A New Adaptive Weighted Mean Filter for Removing Salt-and-Pepper Noise

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***Abstract*—In this letter, we propose a new adaptive weighted mean filter (AWMF) for detecting and removing high level of salt-and-pepper noise. For each pixel, we firstly determine the adaptive window size by continuously enlarging the window size until the maximum and minimum values of two successive windows are equal respectively. Then the current pixel is regarded as noise candidate if it is equal to the maximum or minimum values, otherwise, it is regarded as noise-free pixel. Finally, the noise candidate is replaced by the weighted mean of the current window, while the noise-free pixel is left unchanged. Experiments and comparisons demonstrate that our proposed filter has very low detection error rate and high restoration quality especially for high-level noise.**

***Index Terms*—Filter, noise detection, salt and pepper noise.**

I. Introduction

IMAGES are usually corrupted by impulse noise due to a wide variety of reasons, such as malfunctioning pixels in camera sensors or faulty memory locations in hardware, see [1] for instance. The impulse noise have two common types, which are salt-and-pepper noise (SPN) and random-valued noise. When images are corrupted by SPN, the noisy pixels take only the maximum value or the minimum value, contributing to white and black dots on images.

Many approaches have been proposed to restore images which are corrupted by SPN [1]–[12]. For example, the standard median filter (MF), previous most popular nonlinear filter, has been a hot spot for its good performance on noise reduction and computational efficiency [1]. MF works well for low level of SPN but not satisfactory for high level of SPN [10]. To remove high level of SPN, many approaches have been proposed based on median filter, which include the progressive switching median filter [2], the multi-state median filter [3], improved median filter [4], the noise adaptive soft-switching median filter [5], the adaptive median filter (AMF) [6], the fast and efficient median filter (FEMF) [7], the noise adaptive fuzzy switching median filter (NAFSMF) [8], the new filter proposed in [9] and so on. Among them, we focus on the last four filters and median filter for their efficiency. AMF chooses median in an adaptive window for each pixel which overcomes the drawback of fixed window size in MF, and is efficient for high level of SPN. FEMF uses prior information to get natural pixels for restoration. Without any iteration, it detects impulse noises intuitively, leaving the others unaltered. So it has very fast execution speed. The NAFSMF utilizes the histogram of the corrupted image to identify noise pixels and employs fuzzy reasoning to handle uncertainty present in the extracted local information as introduced by noise. In the new filter proposed in [9], the corrupted pixels are replaced by using a median filter or estimated by their neighbors' values.

In this letter, we propose a new method, adaptive weighted mean filter (AWMF), to remove SPN especially for high-level noise. For a given pixel, firstly, we enlarge its window size continuously until the maximum and minimum values of two successive windows are equal respectively. Secondly, the given pixel value will be replaced by the weighted mean of the current window if it equals the maximum or the minimum values, otherwise, it will be unchanged. Our experimental results show that AWMF has lower detection errors and better restoration image quality than many other existing filters. We remark that the idea of using weighted mean or truncated mean has been used to deal with other types of noise, see [13]–[16] for details.

The outline of this letter is as follows. The AMF filter is reviewed in Section II. Our proposed filter AWMF is presented in Section III. Experimental results and comparisons are presented in Section IV. Finally, we conclude the work in Section V.

II. Review of AMF

In this letter, we use x to represent the original clear image with size of $M \times N$. $x_{i,j}$ denotes the gray value of the pixel location (i,j) in image x, where $(i,j) \in A \equiv \{1,\ldots,M\} \times \{1,\ldots,N\}$. Denote by $[s_{min}, s_{max}]$ the dynamic range of the gray values in image x, then $s_{min} \le x_{i,j} \le s_{max}$. When the image x is corrupted by SPN, values of the corrupted pixels will be replaced by s_{min} or s_{max}. So the pixel $y_{i,j}$ in corrupted image y is given by

$$y_{i,j} = \begin{cases} s_{min}, & with\,probability \quad p \\ s_{max}, & with\,probability \quad q \\ x_{i,j}, & with\,probability \quad 1-p-q \end{cases} \tag{1}$$

where $r = p + q$ defines the noise level. We set $p = q$ in this letter.

In the following, we give a brief review of AMF filter. Denote by $S_{i,j}(w)$ a $(2w+1) \times (2w+1)$ window centered at (i,j), i.e.,

$$S_{i,j}(w) = \{(k,l) : |k-i| \le w, |l-j| \le w, (k,l) \in A\} \tag{2}$$

We use symbols $S_{i,j}^{min}(w)$, $S_{i,j}^{med}(w)$ and $S_{i,j}^{max}(w)$ to represent the minimum, median and maximum values of the window $S_{i,j}(w)$ respectively. The AMF filter tries to detect the noisy

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0	68	255	0	0	70	255
0	255	255	255	255	255	0
0	255	68	67	67	255	0
255	0	255	**66**	78	255	70
255	0	255	255	255	255	255
0	255	0	255	0	0	0
0	78	0	0	255	255	255

Fig. 1. A window case (AMF outputs 78 and AWMF outputs 66 for center pixel).

pixels and then replaces them with the median values of the adaptive windows, leaving noise-free pixels unaltered. Denote by z the restored image. And the algorithm of AMF is as below, referring to [10].

Algorithm 1 AMF

For each pixel $(i, j) \in A$ of noisy image y and restored image z, do
1) Initialize $w = 1, h = 1, w_{max} = 39$.
2) Compute $S_{i,j}^{min}(w), S_{i,j}^{med}(w)$, and $S_{i,j}^{max}(w)$.
3) If $S_{i,j}^{min}(w) < S_{i,j}^{med}(w) < S_{i,j}^{max}(w)$, go to step 5); Otherwise, $w = w + h$.
4) If $w \leq w_{max}$, go to step 2); Otherwise $z_{i,j} = S_{i,j}^{med}(w_{max})$, and stop.
5) If $S_{i,j}^{min}(w) < y_{i,j} < S_{i,j}^{max}(w)$, (i, j) is uncorrupted, $z_{i,j} = y_{i,j}$; Otherwise $z_{i,j} = S_{i,j}^{med}(w)$, and stop.

Generally speaking, AMF works well for SPN removal even at a high noise level. However, there are two drawbacks. The first one is that AMF may cause error in noise detection. For example, if the center pixel value equals to the local maximum (or minimum) value of its window but not salt or pepper noise, it would still be regarded as noise candidate by 5) in Algorithm I, leading to detection error. Fig. 1 shows an example. For the center pixel with value 66, the minimum, median and maximum values are 66,78, 255 respectively in its 3×3 window. Hence the center pixel 66 would be regarded as noise candidate and then replaced by median value 78 of its 3×3 window which leads to detection error and distortion. Another drawback of AMF is that for very high level of noise, the recovered image may lose many details and edges information. To overcome these drawbacks of AMF filter and enhance the image restoration quality, we propose an adaptive weighted mean filter (AWMF) in the following section.

III. Our Method AWMF

To enhance the performance of denoising, based on the working mechanism of AMF filter, the main idea of AWMF is to decrease the detection errors and to replace the noise candidates by better value than median.

Firstly, we introduce a new symbol $S_{i,j}^{mean}(w)$–the weighted mean value of the chosen window $S_{i,j}(w)$–defined as

$$S_{i,j}^{mean}(w) = \begin{cases} \dfrac{\sum\limits_{(k,l)\in S_{i,j}(w)} a_{k,l} * y_{k,l}}{\sum\limits_{(k,l)\in S_{i,j}(w)} a_{k,l}}, & \sum\limits_{(k,l)\in S_{i,j}(w)} a_{k,l} \neq 0 \\ -1, & otherwise \end{cases} \tag{3}$$

and the weight $a_{k,l}$ is set as

$$a_{k,l} = \begin{cases} 1, & S_{i,j}^{min}(w) < y_{k,l} < S_{i,j}^{max}(w) \\ 0. & otherwise \end{cases} \tag{4}$$

Then we can give algorithm of the proposed filter in the following.

Algorithm 2 AWMF

For each pixel $(i, j) \in A$ in noisy image y and restored image z, do
1) Initialize $w = 1, h = 1, w_{max} = 39$.
2) Compute $S_{i,j}^{min}(w), S_{i,j}^{max}(w), S_{i,j}^{mean}(w), S_{i,j}^{min}(w + h)$ and $S_{i,j}^{max}(w + h)$.
3) If $S_{i,j}^{min}(w) = S_{i,j}^{min}(w + h), S_{i,j}^{max}(w) = S_{i,j}^{max}(w + h)$ and $S_{i,j}^{mean}(w) \neq -1$, go to step 5); Otherwise, $w = w + h$.
4) If $w \leq w_{max}$, go to step 2); Otherwise, $z_{i,j} = S_{i,j}^{mean}(w)$, and stop.
5) If $S_{i,j}^{min}(w) < y_{i,j} < S_{i,j}^{max}(w)$, (i, j) is noise-free, $z_{i,j} = y_{i,j}$; Otherwise, (i, j) is noise candidate, $z_{i,j} = S_{i,j}^{mean}(w)$, and stop.

Let us give some detailed explanation of algorithm II. For each pixel, we firstly determine the adaptive window size by continuously enlarging the window sizes until the maximum and minimum values of two successive windows are equal respectively. Then the center pixel is regarded as noise candidate if it is equal to the maximum or the minimum values, otherwise, it is regarded as noise-free pixel. By this way, the detection error can be largely decreased especially for very high noise levels. For example, in Fig. 1, for the center pixel 66, the adaptive window size should be 5 since the maximum ($= 255$) and minimum ($= 0$) values are equal respectively of the successive 5×5 and 7×7 windows. Since 66 is not equal to 255 or 0, it would be regarded as noise-free pixel. Hence, for this pixel, the detection of AWMF is right while that of AMF is wrong.

After noise detection, in AWMF method, the noise candidate is replaced by the weighted mean value of the current window while the noise-free pixel is left unchanged. The weighted mean in AWMF is a better choice than the median in AMF to replace the noisy candidate especially for high levels of noise. There are two reasons for us to choose weighted mean. Firstly, the weighted mean in AWMF excludes the influence of possible noisy pixels while in AMF the output median includes the effect of them. Secondly, we have performed experimental comparisons between weight mean and weighted median under the same conditions in Algorithm 2. The comparisons show that the PSNR of image, in which noise candidates are replaced by weighted mean values, is higher than that of weighted median values on average.

We compare the adaptive window sizes of AMF and AWMF for 'Lena' image with 90% SPN. From Fig. 2 we find that the percentage of pixels with adaptive window radius $w \leq 2$ is over 90% in AWMF, while in AMF the percentage is less than 50%. Meanwhile, the maximum window radius for all the pixels in AWMF is 5 and in AMF it is 20. This illustrates why our algorithm is faster than AMF when noise level is very high.

We remark that in step 3) of Algorithm 2, $S_{i,j}^{mean}(w) = -1$ is a flag which means there is no pixel in $S_{i,j}(w)$ is noise-free and w is not the desired window radius, so we choose to enlarge the window radius in this case in order to get a meaningful weighted mean.

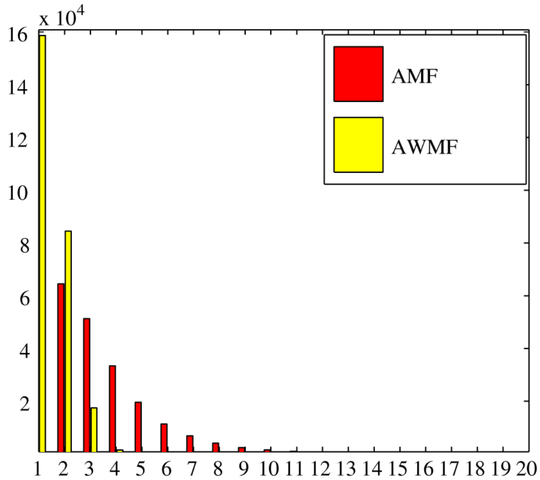

Fig. 2. Comparison of the adaptive window radiuses of AMF and AWMF for 'Lena' image with 90% SPN.

IV. Experimental Results

In our experimental tests, we use six different methods to restore images which have different levels of SPN. The tested images are typical, such as 'Lena', 'Camera', 'Gold Hill' and 'Bridge' (referring to [17]) with size 512×512. The proposed AWMF filter is compared with five representative methods include MF, AMF, NAFSMF, FEMF, and the method in [9].

We use signal-to-noise ratio (PSNR) and detection error rate to evaluate the performance of different methods. Assume that x is the clean image and z is the restored image. M, N denotes the columns and rows of the image. Then PSNR is defined as

$$PSNR = 10log_{10}\frac{255^2}{MSE} \tag{5}$$

$$MSE = \frac{1}{MN}\sum_{i,j}(x_{i,j} - z_{i,j})^2 \tag{6}$$

The detection error rate is defined as

$$Error\ Rate = \frac{\#(C)}{MN} \times 100\% \tag{7}$$

$$C = \{(i,j) \in A : (x_{i,j} \neq z_{i,j})\} \tag{8}$$

where $\#(C)$ represents for the element number of set C.

Parameters of the compared methods are set as below. In method MF, window size $w = 6$. In method AMF, initialization $w = 1$, $h = 1$, $w_{max} = 39$. In method NAFSMF, the maximum of window size $w_{max} = 3$, lower bound $T_1 = 10$, upper bound $T_2 = 30$. In method FEMF, $w_{max} = 40$. In our method AWMF, we set $w = 1$, $h = 1$, $w_{max} = 39$. We remark that for the other five methods except AWMF we either use the recommended parameters as in the original papers or tune the parameters to obtain the optimal results. All the experiments are performed under Windows 7 and MATLAB R2012a with Intel Core i5-3470 CPU@3.20 GHz and 4 GB memory. The programming language is MATLAB.

In Fig. 3, we test 'Lena' image which is corrupted by 90% SPN noise in Fig. 3(a). Fig. 3(b)–(h) show the restoration results by different filters. There exist many patches of noisy pixels which were undetected and unrestored in Fig. 3(b) by MF. From Fig. 3(c) by AMF, we see that edges were made fuzzy and some details were made crude heavily. Some subtle noisy dots are distributed faintly in Fig. 3(d) by NAFSMF. The image quality of

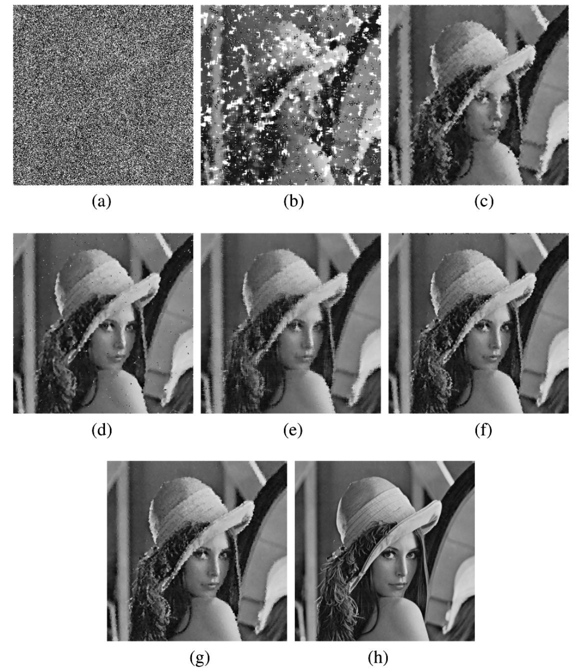

Fig. 3. Restoration results of different median-based filters (a) Noisy(5.61 dB) (b) MF(11.26 dB) (c) AMF(20.74 dB) (d) NAFSMF(22.72 dB) (e) FEMF(21.54 dB) (f) [9](24.50 dB) (g) AWMF(25.04 dB) (h) Clean image 'Lena'.

TABLE I
Results of PSNR(dB) for Different Filters Dealing With Different Noise Levels

Image	Filters	20%	30%	40%	50%	60%	70%	80%	90%	Average
Lena	MF	24.91	24.80	24.65	24.37	23.97	23.10	20.01	11.26	22.13
	AMF	34.62	32.48	30.68	28.89	27.25	25.50	23.49	20.74	27.96
	NAFSMF	34.51	32.50	31.05	29.87	28.75	27.58	26.08	22.72	29.13
	FEMF	31.58	30.72	29.87	28.88	29.72	28.61	27.16	21.54	28.51
	[9]	32.97	32.42	31.80	30.98	29.98	28.76	27.21	24.50	29.83
	AWMF	**36.30**	**35.06**	**33.86**	**32.62**	**31.17**	**29.50**	**27.67**	**25.04**	**31.40**
Cameraman	MF	20.46	20.36	20.21	20.02	19.73	19.18	17.56	11.32	18.61
	AMF	28.80	27.07	25.21	23.94	22.60	21.30	19.62	17.53	23.26
	NAFSMF	29.13	27.33	25.88	24.81	23.88	22.88	21.73	19.76	24.42
	FEMF	25.89	25.15	24.34	23.61	24.02	23.25	22.26	18.46	23.37
	[9]	26.07	25.86	25.40	24.83	24.22	23.30	22.23	20.17	24.01
	AWMF	**30.54**	**29.07**	**27.83**	**26.70**	**25.56**	**24.23**	**22.73**	**20.73**	**25.92**
Gold Hill	MF	22.18	22.15	22.05	21.93	21.73	21.36	19.48	11.71	20.32
	AMF	29.83	28.36	27.02	25.67	24.39	23.16	21.64	19.72	24.97
	NAFSMF	31.35	29.49	28.15	27.01	26.08	25.12	23.97	21.74	26.61
	FEMF	27.15	26.60	25.98	26.19	25.64	25.00	24.06	20.98	25.20
	[9]	27.74	27.58	27.09	26.54	25.90	25.03	24.01	21.86	25.72
	AWMF	**32.47**	**30.94**	**29.60**	**28.34**	**27.17**	**25.97**	**24.57**	**22.85**	**27.74**
Bridge	MF	20.56	20.44	20.27	20.07	19.80	19.35	17.66	11.27	18.68
	AMF	28.45	27.00	25.60	24.24	22.93	21.56	20.00	18.05	23.48
	NAFSMF	29.14	27.43	26.14	25.00	24.04	23.10	21.95	19.86	24.58
	FEMF	25.55	24.99	24.38	24.67	24.05	23.31	22.28	18.91	23.52
	[9]	26.20	25.91	25.48	24.92	24.25	23.39	22.24	20.42	24.10
	AWMF	**30.47**	**29.15**	**27.93**	**26.69**	**25.49**	**24.20**	**22.74**	**20.90**	**25.95**

Fig. 3(e), Fig. 3(g) and Fig. 3(h) are better than the previous, but in Fig. 3(e) most of details are blurred, leading its PSNR as low as 21.50 dB. Fig. 3(g) and Fig. 3(h) seem quite similar, however, the PSNR of Fig. 3(h) by our AWMF is about 0.54 dB higher than Fig. 3(g) by method proposed in [9]. Therefore, we could conclude that our method AWMF is effective in edge preserving and smoothing.

Table I shows the PSNR values for different levels of SPN and different images. We can easily get that PSNR of MF is the lowest. From data of image 'Lena', we find that PSNR values of AMF are greater than FEMF when noise levels are less than 50%, and otherwise they are opposite. Similar conditions occur in NAFSMF and method proposed in [9]. The average PSNR

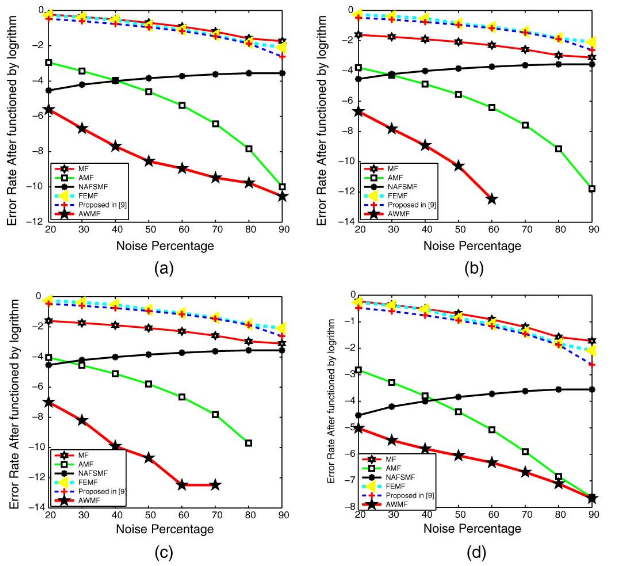

Fig. 4. Error rate curve after logarithm operation for filters for different images (a) 'Lena' (b) 'Cameraman' (c) 'Gold Hill' (d) 'Bridge'.

of AWMF is 31.4018 dB, and that of method proposed in [9] is 29.8285 dB. It demonstrates that our proposed AWMF performs better than other filters above mentioned, in particular, when restoring high levels of SPN.

Fig. 4 shows the error rate curves after logarithm operation for different levels of SPN. Here the error means that an original noisy pixel detected wrongly as noise-free and the opposite. From Fig. 4(a)–(d), we know that the errors of FEMF and method in [9] are very high, near to each other basically. The reason is that they detect noise candidates according to prior information on a natural image, intuitively regarding the maximum or minimum values as noise candidates. Only curves of NAFSMF take on ascending movements gradually. The errors of AWMF are always the lowest among all. The phenomenon that curves disappear when noise level greater than some percentage in Fig. 4(b)–(c) is because error rates, which is 0 originally, become infinity by logarithm operation. Namely, sometimes AWMF or AMF may detect all the noisy pixels if the parameters are set appropriately. Accordingly, AWMF is superior to other methods in detection accuracy clearly.

Table II states that computational time for different filters with different noise levels. Clearly, the average computational time of MF is the shortest, and method proposed in [9] is the longest. The proposed AWMF ranks in the middle but is superior than AMF. The computational time of AMF and NAFSMF increases with noise level. By contrast, the computational time of the other filters include the AWMF filter approximately keep steady for different levels of SPN.

V. Conclusion

In this letter, we have proposed an improved method based on AMF that can perform better in restoring image corrupted by high levels of SPN. It has much higher detection accuracy than AMF especially for high-level SPN. The computational time is similar for each level of SPN. Experimental tests show that our proposed AWMF method could perform better than many other existing filters.

TABLE II
Results of Computational Time for Different Filters Dealing With Different Noise Levels. Unit(secs)

Image	Filters	20%	30%	40%	50%	60%	70%	80%	90%	Average
Lena	MF	3.5880	3.5724	3.4788	3.4632	3.4008	3.3696	3.2760	3.1512	3.4125
	AMF	6.0684	5.8344	5.9748	6.3492	7.1292	8.2837	10.7485	17.7217	8.5138
	NAFSMF	2.6520	3.8220	5.0700	6.2556	7.3944	8.6893	9.8125	10.7797	6.8094
	FEMF	4.6020	4.4928	4.5240	4.5864	4.7268	4.7424	4.7268	6.2712	4.8341
	[9]	11.4973	12.0433	12.2461	12.0745	11.4037	11.3257	11.2321	11.1229	11.6182
	AWMF	7.5036	6.6612	6.4428	6.4428	6.4584	6.6300	6.8016	7.5192	6.8075
Cameraman	MF	0.9516	0.9048	0.8892	0.8736	0.8736	0.8424	0.8268	0.7956	0.8697
	AMF	1.8720	1.4976	1.4976	1.6224	1.7472	2.0592	2.6832	4.5396	2.1899
	NAFSMF	0.7332	0.98281	1.3104	1.5912	1.9032	2.184	2.4492	2.7768	1.7414
	FEMF	1.1544	1.1076	1.092	1.1076	1.1700	1.1700	1.2168	1.6068	1.2032
	[9]	2.886	2.9484	3.0576	2.9796	2.9952	2.9484	2.9328	2.9172	2.9582
	AWMF	1.9812	1.7160	1.6536	1.5912	1.5912	1.6380	1.6380	1.8876	1.7121
Gold Hill	MF	0.9204	0.9048	0.8892	0.8892	0.8892	0.8268	0.8112	0.7956	0.8658
	AMF	1.4352	1.4508	1.5600	1.5756	1.7628	2.0748	2.6832	4.3680	2.1138
	NAFSMF	0.6552	0.9672	1.2636	1.5600	1.8252	2.1372	2.4024	2.6832	1.6868
	FEMF	1.1232	1.1544	1.1076	1.1700	1.1700	1.1544	1.1544	1.5756	1.2012
	[9]	2.9328	2.9484	3.0420	3.0108	2.9796	2.9796	2.9796	2.9640	2.9796
	AWMF	1.8408	1.7004	1.7160	1.6068	1.6380	1.5756	1.6224	1.8408	1.6926
Bridge	MF	3.7284	3.6036	3.6036	3.4632	3.4320	3.3540	3.2604	3.2916	3.4671
	AMF	5.9436	6.0528	6.2244	6.5832	7.2696	8.5333	10.9513	17.9869	8.6932
	NAFSMF	2.6832	3.8220	5.0700	6.2088	7.3788	8.5333	9.6721	10.9981	6.7958
	FEMF	4.4772	4.4304	4.3992	4.5864	4.5708	4.6332	4.6800	6.3960	4.7717
	[9]	11.1073	11.3881	11.4037	11.6065	11.5441	11.3569	11.3257	11.2945	11.3783
	AWMF	7.4568	6.7860	6.5052	6.3336	6.2868	6.3024	6.5676	7.3788	6.7022

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