainty measurement of the qualitative concept, which is determined by both the randomness and the fuzziness of the concept. It represents the value region in which the drop is acceptable by the concept, while reflecting the correlation of the randomness and the fuzziness of the concept. H_e is the uncertainty measurement of E_n. Given these three characteristics, a set of cloud drops can be generated with certainty degree by the normal cloud generator CG. Each pixel in the image is the cloud drop and composes the cloud. These cloud drops are given input to the backward cloud generator CG^{-1}. The outputs of CG^{-1} are three parameters of cloud E_x, E_n and H_e. This is shown in Fig.1.

When the drops are approaching the expected value E_x, the certainty degrees and the contribution degrees of the drops are increasing. Therefore, in the cloud, the drop communities contribute to the concept with the different contribution degrees [20]. In fact, the drops located within $[E_x - 3E_n, E_x + 3E_n]$ take up to 99.99% of the whole quantity and contribute 99.74% to the concept. Thus, the drops are located out of domain $[E_x - 3E_n, E_x + 3E_n]$, and their contributions to the concept can be neglected. This is "3En rule". According to the normal cloud generator (CG), the certainty degree of each drop is a probability distribution rather than a fixed value. It means that the certainty degree of each drop is a random value in a dynamic range. If He of the cloud is 0, then the certainty degree of each drop will change to be a fixed value.

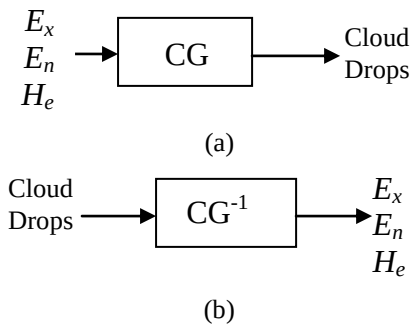
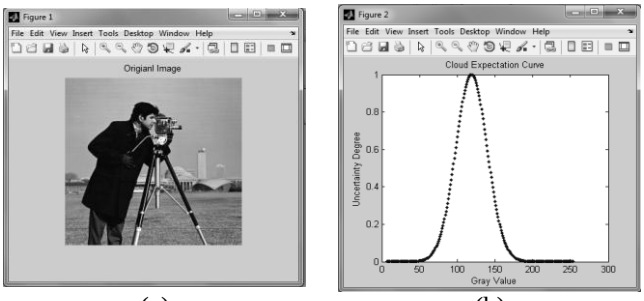


Fig.1. (a). Forward Cloud Generator (b). Backward Cloud Generator

The fixed value is the expectation value of the certainty degree. In fact, the value is also the unbiased estimation for the average value of the certainty degrees in the range. All the drops and their expectations of certainty degrees can compose a curve, and the curve is the cloud expectation curve (CEC). The CEC of cameraman image is shown in the Fig.2.



(a) (b)

Fig.2. (a).Cameraman Image (b).CEC

3. WEIGHTED FUZZY MEAN FILTER

The proposed WFMF is a double stage filter, where the first stage is the noisy pixel detector and the second stage is the noisy pixels replacement filter. When a noisy pixel is detected in the first stage, it is subjected to the next filtering stage. Otherwise, when a pixel is classified as noise-free, it will be retained and the filtering action is avoided without altering any fine details and textures that are contained in the original image.

3.1 NOISY PIXEL DETECTOR

Similar to other impulse detection algorithm, this Noisy Pixel Detector (NPD) uses prior information about the impulsive noise with the following assumptions

- Only the proportions of image pixels are corrupted while other pixels are noise-free.
- Noisy pixels take a very large value as positive impulse or a very small value as negative impulse.

Normally, the impulsive noise is modeled as salt and pepper noise. The salt noise takes the pixel value of 255 and pepper noise takes the pixel value of 0. These two pixel values are used

to identify the noisy pixels in the image. The NPD checks the value of every pixel in the image. If the pixel value is '0' or '255', the pixel value will be replaced by '0'. Otherwise, the pixel is left unchanged.

$$N(i,j)=\begin{cases} 0 & \text{if } P(i,j)=0 \text{ or } 255 \\ P(i,j) & \text{otherwise} \end{cases} \quad (2)$$

3.2 NOISY PIXEL REPLACEMENT FILTER

The Noisy Pixel Replacement Filter (NPRF) replaces the noise pixel marked with $N_{i,j}$ = 0by the weighted fuzzy mean value of the remaining pixels in the square filtering window $W_{i,j}^{2N+1}$ of size 2*N* + 1.

$$W_{i,j}^{2N+1}=\{x_{i+s,j+t}\}, where\ s,t\in(-N,..0,...N) \quad (3)$$

Step 1: Set the window size by initializing *N* = 1. Then, E_x of each uncorrupted pixels in $W_{i,j}^{2N+1}$ is calculated using the formulae,

$$E_x=\frac{1}{n}\sum_{x_{i+s,j+t}\in W_{i,j}^{2N+1}} x_{i+s,j+t} \quad (4)$$

Step 2: Calculate En using the following formulae,

$$E_n=\sqrt{\frac{\pi}{2}}\times\frac{1}{n}\sum_{x_{i+s,j+t}\in W_{i,j}^{2N+1}}\left|x_{i+s,j+t}-E_x\right| \quad (5)$$

Step 3: Calculate weights for x_i+s, $j+t$

$$w_{i+s,j+t}=\exp\left(-\left(x_{i+s,j+t}-E_x\right)^2/2E_n^2\right) \quad (6)$$

Step 4: Calculate the weighted mean

$$Y_{i,j}=\sum_{x_{i+s,j+t}\in W_{i,j}^{2N+1}} w_{i+s,j+t}x_{i+s,j+t}\Big/ w_{i+s,j+t} \quad (7)$$

Step 5: Replace the noisy pixels $N_{i,j}$ by weighted mean $Y_{i,j}$.

4. EVALUATION CRITERIA

The evaluation measures are used in this paper, as follows,

a) The Root Mean Square Error (RMSE) between the reference image R and fused image F is given by,

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}[R(i,j)-F(i,j)]^2}{N^2}} \quad (8)$$

b) The Peak Signal to Noise Ratio (PSNR) between the reference image R and fused image F is given by,

$$\text{PSNR}=10\log_{10}(255)^2/(\text{RMSE})^2 \text{ (db)} \quad (9)$$

c) Quality index of the reference image (R) and fused image (F) is given by [17],

$$QI=\frac{4\sigma_{ab}ab}{(a^2+b^2)(\sigma_a^2+\sigma_b^2)} \quad (10)$$

The maximum value *Q* = 1 is achieved when two images are identical, where a and b are mean of images, $\sigma_{a,b}$ be covariance of R and F, σ_a^2 , σ_b^2 be the variance of image R, F.

5. RESULTS

For simulation, three test (lena, fingerprint and medical) images are taken and salt & pepper noise is added to them with noise level varying from 10% to 90% with increments of 10%. In this work, it is assumed that the images are corrupted by P% salt & pepper noise in which the salt is made up of 0.5P% and pepper is made up of 0.5P%. The restoration results of SMF, RMF, PSMF, FMF and WFMF for the noise level of 0.5 are shown in Fig.3. Table.1- Table.9 shows the performance of above filters in terms of RMSE, PSNR & QI for the above test images. From the results, it is inferred that only FMF and WFMF are able to produce reconstructed images with good image detail preservation. However, the proposed WFMF has a better noise suppression ability in terms of RMSE, PSNR and QI.

6. CONCLUSION

In this paper, a weighted fuzzy mean filter for impulse noise removal has been proposed and implemented. It represents the uncertainties of the noise perfectly by using cloud model, which is helpful in removing the noise. In addition, the above filter identifies the noise pixel directly, without needing to sort the pixel gray values, which immensely increases the computational efficiency in noise detection. Even if the noise density is closes to 0.90, the texture, the details, and the edges of the images restored by the WFM filter are preserved with good visual effect. In total, the proposed WFM filter is a moderately simple denoising filter with good detail preservation.

Table.1. RMSE Comparison Table of various filters for Lena image at different noise densities

Noise	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Noisy	42.9179	61.0869	74.5267	85.9586	96.3992	105.5109	113.9568	121.8739	129.1771
SMF	5.5531	9.0029	17.0932	28.8017	43.8701	61.5506	80.57	99.9568	118.3591
RMF	5.4953	8.9327	16.7715	28.2864	43.2499	61.2729	81.2789	102.0663	121.0087
PSMF	3.3761	5.7603	9.4421	14.4722	23.8055	62.1083	81.106	100.371	118.5776
FMF	2.0988	3.411	4.6671	6.0736	7.8783	10.2572	13.1727	18.065	26.0158
WFMF	1.8743	2.8983	3.7233	4.7331	5.8568	7.2984	9.3908	13.0278	19.857

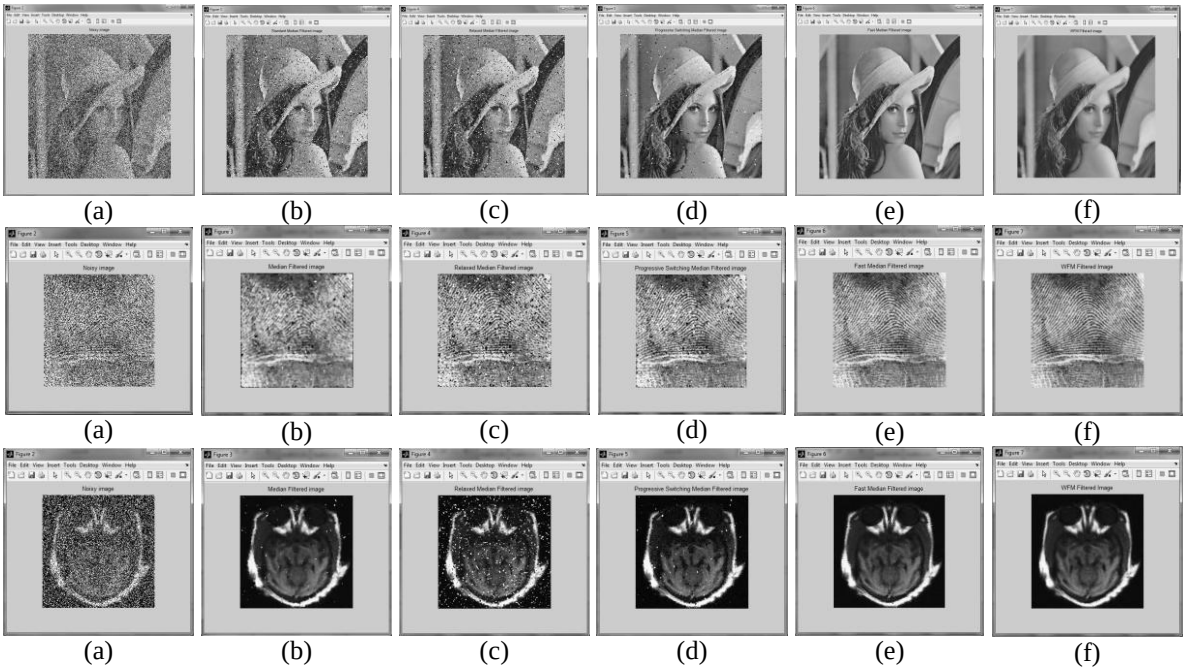


Fig.3. Result of Image Denoising at 50% of noise level for various filters
Row1: Lena Image, Row2: Fingerprint Image, Row3: Medical Image
(a). Noisy Image (b)-(f). Denoised Images {using (b). SMF, (c). RMF, (d). PSMF, (e). FMF and (f). WFMF}

Table.2. PSNR (in Decibels) Comparison Table of various filters for Lena image at different noise densities

Noise	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Noisy	15.478	12.4118	10.6846	9.445	8.4493	7.6649	6.996	6.4126	5.9071
SMF	33.2401	29.0432	23.4743	18.9424	15.2874	12.3462	10.0073	8.1346	6.6668
RMF	33.331	29.1111	23.6394	19.0992	15.4111	12.3854	9.9313	7.9532	6.4745
PSMF	37.5625	32.9219	28.6294	24.9201	20.5972	12.2678	9.9497	8.0986	6.6508
FMF	41.6914	37.4732	34.7499	32.4619	30.2022	27.9102	25.7373	22.994	19.826
WFMF	42.674	38.8879	36.7121	34.628	32.7775	30.8663	28.6768	25.8334	22.1725

Table.3. QI Comparison Table of various filters for Lena image at different noise densities

Noise	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Noisy	0.6913	0.4944	0.3661	0.2723	0.1982	0.1408	0.0962	0.0576	0.0274
SMF	0.9932	0.9823	0.9384	0.8387	0.6782	0.4857	0.3111	0.1714	0.0755
RMF	0.9934	0.9826	0.9406	0.8437	0.6849	0.4883	0.305	0.1586	0.0642
PSMF	0.9975	0.9928	0.9808	0.9563	0.8915	0.5	0.3287	0.1865	0.0836
FMF	0.999	0.9975	0.9952	0.9919	0.9864	0.977	0.962	0.9285	0.8529
WFMF	0.9955	0.9907	0.9854	0.9792	0.972	0.9637	0.9521	0.9317	0.8716

Table.4. RMSE Comparison Table of various filters for fingerprint image at different noise densities

Noise	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Noisy	43.66	61.6325	75.314	87.0368	97.4665	106.2	114.8	122.84	130.28
SMF	30.74	33.122	35.409	38.774	44.064	51.8	65.75	87.79	112.9
RMF	17.15	22.172	28.909	38.978	52.668	68.4	86.91	105.1	123.5
PSMF	14.85	19.468	23.73	30.527	40.796	68.3	86.37	103.5	121.2
FMF	7.141	11.438	15.778	20.346	25.553	31.2	36.95	43.93	51.69

WFMF	6.416	9.8505	13.149	16.759	20.496	25.1	30.28	36.35	42.83

Table.5. PSNR (in Decibels) Comparison Table of various filters for fingerprint image at different noise densities

Noise	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Noisy	15.33	12.3346	10.5933	9.3367	8.3537	7.605	6.9322	6.3441	5.8335
SMF	18.38	17.728	17.149	16.36	15.249	13.9	11.77	9.262	7.078
RMF	23.45	21.215	18.91	16.314	13.7	11.4	9.349	7.697	6.301
PSMF	24.7	22.344	20.625	18.437	15.919	11.4	9.403	7.833	6.46
FMF	31.06	26.964	24.17	21.961	19.982	18.2	16.78	15.28	13.86
WFMF	31.99	28.262	25.753	23.646	21.897	20.1	18.51	16.92	15.5

Table.6. QI Comparison Table of various filters for fingerprint image at different noise densities

Noise	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Noisy	0.701	0.5122	0.3802	0.2839	0.2071	0.154	0.1045	0.0649	0.0333
SMF	0.759	0.7276	0.6985	0.6527	0.5788	0.49	0.342	0.184	0.078
RMF	0.935	0.8936	0.8271	0.7158	0.5562	0.4	0.24	0.136	0.058
PSMF	0.952	0.9194	0.8834	0.8159	0.6997	0.42	0.268	0.161	0.072
FMF	0.99	0.9732	0.9486	0.9135	0.863	0.8	0.713	0.592	0.464
WFMF	0.992	0.9801	0.9641	0.9407	0.9098	0.86	0.797	0.699	0.576

Table.7. RMSE Comparison Table of various filters for medical image at different noise densities

Noise	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Noisy	49.8167	70.6097	85.6654	99.3721	111.3016	121.9402	131.7756	141.0683	149.4242
SMF	5.4349	6.6962	7.9336	9.9976	16.8679	31.7694	55.6585	87.7627	121.1248
RMF	4.059	8.7746	17.3907	29.9406	47.6717	69.2209	91.3103	116.3404	138.1215
PSMF	4.7298	7.155	9.4854	13.5874	20.8744	36.9722	91.848	114.7797	135.9117
FMF	1.8479	3.1804	4.9118	6.6929	8.9121	13.1081	17.7655	27.1078	39.0749
WFMF	1.3432	2.221	3.4652	4.5403	6.2076	9.6021	14.4793	23.5216	39.1917

Table.8. PSNR (in Decibels) Comparison Table of various filters for medical image at different noise densities

Noise	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Noisy	14.1833	11.1535	9.4747	8.1855	7.2008	6.4079	5.7341	5.1422	4.6424
SMF	33.427	31.6142	30.1414	28.1329	23.5896	18.0906	13.2202	9.2646	6.4661
RMF	35.9625	29.2663	23.3244	18.6056	14.5656	11.3261	8.9204	6.8162	5.3256
PSMF	34.6339	31.0386	28.5897	25.4681	21.7385	16.7733	8.8694	6.9335	5.4657
FMF	42.7975	38.0811	34.3059	31.6185	29.1312	25.78	23.1392	19.4689	16.2929
WFMF	45.5681	41.1999	37.3362	34.9891	32.2723	28.4835	24.9158	20.7015	16.2669

Table.9. QI Comparison Table of various filters for medical image at different noise densities

Noise	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Noisy	0.7022	0.5087	0.3789	0.2779	0.2012	0.1441	0.0979	0.0578	0.0268
SMF	0.9954	0.993	0.9902	0.9845	0.9567	0.8577	0.6455	0.3557	0.1452
RMF	0.9975	0.9882	0.9547	0.8745	0.7203	0.5178	0.3422	0.173	0.0699
PSMF	0.9966	0.9923	0.9865	0.9729	0.9382	0.8251	0.3482	0.1888	0.0804
FMF	0.9995	0.9984	0.9963	0.9931	0.9878	0.9737	0.9516	0.8858	0.7598
WFMF	0.9997	0.9992	0.9981	0.9968	0.9939	0.9852	0.9654	0.902	0.6825

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