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Application of FFDNET for Image Denoising On Microarray Images

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Abstract*: Microarray technology allows the simultaneous profiling of thousands of genes. Denoising is an important pre-processing step in microarray image analysis for accurate gene expression profiling. In this paper, as FFDNet provides model independent denoising technique, it is been applied on microarray images. FFDNet is validated on AWGN based images and real noisy images trained network. The application is compared with the standard denoising methods. The results revealed that optimal sigma value to efficiently remove noise while preserving details for AWGN based images and real noisy trained methods were 15 and 20 respectively. Overall, the performance of the FFDNet is better compared to other metrics considered in the study as it is flexible, effective and fast. It is also capable to maintain the trade-off between denoising and feature preservation.

Keywords : **Microaray, Denoising, FFDNET, AWGN, Sigma Value, Performance metrics..**

I. INTRODUCTION

The Microarray technology can be visualized as a tool that opens the cell content, extracting its genetic content, identifying the genes that are activated and capable of generating those genes for purpose of analysis and reporting [1]. Microarray provides the multiple-gene expression simultaneously. Microarray finds its applications in the field of antibiotic treatment, in early cancer detection, early detection of oral lesions [2]. Typical microarray procedure for preparing a microarray slide involves sample preparation, labeling, hybridization, washing, image acquisition, and data analysis. After image acquisition, they are preprocessed before the data analysis. The preprocessing pipeline of microarray images typically includes gridding and spot-fixing, segmentation and intensity extraction [3]. Since the advent of microarray, noise has been an inherent part of microarray images. Typically, major noise in the microarray images is due to the optical procedures involved in the preparation of the sample slides and the complex biochemical reaction-taking place during acquisition [4]. The noise in the images makes it tedious for decision making during the data analysis. As based on the data analysis most of the decisions for respective applications are made. This makes denoising of the microarray images as one of the critical parts of the preprocessing pipeline. Two well established models in microarray denoising are transform domain approach and spatial filtering. Recent trends have shown significant development in the field of machine learning/deep learning [5] based methods that are mainly of two kinds, supervised learning methods and unsupervised learning methods. The main advantage of these methods lies in the learning feature that they have incorporated. Based on the extent of training using the existing data determine the performance of the supervised learning algorithm and the extent of learning based on the data acquired for a particular application determine the efficiency of the unsupervised learning algorithm. Numerous researchers have contributed to the field of denoising of microarray images. Some of the noted contributions are mentioned to provide a wide range of methods developed in this field. In order to remove the random noise in the images, a stationary wavelet-based method was developed[6]. Utilizing optimize spatial resolution (OSR) and spatial domain filtering (SDF) denoising of microarray images was performed[7]. A framework was developed in order to remove both additive and multiplicative noise in the images as proposed in [8]. Fuzzy filtering based method for denoising of microarray-based images was developed [9]. Utilizing a peer group concept a switching scheme based on the impulse detection mechanism was developed [10]. Coefficients of subbands in the wavelet domain were employed for smoothening the noise levels was developed in [11]. FFDNet is a recent technique based on the neural network based method[12]. The main advantages of FFDnet are it is a fast and flexible denoising neural network. FFDNet is capable of dealing with the noise spatially variant noise and noise of different levels. In order to maintain the trade-off between the noise reduction and detail prevention noise level maps are provided. FFDNet exhibit potentially appealing results on both synthetic noise and real-world noise. The features exhibited are not present in various methods mentioned in the above paragraph.

II. MATERIALS AND METHOD

FFDNet provides various variants of noise models. Two types of models explored for microarray images utilizing the FFDNet: Additive White Gaussian Noise (AWGN) based model and real images based model.

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The network employed for denoising of the microarray-based images is shown in figure 1. The noisy image y is downsampled into four sub-images. The sub-images are concatenated with the noise level map M to form a tensor of $\tilde{y}$ size

$$\frac{W}{2} \times \frac{H}{2} \times (4C+1)$$

The tensor $\tilde{y}$ is passed as input to the convolution neural network (CNN) having 3×3convolutional layers. Each layer consists of three kinds of operations: convolution (conv), Rectified Linear Units (ReLU) [13] and Batch Normalization (BN)[14] as depicted in figure 1. Conv+ReLU is performed in the first layer, the middle layer follows Conv+BN+ReLU and the last layer performs Conv. In order to maintain feature maps unchanged for each convolution layer, zero-padding is employed. Upsampling operation is performed after the last layer to obtain a clean image x of size$W \times H \times C$.

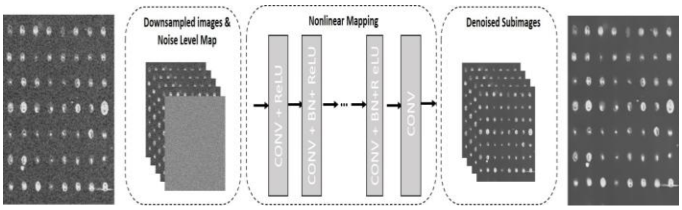

Fig. 1. The netwok architecture of FFDNET technique

In-order to maintain the complexity and performance the number of layers was empirically set as 15 and channels of feature maps as 64. The standard microarray images were acquired from TBDB microarray database .The network was trained on 400 BSD images, 400 images selected from ImageNet [15], and the 4,744 images from the Waterloo Exploration Database [16]. Images were randomly cropped 128×8000 patches from these images for training. The training was carried out from a noise range of (0, 75).

A. AWGN BASED METHOD

In this subsection, we test FFDNet on synthetic microarray images corrupted by spatially invariant AWGN. For grayscale image denoising, we mainly compare FFDNet with state-of-the-art methods AF [17], SSWF [18], STWF [19], SUSAN [20], and FFDNet [12]. Note that AF, SSWF, STWF, SUSAN are representative model-based methods based on nonlocal self-similarity prior, whereas FFDNet is discriminative learning based methods. The noise level was varied from 0 to 50 in incremental steps of 5. The analysis between the noisy and denoised images was carried out with six metrics: MSE, PSNR, SSIM, WSNR, MAE, and VIF.

B.EAL NOISY IMAGES

The FFDNet is tested for microarray images based on the training obtained from real-world images. The sigma value was varied from 0 - 50 in steps of 5. The training of the network was carried out using the standard dataset [15, 16] The post-processing of the images included the image analysis step in order to obtain the optimal sigma value tailored to the microarray application. Similar to the AWGN based study six analysis metric MSE, PSNR, SSIM, WSNR, MAE and VIF were utilized.

III. RESULTS

AWGN based denoising output images are depicted in figure 2. The noise level map utilized range from (0-50). The noisy images and corresponding denoised images are paneled in figure 2. Visual validation in figure 2 shows that the optimal value for maintaining the image details and the denoising is 15. Figure 3 depicts the denoised images with varied noise level maps. Qualitative validation reveals that the optimal sigma value in the case of real images based training is 20. In the metric table in figure 4 corresponding to AWGN based study, it can be observed that in the initial stage of the noise MSE and MAE is very low (below 15) compared to other methods. It reveals that the applied method is capable of handling noise at low levels. PSNR at low levels has higher values; the values take larger steps to get lower values till sigma 15. Post sigma 15 PSNR stabilizes and goes on reducing at a constant rate. SSIM and VIF in the initial noise level have high values and go on reducing as the noise level increases. It can be observed that even in these two cases the values start stabilizing after noise level 15. WSNR has higher values compared to other methods, this might be due to the measurement is made in the spatial domain. An overall observation that might be understood from the above analysis is that till noise level 15 FFDNet optimally reduces the noise. The obtained values can be set as the optimal value for denoising images using FFDNet in microarray applications.

Real noise analysis is as shown in figure 5 MSE and MAE the values goes on increasing as the sigma value increases. The stabilization of the values is attained after the sigma value 20. PSNR for FFDNet has higher values compared to other methods and goes on reducing as the noise level increases. Compared to other methods the PSNR is higher for the applied method. SSIM and VIF have higher values than filtering based methods. Both the values go on reducing as the sigma value increases; it attains stability only after sigma value 20. In the case of WSNR also goes on reducing and get stability after the sigma value 20. A general observation reveals that the sigma value in case of real-world based trained network method for denoising can be set as 20 for the microarray application

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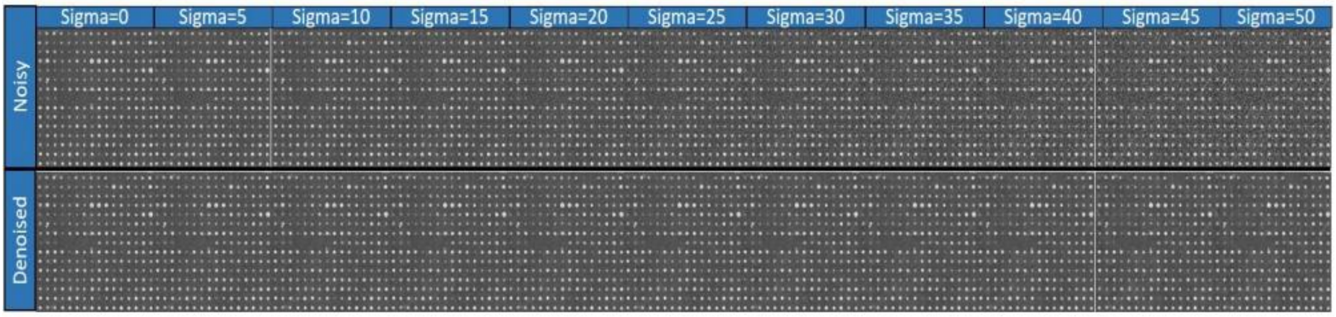

Figure 2: The figure depicts the variation in the denosing using FFDNet. The first row shows the noisy images and the second rows the corresponding denoised images for various sigma levels.

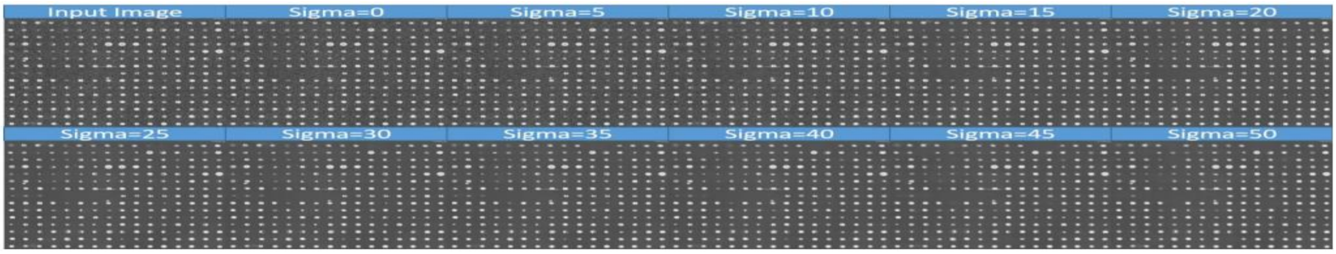

Figure 3: The figure depicts the variation in denosing using FFDNet. The image depicts the original input image and corresponding denoised images for various sigma value.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE
													Demo_AWGN_Gray																	
	Averaging Filter						Sureshrink Wavelet Filter						Soft Thresholding wavelet filter						SUSAN Filter						FFDNet					
	MSE	PSNR	SSIM	WSNR	MAE	VIF	MSE	PSNR	SSIM	WSNR	MAE	VIF	MSE	PSNR	SSIM	WSNR	MAE	VIF	MSE	PSNR	SSIM	WSNR	MAE	VIF	MSE	PSNR	SSIM	WSNR	MAE	VIF
0	303.465	23.3097	0.47891	327.209	13.6709	0.48791	181.473	25.5427	0.58308	329.779	11.0332	0.51893	7050.19	9.6488	0.13723	310.546	82.9405	0.41259	272.347	23.7796	0.49372	327.886	13.1238	0.51739	0.77079	49.2614	0.99907	352.702	0.59779	0.99359
5	306.089	23.2723	0.47706	327.164	13.7309	0.46026	192.214	25.2929	0.56871	329.509	11.3395	0.47602	7021.52	9.66649	0.13957	310.564	82.7365	0.40621	274.656	23.7429	0.49261	327.84	13.1726	0.48608	24.222	34.2887	0.96433	338.112	3.91427	0.75701
10	314.277	23.1577	0.47122	327.038	13.9116	0.40876	216.51	24.776	0.54236	328.95	11.9794	0.4097	6918.56	9.73065	0.14787	310.628	82.0336	0.39278	281.773	23.6318	0.48901	327.711	13.329	0.42948	78.1397	29.2021	0.87585	333.096	7.05232	0.55802
15	328.05	22.9714	0.46183	326.838	14.2059	0.35866	243.662	24.2629	0.52001	328.385	12.6244	0.35316	6780.43	9.81823	0.15834	310.715	81.0155	0.36819	293.601	23.4532	0.48337	327.508	13.5829	0.37526	135.42	26.814	0.76656	330.806	9.33513	0.45361
20	347.29	22.7239	0.44962	326.576	14.6158	0.31537	276.804	23.7091	0.49237	327.779	13.3601	0.30485	6628.26	9.91681	0.16817	310.814	79.776	0.33587	310.381	23.2119	0.47574	327.24	13.9442	0.32861	183.635	25.4912	0.65877	329.592	10.9544	0.39313
25	372.037	22.4249	0.4355	326.264	15.1355	0.27875	313.214	23.1724	0.46214	327.194	14.1129	0.26624	6475.65	10.018	0.1756	310.915	78.3829	0.30124	332.219	22.9166	0.46683	326.916	14.4134	0.2895	220.836	24.6901	0.57169	328.833	12.0664	0.35411
30	402.387	22.0844	0.41998	325.911	15.7568	0.24816	347.43	22.7221	0.4363	326.696	14.7784	0.235	6331.25	10.1159	0.1799	311.013	76.895	0.26822	359.585	22.5728	0.45662	326.545	14.9905	0.25658	250.157	24.1487	0.50654	328.313	12.8428	0.3259
35	438.324	21.7129	0.40348	325.531	16.4698	0.22238	377.649	22.3599	0.42114	326.292	15.3319	0.21089	6199.81	10.207	0.18123	311.105	75.3774	0.23863	392.768	22.1894	0.44562	326.138	15.6714	0.22903	273.421	23.7625	0.46434	327.935	13.3814	0.30408
40	479.689	21.3212	0.38696	325.131	17.2585	0.20066	404.537	22.0612	0.40921	325.952	15.7889	0.19271	6084.64	10.2885	0.18009	311.188	73.9144	0.21296	432.664	21.7693	0.4337	325.696	16.4569	0.20568	292.436	23.4705	0.43919	327.636	13.7629	0.28642
45	526.628	20.9158	0.37042	324.719	18.1131	0.18217	434.125	21.7547	0.39013	325.604	16.3023	0.17466	5987.59	10.3583	0.177	311.262	72.5759	0.19086	480.054	21.3179	0.42101	325.226	17.3487	0.18576	309.215	23.2282	0.42378	327.374	14.0607	0.27099
50	579.047	20.5037	0.3543	324.302	19.0222	0.16631	460.789	21.4958	0.37601	325.318	16.7643	0.16175	5910.18	10.4148	0.17256	311.327	71.4215	0.17188	536.327	20.8365	0.40728	324.728	18.3556	0.16864	324.94	23.0128	0.41293	327.126	14.3216	0.25735

Fig 4: The figure depicts the measured performance metrics for AWGN based approach

														Demo_Real_Gray																
	Averaging Filter						Sureshrink Wavelet Filter						Soft Thresholding wavelet filter						SUSAN Filter						FFDNet					
	MSE	PSNR	SSIM	WSNR	MAE	VIF	MSE	PSNR	SSIM	WSNR	MAE	VIF	MSE	PSNR	SSIM	WSNR	MAE	VIF	MSE	PSNR	SSIM	WSNR	MAE	VIF	MSE	PSNR	SSIM	WSNR	MAE	VIF
0	303.465	23.3097	0.47891	327.209	13.6709	0.48791	181.473	25.5427	0.58308	329.779	11.0332	0.51893	7050.19	9.6488	0.13723	310.546	82.9405	0.41259	272.347	23.7796	0.49372	327.886	13.1238	0.51739	0.77078	49.2615	0.9991	352.702	0.59777	0.99359
5	303.465	23.3097	0.47891	327.209	13.6709	0.48791	181.473	25.5427	0.58308	329.779	11.0332	0.51893	7050.19	9.6488	0.13723	310.546	82.9405	0.41259	272.347	23.7796	0.49372	327.886	13.1238	0.51739	3.74217	42.3996	0.9941	346.476	1.5066	0.97034
10	303.465	23.3097	0.47891	327.209	13.6709	0.48791	181.473	25.5427	0.58308	329.779	11.0332	0.51893	7050.19	9.6488	0.13723	310.546	82.9405	0.41259	272.347	23.7796	0.49372	327.886	13.1238	0.51739	45.9308	31.5098	0.9034	335.957	5.5223	0.7738
15	303.465	23.3097	0.47891	327.209	13.6709	0.48791	181.473	25.5427	0.58308	329.779	11.0332	0.51893	7050.19	9.6488	0.13723	310.546	82.9405	0.41259	272.347	23.7796	0.49372	327.886	13.1238	0.51739	207.44	24.9619	0.468	329.441	11.9359	0.4008
20	303.465	23.3097	0.47891	327.209	13.6709	0.48791	181.473	25.5427	0.58308	329.779	11.0332	0.51893	7050.19	9.6488	0.13723	310.546	82.9405	0.41259	272.347	23.7796	0.49372	327.886	13.1238	0.51739	243.704	24.2622	0.4192	328.733	12.9393	0.3474
25	303.465	23.3097	0.47891	327.209	13.6709	0.48791	181.473	25.5427	0.58308	329.779	11.0332	0.51893	7050.19	9.6488	0.13723	310.546	82.9405	0.41259	272.347	23.7796	0.49372	327.886	13.1238	0.51739	260.886	23.9663	0.4086	328.418	13.2995	0.3317
30	303.465	23.3097	0.47891	327.209	13.6709	0.48791	181.473	25.5427	0.58308	329.779	11.0332	0.51893	7050.19	9.6488	0.13723	310.546	82.9405	0.41259	272.347	23.7796	0.49372	327.886	13.1238	0.51739	274.229	23.7497	0.4016	328.187	13.5422	0.3198
35	303.465	23.3097	0.47891	327.209	13.6709	0.48791	181.473	25.5427	0.58308	329.779	11.0332	0.51893	7050.19	9.6488	0.13723	310.546	82.9405	0.41259	272.347	23.7796	0.49372	327.886	13.1238	0.51739	285.327	23.5774	0.396	328	13.729	0.3103
40	303.465	23.3097	0.47891	327.209	13.6709	0.48791	181.473	25.5427	0.58308	329.779	11.0332	0.51893	7050.19	9.6488	0.13723	310.546	82.9405	0.41259	272.347	23.7796	0.49372	327.886	13.1238	0.51739	295.311	23.428	0.3908	327.82	13.8896	0.3014
45	303.465	23.3097	0.47891	327.209	13.6709	0.48791	181.473	25.5427	0.58308	329.779	11.0332	0.51893	7050.19	9.6488	0.13723	310.546	82.9405	0.41259	272.347	23.7796	0.49372	327.886	13.1238	0.51739	305.735	23.2773	0.3852	327.615	14.0486	0.2919
50	303.465	23.3097	0.47891	327.209	13.6709	0.48791	181.473	25.5427	0.58308	329.779	11.0332	0.51893	7050.19	9.6488	0.13723	310.546	82.9405	0.41259	272.347	23.7796	0.49372	327.886	13.1238	0.51739	315.346	23.1429	0.3802	327.425	14.1927	0.2853

Fig 5: The figure depicts the measured performance metrics for real noisy based approach

IV. DISCUSSION AND CONCLUSION

has proven to be more efficient than the state of the art methods that are compared. The FEDNet has the ability to perform better and capable to learn the noise model to increase the image quality. AWGN based study is considered in the work as it is one of the standard models considered for generating noise in the image processing domain. The main challenge that remains in the domain of denoising is to maintain the tradeoff between noise reduction and details preservation. The result demonstrates that the details preservation and noise reduction is balanced by FFDnet compared to other methods compared in the article.Technical papers submitted for publication must advance the state of knowledge and must cite relevant prior

work. The applied technique of FFDNet on the microarray images has proven to be more efficient than the state of the art methods that are compared. The FEDNet has the ability to perform better and capable to learn the noise model to increase the image quality. AWGN based study is considered in the work as it is one of the standard models considered for generating noise in the image processing domain. The main challenge that remains in the domain of denoising is to maintain the tradeoff between noise reduction and details preservation. The result demonstrates that the details preservation and noise reduction is balanced by FFDnet compared to other methods
compared in the article.

In figure 2 it can be observed that as the noise level increases, in the initial stage the FFDNet is able to maintain the tradeoff between denoising and feature preservation. In contrary to the other methods that fail to achieve this tradeoff even in the initial stage of increasing noise level. In figure 3 The filters that are compared with the FFDNet are static in nature, they do not learn noise patterns from the data through training rather they depend on the model based denoising that might not be close to the real noise. The number of layers for the study and feature was set empirically as 15 and 64 as they gave optimal results based on the other values tried. As mentioned in the methods section only spatially invariant AWGN was carried out. The methods employed for comparison are not capable to handle variant AWGN. Comparison of FFDnet and other state-of-art methods would have resulted in unfair manner. It was observed in the study that the FFDNet based method performs better in the non-uniform noise level map rather than on the uniform map. This observation is in line with the original FFDNet based study [12]. In the case of uniform noise level map FFDNet based method tend to harm the details in the image and erase of the feature of the image.

In the case of real noisy images, FFDNet performs better as the metric table demonstrates in figure 5. It can be observed that the measured values for various noise levels remain the same and the noise levels vary in the case of FFDNet. This is due to the capability of FFDNet to take varying noise levels as input to perform better denoising. This feature does not exist in other filtering techniques that are considered in the study. Overall the performance of the FFDNet is better compared to other metric considered in the study as it is flexible, effective and fast. It is also capable to maintain the trade-off between denoising and feature preservation.

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