Denoising performance analysis of adaptive decision based inverse distance weighted interpolation (DBIDWI) algorithm for salt and pepper noise

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ABSTRACT

Due to its superior performance for denoising an image, which is contaminated by impulsive noise, an adaptive decision based inverse distance weighted interpolation (DBIDWI) algorithm is one of the most dominant and successful denoising algorithm, which is recently proposed in 2017, however this DBIDWI algorithm is not desired for denoising the full dynamic intensity range image, which is comprised of min or max intensity. Consequently, the research article aims to study the performance and its limitation of the DBIDWI algorithm when the DBIDWI algorithm is performed in both general images and the images, which are comprised of min or max intensity. In this simulation experiments, six noisy images (Lena, Mobile, Pepper, Pentagon, Girl and Resolution) under salt&pepper noise are used to evaluate the performance and its limitation of the DBIDWI algorithm in denoised image quality (PSNR) perspective.

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1. GENERAL OVERVIEW

In general, an impulsive noise is created in a digital image [1-3] because of camera sensor malfunction or communication fault therefore many denoising algorithms [4-24] have be invented for advance applications [25-28]. One of the most dominant and successful denoising algorithms is the standard median filter (SMF) [4-6], which is invented for denoising salt and pepper noise however its performance is limited because the SMF is processed all pixels (both noisy and noiseless). Later, the alternative denoising algorithms [7-24] based on detecting and denoising techniques are intensively invented for improving denoising performance. Recently, one of the most powerful and effective denoising algorithm is an adaptive decision based inverse distance weighted interpolation (DBIDWI) algorithm [29], which is proposed in 2017. Due to the constrain of its characteristic process, this denoising algorithm can be only performed on image, which is comprised of min or max intensity range thereby the research article aims to study the performance and its limitation of the DBIDWI algorithm.

The research article is aligned as follow: the general overview is offered in section 1 and the main concept of DBIDWI (Decision Based Inverse Distance Weighted Interpolation) is offered in section 2. Later, the comprehensive simulated consequence and its experimental outline are offered in section 3 and section 4, respectively.

2. THE MAIN CONCEPT OF DBIDWI (DECISION BASED INVERSE DISTANCE WEIGHTED INTERPOLATION)

The denosing algorithm based on DBIDWI algorithm [29] compounds of the detecting and denoising technique as offering in the following sub-section. Overall flowchart of denosing sub-process based on DBIDWI (Decision Based Inverse Distance Weighted Interpolation) as shown in Figure 1.

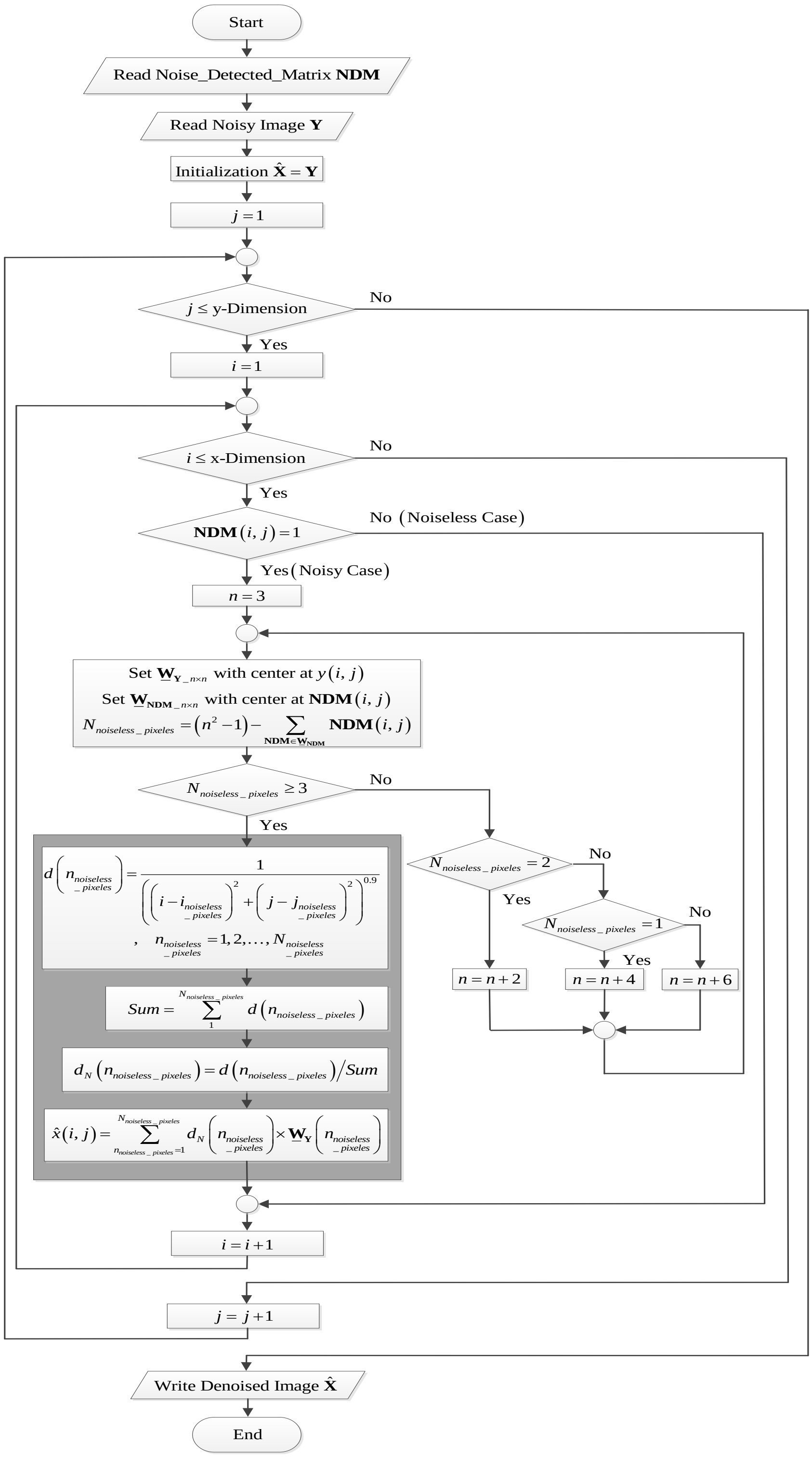

Figure 1. Overall flowchart of denosing sub-process based on DBIDWI (Decision Based Inverse Distance Weighted Interpolation)

2.1. Detecting Sub-Process of the DBIDWI Based Denoising Algorithm

At first, the detecting process of the DBIDWI based denosing algorithm simply checks every pixels and defined that pixel is noisy $\mathbf{NDM}(i,j)=1$ if the pixel intensity is min (0) or max (255) in dynamic range otherwise the pixel is noiseless $\mathbf{NDM}(i,j)=0$.

2.2. Denoising Sub-Process of the DBIDWI Based Denoising Algorithm

Step 1. The denosing sub-process filters only noisy pixels, which are classified from the previous detecting sub-process, by creating the calculated window $\underline{\mathbf{W}}_{\mathbf{Y}\_n\times n}$, which is initially set at 3×3 (or $n=3$) with center at noisy pixel $y(i,j)$ and, later, the noiseless pixels are counted in that window $\underline{\mathbf{W}}_{\mathbf{Y}\_n\times n}$. Support that noiseless pixels $N_{noiseless\_pixeles}$ are counted and less than 3 pixels (in order to prevent blur and unreliable case) therefore calculated window expands by 1 pixel (as shown in following figure) and the noiseless pixels are recounted in the expanded window $\underline{\mathbf{W}}_{\mathbf{Y}\_n\times n}$ again until there are more than 3 noiseless pixels in the expanded window.

Step 2. Support that there are more than 3 noiseless pixels in the expanded window therefore the inverse distance of noiseless pixels $d\left(n_{noiseless\_pixeles}\right)$ is computed as following equation:

$$d\left(n_{noiseless\_pixeles}\right)=\left(\left(i-i_{noiseless\_pixeles}\right)^2+\left(j-j_{noiseless\_pixeles}\right)^2\right)^{-0.9},n_{noiseless\_pixeles}=1,2,\ldots,N_{noiseless\_pixeles} \tag{1}$$

Step 3. The noisy pixel $y(i,j)$ are replacing denoised pixel $\hat{x}(i,j)$, which is computed as following equation:

$$\hat{x}(i,j)=\sum_{n_{noiseless\_pixeles}=1}^{N_{noiseless\_pixeles}} d_N\left(n_{noiseless\_pixeles}\right)\times\underline{\mathbf{W}}_{\mathbf{Y}}\left(n_{noiseless\_pixeles}\right) \tag{2}$$

Where,

$$d_N\left(n_{noiseless\_pixeles}\right)=d\left(n_{noiseless\_pixeles}\right)\Big/\sum_{1}^{N_{noiseless\_pixeles}} d\left(n_{noiseless\_pixeles}\right) \tag{3}$$

The overall flowchart of denosing sub-process based on DBIDWI (Decision Based Inverse Distance Weighted Interpolation) can be appeared as following figure.

3. COMPUTATIONAL EXAMPLES

3.1. EXAMPLE 1

Support that the the calculated window $\underline{\mathbf{W}}_{\mathbf{Y}\_n\times n}$ of the interested noisy pixel $y(i,j)$ can be formulated as following.

$y(i-1,j-1)=125$	$y(i,j-1)=131$	$y(i+1,j-1)=118$
$y(i-1,j)=0$	$y(i,j)=255$	$y(i+1,j)=0$
$y(i-1,j+1)=120$	$y(i,j+1)=0$	$y(i+1,j+1)=255$

and the noise detected matrix of the calculated window can be formulated as following.

$$\mathbf{NDM} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix}$$

Step 1. The denosing sub-process filters only noisy pixels, which are classified from the previous detecting sub-process, by creating the calculated window.

$$\underline{\mathbf{W}}_{\mathbf{Y}\_3\times 3} = \begin{bmatrix} 125 & 131 & 118 \\ 0 & 255 & 0 \\ 120 & 0 & 255 \end{bmatrix}$$

From noise detected matrix can $\mathbf{NDM}$, the noiseless pixels are counted in that window $\underline{\mathbf{W}}_{\mathbf{Y}\_n\times n}$ therefore $N_{noiseless\_pixeles} = 3$.

Step 2. Support that there are more than 3 noiseless pixels in the expanded window therefore the inverse distance of noiseless pixels $d\left(n_{noiseless\_pixeles}\right)$ is computed as following equation:

$$d\left(n_{\substack{noiseless\\\_pixeles}}\right) = \left(\left(i - i_{\substack{noiseless\\\_pixeles}}\right)^2 + \left(j - j_{\substack{noiseless\\\_pixeles}}\right)^2\right)^{-0.9}, n_{\substack{noiseless\\\_pixeles}} = 1, 2, \ldots, N_{\substack{noiseless\\\_pixeles}} \tag{4}$$

$$d = \begin{bmatrix} 0.5359 & 1 & 0.5359 \\ 1 & 0 & 1 \\ 0.5359 & 1 & 0.5359 \end{bmatrix} \rightarrow d\left(n_{\substack{noiseless\\\_pixeles}}\right) = \begin{bmatrix} 0.5359 & 0 & 0.5359 \\ 0 & 0 & 0 \\ 0.5359 & 0 & 0 \end{bmatrix}$$

Therefore,

$$d_N\left(n_{noiseless\_pixeles}\right) \times \underline{\mathbf{W}}_{\mathbf{Y}}\left(n_{noiseless\_pixeles}\right) = \begin{bmatrix} 125 & 131 & 118 \\ 0 & 255 & 0 \\ 120 & 0 & 255 \end{bmatrix} \cdot \begin{bmatrix} 0.5359 & 0 & 0.5359 \\ 0 & 0 & 0 \\ 0.5359 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 41.66 & 0 & 39.33 \\ 0 & 0 & 0 \\ 40 & 0 & 0 \end{bmatrix}$$

Step 3. The noisy pixel $y(i, j)$ are replaced by the denoised pixel $\hat{x}(i, j)$, which is computed as following equation:

$$\hat{x}(i, j) = \sum_{n_{noiseless\_pixeles}=1}^{N_{noiseless\_pixeles}} d_N\left(n_{noiseless\_pixeles}\right) \times \underline{\mathbf{W}}_{\mathbf{Y}}\left(n_{noiseless\_pixeles}\right) \tag{5}$$

$$\hat{x}(i, j) = (41.66 + 39.33 + 40) = 121$$

3.2. EXAMPLE 2

Support that the the calculated window $\underline{\mathbf{W}}_{\mathbf{Y}\_n\times n}$ of the interested noisy pixel $y(i, j)$ can be formulated as following.

$y(i-2, j-2) = 0$	$y(i-1, j-2) = 0$	$y(i, j-2) = 255$	$y(i+1, j-2) = 0$	$y(i+2, j-2) = 255$
$y(i-2, j-1) = 0$	$y(i-1, j-1) = 255$	$y(i, j-1) = 255$	$y(i+1, j-1) = 0$	$y(i+2, j-1) = 188$
$y(i-2, j) = 0$	$y(i-1, j) = 0$	$y(i, j) = 255$	$y(i+1, j) = 255$	$y(i+2, j) = 0$
$y(i-2, j+1) = 255$	$y(i-1, j+1) = 112$	$y(i, j+1) = 114$	$y(i+1, j+1) = 255$	$y(i+2, j+1) = 255$
$y(i-2, j+2) = 255$	$y(i-1, j+2) = 0$	$y(i, j+2) = 0$	$y(i+1, j+2) = 255$	$y(i+2, j+2) = 111$

and the noise detected matrix of the calculated window can be formulated as following.

$$\mathbf{NDM} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 0 \end{bmatrix}$$

Step 1. The denosing sub-process filters only noisy pixels, which are classified from the previous detecting sub-process, by creating the calculated window.

$$\underline{\mathbf{W}}_{\mathbf{Y}\_3\times 3} = \begin{bmatrix} 255 & 255 & 0 \\ 0 & 255 & 255 \\ 112 & 114 & 255 \end{bmatrix} \text{ and } \quad \mathbf{NDM} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}$$

From noise detected matrix can $\mathbf{NDM}$, the noiseless pixels are counted in that window $\underline{\mathbf{W}}_{\mathbf{Y}\_3\times 3}$ therefore $N_{noiseless\_pixeles} = 2$.

Support that noiseless pixels $N_{noiseless\_pixeles} = 2$ are counted and less than 3 pixels therefore calculated window expands by 1 pixel.

$$\underline{\mathbf{W}}_{\mathbf{Y}\_5\times 5} = \begin{bmatrix} 0 & 0 & 255 & 0 & 255 \\ 0 & 255 & 255 & 0 & 118 \\ 0 & 0 & 255 & 255 & 0 \\ 255 & 112 & 114 & 255 & 255 \\ 255 & 0 & 0 & 255 & 111 \end{bmatrix} \text{ and } \quad \mathbf{NDM} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 0 \end{bmatrix}$$

From noise detected matrix can $\mathbf{NDM}$, the noiseless pixels are counted in that window $\underline{\mathbf{W}}_{\mathbf{Y}\_5\times 5}$ therefore $N_{noiseless\_pixeles} = 4$.

Step 2. Support that there are more than 3 noiseless pixels in the expanded window therefore the inverse distance of noiseless pixels $d\left(n_{noiseless\_pixeles}\right)$ is computed as following equation:

$$d\left(n_{\substack{noiseless\\\_pixeles}}\right)=\left(\left(i-i_{\substack{noiseless\\\_pixeles}}\right)^2+\left(j-j_{\substack{noiseless\\\_pixeles}}\right)^2\right)^{-0.9},n_{\substack{noiseless\\\_pixeles}}=1,2,\ldots,N_{\substack{noiseless\\\_pixeles}} \tag{6}$$

$$d=\begin{bmatrix}0.1539 & 0.2349 & 0.2872 & 0.2349 & 0.1539\\ 0.2349 & 0.5359 & 1 & 0.5359 & 0.2349\\ 0.2872 & 1 & 0 & 1 & 0.2872\\ 0.2349 & 0.5359 & 1 & 0.5359 & 0.2349\\ 0.1539 & 0.2349 & 0.2872 & 0.2349 & 0.1539\end{bmatrix}$$

$$d\left(n_{\substack{noiseless\\\_pixeles}}\right)=\begin{bmatrix}0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0.2349\\ 0 & 0 & 0 & 0 & 0\\ 0 & 0.5359 & 1 & 0 & 0\\ 0 & 0 & 0 & 0 & 0.1539\end{bmatrix}$$

Therefore,

$$d_N\left(n_{noiseless\_pixeles}\right)\times\underline{\mathbf{W}}_{\mathbf{Y}}\left(n_{noiseless\_pixeles}\right)=\begin{bmatrix}0 & 0 & 255 & 0 & 255\\ 0 & 255 & 255 & 0 & 118\\ 0 & 0 & 255 & 255 & 0\\ 255 & 112 & 114 & 255 & 255\\ 255 & 0 & 0 & 255 & 111\end{bmatrix}\cdot\begin{bmatrix}0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0.2349\\ 0 & 0 & 0 & 0 & 0\\ 0 & 0.5359 & 1 & 0 & 0\\ 0 & 0 & 0 & 0 & 0.1539\end{bmatrix}$$

$$d_N\left(n_{noiseless\_pixeles}\right)\times\underline{\mathbf{W}}_{\mathbf{Y}}\left(n_{noiseless\_pixeles}\right)=\begin{bmatrix}0 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 14.40\\ 0 & 0 & 0 & 0 & 0\\ 0 & 31.18 & 59.23 & 0 & 0\\ 0 & 0 & 0 & 0 & 8.87\end{bmatrix}$$

Step 3. The noisy pixel $y(i,j)$ are replaced the denoised pixel $\hat{x}(i,j)$, which is computed as following equation:

$$\hat{x}(i,j)=\sum_{n_{noiseless\_pixeles}=1}^{N_{noiseless\_pixeles}} d_N\left(n_{noiseless\_pixeles}\right)\times\underline{\mathbf{W}}_{\mathbf{Y}}\left(n_{noiseless\_pixeles}\right)$$
$$\hat{x}(i,j)=\left(31.18+59.23+14.40+8.87\right)=113.69 \tag{7}$$

4. COMPREHENSIVE SIMULATED CONSEQUENCE

The numerical experiment is conducted by using MATLAB program on six simulated data, which are comprised of Lena (256x256), Pepper (256x256), Resolution (128x128), Girl-Tiffany (256x256), Baboon (256x256), House (128x128), used to evaluate the upper and lower range of DBIDWI performance. First, all original data are added by Salt and Pepper Noise from 5% to 90% for forming the noisy data. Later these noisy data are filtered to suppress Salt and Pepper Noise by DBIDWI algorithm. From the numerical consequences, the quality measurement (PSNR) of the denoised image by DBIDWI algorithm are indicated in Table 1 for Lena (256x256), Pepper (256x256), Resolution (128x128) and Table 2 for Girl-Tiffany (256x256), Baboon (256x256), House (128x128). The DBIDWI algorithms can improve the image quality in almost all simulated data, except for Resolution (128x128) because the Resolution image is comprised of max ("255") and min ("0") in intensity dynamic range.

5. CONCLUSION

This research article aims to exhaustively evaluate the upper and lower range of DBIDWI performance, one of the most dominant and successful denoising algorithm, which is recently proposed in 2017, under Salt and Pepper Noise at several density. Comprehensive simulated consequences conduct on six simulated data, which are comprised of Lena (256x256), Pepper (256x256), Resolution (128x128), Girl-Tiffany (256x256), Baboon (256x256), House (128x128). Due to the limitation of noise detection process of the DBIDWI algorithms, the DBIDWI algorithms has obviously improve the image quality

(PSNR) in almost all simulated data, except for Resolution (128x128) because the Resolution image is comprised of max and min in intensity dynamic range.

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The research project was funded by Assumption University. Comprehensive Simulated Consequence of Salt and Pepper Noise (Lena, Pepper, Resolution) as shown in Table 1 and Comprehensive Simulated Consequence of Salt and Pepper Noise (Girl, Babool, House) as shown in Table 2.

Table 1. Comprehensive Simulated Consequence of Salt and Pepper Noise (Lena, Pepper, Resolution)

SPN	PSNR (dB)			
Tested Images	Noise Density	Observed Image	Denoising Algorithm SMF	DBIDWI
	5	18.7139	31.6421	43.7281
	10	15.6564	30.7076	40.5308
	15	13.8274	29.2982	38.6418
	20	12.6389	27.6257	37.2258
	25	11.6783	25.4101	35.9382
	30	10.8971	23.6811	35.1593
	35	10.2240	20.8127	34.1656
	40	9.6481	19.0080	33.3373
Lena	45	9.0745	16.8389	32.7176
(256x256)	50	8.6553	15.4758	32.1273
	55	8.2118	13.8573	31.4207
	60	7.7813	12.3280	30.8325
	65	7.4884	11.3251	30.1591
	70	7.1697	10.2861	29.5147
	75	6.8497	9.1271	28.7243
	80	6.5846	8.3331	27.9712
	85	6.3241	7.5344	27.3899
	90	6.0604	6.8241	26.1503
	5	18.4752	32.2578	45.2269
	10	15.3798	30.6116	42.3736
	15	13.5570	28.8470	40.2444
	20	12.3593	26.5888	38.9573
	25	11.3929	24.2073	37.7392
	30	10.6242	22.0663	36.7617
	35	9.9742	20.3774	36.0150
	40	9.3998	18.4321	35.0674
Pepper	45	8.8599	16.6168	34.1463
(256x256)	50	8.3843	14.8506	33.3663
	55	7.9930	13.4655	32.8686
	60	7.6189	12.0128	32.1738
	65	7.2684	10.8920	31.5987
	70	6.9246	9.7704	30.7429
	75	6.6418	8.8751	29.8355
	80	6.3710	8.0166	29.0865
	85	6.1097	7.2402	28.0305
	90	5.8582	6.5767	27.0502
	5	16.1344	18.2861	8.6930
	10	13.4819	17.9425	8.5201
	15	11.4968	17.0880	8.4935
	20	10.1271	16.2124	8.3813
	25	9.2699	15.2214	8.2850
	30	8.4430	14.4548	8.1603
	35	7.9307	13.6304	8.2997
	40	7.3308	12.6223	7.7616
Resolution	45	6.6368	11.3597	8.0067
(128x128)	50	6.2938	10.4851	7.9123
	55	5.8134	9.4501	7.8132
	60	5.4436	8.5925	7.3368
	65	5.0770	7.6495	7.4990
	70	4.6795	6.6295	7.6584
	75	4.5178	6.3093	7.2709
	80	4.1940	5.3585	7.1479
	85	3.9342	4.7261	7.1875
	90	3.7113	4.2234	6.7209

Table 2. Comprehensive Simulated Consequence of Salt and Pepper Noise (Girl, Babool, House)

SPN	PSNR (dB)			
Tested Images	Noise Density	Observed Image	Denoising Algorithm SMF	DBIDWI
Girl (256x256)	5	16.4490	32.4867	39.3666
	10	13.6890	31.5583	38.4352
	15	11.9287	27.6179	37.2170
	20	10.6567	25.5153	36.5714
	25	9.5498	22.9614	35.6831
	30	8.8677	20.7738	35.3124
	35	8.0984	18.4410	34.2244
	40	7.5798	16.5146	33.9797
	45	7.0728	14.8145	33.5408
	50	6.5712	13.0319	32.5247
	55	6.2085	11.8226	32.2016
	60	5.8609	10.4981	31.7084
	65	5.4832	9.1396	30.9636
	70	5.1311	8.0463	30.4654
	75	4.8712	7.1994	29.8662
	80	4.5674	6.2520	29.0774
	85	4.3054	5.4218	28.0161
	90	4.0573	4.7465	27.2722
Baboon (256x256)	5	18.3478	23.9895	36.1359
	10	15.3487	23.6544	33.2575
	15	13.5147	23.2700	31.6498
	20	12.3118	22.4812	30.4077
	25	11.2475	21.5168	29.2422
	30	10.5359	20.3469	28.2835
	35	9.8452	19.0069	27.5608
	40	9.2209	17.3112	26.8943
	45	8.7539	16.0041	26.2777
	50	8.2874	14.4515	25.6545
	55	7.8818	12.9283	25.1386
	60	7.5157	11.8221	24.6837
	65	7.1699	10.6948	24.1713
	70	6.8384	9.7247	23.7276
	75	6.5529	8.7578	23.1560
	80	6.2716	7.9464	22.6997
	85	6.0284	7.2064	22.0527
	90	5.7656	6.5137	21.4337
House (128x128)	5	18.9718	30.1753	42.1753
	10	15.6476	29.0356	39.0690
	15	13.8890	27.4858	36.9181
	20	12.5750	26.0908	35.5357
	25	11.7097	23.5210	34.4250
	30	10.8407	21.0572	33.5938
	35	10.1419	19.3008	32.5539
	40	9.6803	18.2477	32.0582
	45	9.2177	16.8124	31.4105
	50	8.6874	15.0785	30.7397
	55	8.3115	13.4003	30.3604
	60	7.8884	12.1566	29.4279
	65	7.4948	10.9961	28.1472
	70	7.1918	9.9079	27.9033
	75	6.9228	9.0571	26.7577
	80	6.6590	8.3211	26.3853
	85	6.3607	7.4251	24.8536
	90	6.1513	6.8677	24.3930

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