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Bit Depth Expansion via Estimation of Bit Value Expectation

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Abstract

Bit-depth expansion is a method to increase the number of bit. It is getting important as the needs of HDR (High Dynamic Range) display or resolution of display have been increased because the level of luminance or expressiveness of color is proportional to the number of bit in the display. In this paper, we present effective bit-depth expansion algorithm for conventional standard 8 bit-depth content to display in high bit-depth device (10 bits). Proposed method shows better result comparing with recently developed methods in quantitative (PSNR) with low complexity.

1. Introduction

Bit-depth means the number of bits to be used for representing the intensity value. 8-bits are used for rendering current video or image contents with 256-level intensities. However, HDR display devices are appeared to provide high luminance for viewers. Those displays work on 10-bits. To render current contents, which are sometimes called 'legacy contents' and stored in 8-bits precision, in 10-bits HDR display, 8-bits contents have to have more 2-bits (see Figure 1). Bit-depth expansion is the process to add more bit-depth from low bit-depth (LBD) to high bit-depth (HBD). For example, when 6-bits DVD videos are displayed on 8-bit device or internal bit-depth increase (IDBI) scheme is used for standard video codec HEVC to improve the precision. Sometimes, original signal is truncated during the transmission so bit-depth expansion could be a useful solution to reconstruct truncated signal. [1-11]

However, unfortunately, bit-depth expansion is ill posed problem because generating n-more bits from insufficient information. In this paper, we formulate bit-depth expansion problem as MAP (Maximum a Posteriori) estimating process which estimates HBD data with LBD data and its neighborhood information. Proposed algorithm is efficient in computation and outperforms existing bit-depth expansion algorithms in quantitative measurement, numerically.

This paper is organized as flows. In section 2, we describe our bit-depth expansion problem. We briefly review the existing bit-depth algorithms in section 3. Section 4 explains the proposed algorithm. The experimental results for test images are presented in section 5 to show the effectiveness of proposed in section 5. Section 6 summarizes our work and provides further work.

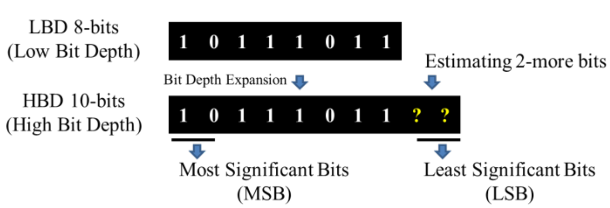

Figure 1. An example of bit-depth expansion from 8-bits to 10-bits

2. Problem Setup

We formulate the bit-depth expansion problem as estimating the least significant bit (LSB) values which have maximum probability given LBD in the equation 1. We define the LSB value, which we want to estimate for bit-depth expansion, to be $\mathrm{y}'_{\mathrm{LSB}}$ and LBD to be $\mathrm{x}_{\mathrm{LBD}}$ in the equation 1. The $\mathrm{N} \times \mathrm{N}$ neighborhood pixels are defined to be $\mathrm{x}^{\mathrm{N}}_{\mathrm{LBD}}$ also in the equation 1. The estimated LSB $\mathrm{y}'_{\mathrm{LSB}}$ is any integer between 0 and $2^{\mathrm{n}} - 1$, where n is the number of LSB. For example, when we expand 8-bits LBD contents to 10-bits HBD contents, n is 2 and C could be any integer between 0 and 3 which maximize the conditional probability in the equation 1.

$$y'_{LSB} = \arg max_{c=1}^{C} P(y = c | x_{LBD}, x^{N}_{LBD}) \qquad (1)$$

Finally, when LSB is estimated, HDB value, which is defined to be x'_{HBD}, is reconstructed by adding LSB to LBD value in the equation 2.

$$x'_{HBD} = 2^n \times x_{LBD} + y'_{LSB} \qquad (2)$$

3. Related Work

There are many previous methods to expand bit-depth [1-11]. The simplest method is 'Zero-Padding' (ZP) [2] which estimates $\mathrm{y}'_{\mathrm{LSB}}$ as 0 (see Figure 2). By shifting n-bits from LBD, ZP could be implemented very easily in the equation 3 and 4. ZP has small computational complexity for its advantage. However, it magnifies small noise to be big step error such as 'Contouring artifact'. Reconstructed HBD contents have steep change in the homogeneous regions and could not be the maximum value in HBD.

$$x'_{HBD} = 2^n \times x_{LBD} \qquad (3)$$

$$x'_{HBD} = x_{LBD} \ll n \qquad (4)$$

Figure 2. An example of Zero Padding (ZP) from 8-bits to 10-bits

To overcome the disadvantages of ZP, Bit-Replica (BR) [2] and Multiplication by an Ideal Gain (MIG) [2] methods are introduced. In BR, the high n-bits which are called 'MSB' are appeared in the LSB (see Figure 3). We define the number of HBD to be H and the number of LBD in the equation 5 and 6, so n = H - L. The equation 6 shows how to reconstruct HBD by BR.

$$x'_{HBD} = (x_{LBD} \gg n) + \{x_{LBD} \ll (L - n)\} \qquad (5)$$

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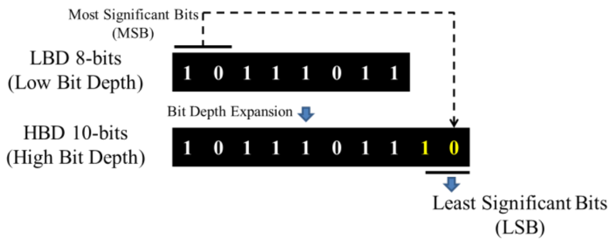

Figure 3. An example of Bit Replica (BR) from 8-bits to 10-bits

In MIG, reconstructed HBD is obtained by multiplying the maximum value's ratio, HBD ($2^H - 1$) over LBD ($2^L - 1$), to the LBD.

$$x'_{HBD} = \frac{2^H - 1}{2^L - 1} \times x_{LBD} \tag{6}$$

BR and ZP overcome ZP's problem, those methods don't consider neighborhood and estimate LSB values based on only LBD value, which can make the contour artifact also. To solve the contour artifact, Daly proposed the predictive de-contouring method with low-pass filter which is defined to be K_{LF} in the equation 7[1]. This method is based on ZP, but LSB values are updated based on the difference between low pass-filtered ZP and truncated and zero padded low-pass filtered ZP. The equation 7 shows Daly's method. This method considers not only certain pixel's LBD value but also its neighborhood values to reduce contour artifact.

$$x_{HBD}^{ZP} \triangleq 2^n \times x_{LBD}$$
$$\widetilde{x_{HBD}^{ZP}} \triangleq x_{HBD}^{ZP} * K_{LF}$$

$$x'_{HBD} = x_{HBD}^{ZP} + \{\widetilde{x_{HBD}^{ZP}} - \left(\widetilde{x_{HBD}^{ZP}} \gg (H-L)\right) \ll (H-L)\} \tag{7}$$

Chun proposed adaptive filter based 2-step bit-depth expansion approach [2] which is also based on ZP. 1st step is zero padding and 2nd step is adaptive filtering. In this method, every pixel is checked the possibility of low-pass filtering adaptively. A pixel, which has high variance with its neighborhood, is updated by low-pass filtering to remove contour.

Because all of those methods cannot remove contour completely, flooding based approach [8][9] is proposed as poster processing. This method checks contour-ness by scanning all the pixels after bit-depth expansion and interpolates all the pixels in the regions which are detected as contour artifact. It can remove contour artifact well, but it has high complexity because it scans all the pixels and check the possibility of the contour artifact.

To remove computational complexity and contour artifact, Mittal used minimum risk based classification for the bit-depth expansion method [7]. At first, it predicts pixel's error distribution model based on neighborhood pixels and calculates all the posterior probability of all the possible output. Then, all the possible outputs' risks are calculated based on the probabilities. After sorting the risks, the value which has the minimum risk is updated as LSB. This method gives better result in PSNR compared to other methods, but calculating risks and sorting them require high complexity.

4. Proposed Method

The proposed method is designed to solve the equation 1. The proposed approach is based on minimum risk, but instead of calculating minimum risk, it uses expectation, which maximizes a posteriori, to reduce complexity. We approximate the maximizing a posteriori as estimating expectation in the equation 8, because just picking one value makes high risk so expectation distributes the error for all the candidates.

$$y'_{LSB} = \arg max_{c=1}^{C} P(y = c | x_{LBD}, x_{LBD}^{N})$$
$$\approx \sum_{c=1}^{2^n} c \times P(y = c | x_{LBD}, x_{LBD}^{N}) \tag{8}$$

The proposed method can be divided into two parts. The first part calculates a posteriori of LSB candidate and the second part estimates expectation of LSB with a posteriori. And then HBD can be updated with the estimation of expectation to make high PSNR. This is almost same as 'coarse and fine' strategy. We expand LBD by ZP, BR or MIG, coarsely, and then with updating LSB, HBD can be tuned finely.

4.1. Coarse Expansion Part

4.1.1. Initial HBD Estimation

Proposed method estimate HBD, initially by any simple methods such as ZP, BR, or MIG. The simple method is enough for expanding because LSB can be updated in the next part for the fine tuning. For this paper, we select MIG in the equation 6 for expanding LSB.

$$x_{HBD}^{Initial} = MIG(x_{LBD}) \tag{8}$$

4.1.2. Modeling of Error Distribution

To model a posteriori, we define the probability model, which is used Min Risk [7] based bit-depth expansion method. The probability modeling process is composed of 3 stages. At first, LSB value is predicted, which is defined as x_{HSB}^{P} in the equation 9, with the average value of 8 neighbor pixels (N).

$$x_{HSB}^{P}(i,j) = \frac{1}{8} \sum_{(m,n) \in N} x_{HBD}^{Initial}(i+m, j+n) \tag{9}$$

Secondly, we define the estimation error to be the difference between $x_{HBD}^{Initial}$ and $x_{LSB}^{P}(i,j)$ in the equation 10.

$$E(i,j) = x_{HBD}^{Initial} - x_{HSB}^{P}(i,j) \tag{10}$$

Finally, by making the histogram of $E(i,j)$ and normalizing the histogram with the total number of image pixels (N, in the equation 11), the probability of error distribution is estimated.

$$P_{error}(E) = \frac{Hist(E)}{N}, where\ N \triangleq Number\ of\ All\ Pixels \tag{11}$$

4.2. Fine Expansion Part

4.2.1. Modeling of a Posteriori

We assume a posteriori is controlled by the error distribution $P_{error}(E)$ in the equation 11. As the distribution, $P_{error}(E)$, shows the error distribution of the entire image, the difference between predicted value and the candidate of LSB value is also governed by the distribution. Given, LBD value and location of certain pixel, a posteriori of LSB c is defined to be the error distribution of difference between predicted value and LSB c in the equation 12.

$$P(y=c|x_{LBD},x_{LBD}^{N})=\frac{P_{error}(x_{HSB}^{P}(i,j)-c)}{\sum_{C}P_{error}(x_{HSB}^{P}(i,j)-c)}$$
$$,where\ c\in C=\{1,2,\ldots,2^{n}-1\} \qquad (12)$$

4.2.2. Updating LSB

After estimating a posteriori, LSB value for the fine tuning is updated by the expectation of all possible LSB. Because the expectation value may be the real number, finally, we use round function to make it as integer.

$$y'_{LSB}=round\left(\sum_{c\epsilon C}c\times P(y=c|x_{LBD},x_{LBD}^{N})\right),$$
$$where\ c\in C=\{1,2,\ldots,2^{n}-1\} \qquad (13)$$

Finally, the equation 2 therefore becomes

$$x'_{HBD}=x_{HBD}^{Initial}+y'_{LSB}. \qquad (14)$$

5. Experimental Result

In this section, we show the performance of the proposed algorithm by comparing with other bit-depth expansion algorithm for computational complexity and quantitative and qualitative image quality. ZP, BR, MIG, Daly, Adaptive Filter based, Flooding based, and Minimum Risk are selected for the comparative algorithm and totally, 8-bits, 19 images are chosen for the test data set. The final results are presented in Figure 4 and 5.

Test images are truncated by LSB 2-bits, and other 7 algorithms and proposed algorithm are tested for expanding LSB 2- bits. The truncated test images are reconstructed as 8-bit images and for comparing the reconstructed images with original image, PSNR (Peak Signal to Noise Ratio) is used for quality measurement.

PSNR is used to compare the performance of image quality of different algorithms, numerically [2]. All the research papers related to bit-depth expansion have used PSNR to show their performance. For 8-bit depth image, PNSR is given by

$$\mathrm{PSNR}=10\times\log_{10}\frac{255^{2}}{MSE},. \qquad (15)$$

MSE (Mean Square Error) is defined to be

$$\mathrm{MSE}\triangleq\frac{SE}{W\times H}, \qquad (16)$$

and when SE (Square Error) is given by:

$$\mathrm{SE}\triangleq\sum_{j=1}^{H}\sum_{i=1}^{W}(I_{Original}(i,j)-I_{Reconstructed}(i,j))^{2} \qquad (17)$$
$$,where\ W: image\ width, H: image\ height$$

Proposed algorithm shows 47.15 for the average PSNR and this is the best result among the other 7 algorithm because in PSNR aspect, expectation value distributes the reconstruction error to the all LSB candidates. For the detailed performance comparisons, please see the Table 1 and Figure 4.

We also compare computational complexity with computing time. ZP algorithm is the simplest one because it just fills out zero automatically. BR and MIG also require simple replacement and multiplication. This is the reason why they have poor PSNR performance. Flooding based, Minimum Risk, and Adaptive Filter based algorithms have post processing to increase PSNR. So, it takes much time comparing with simple bit-depth expansion algorithms. Proposed algorithm is able to achieve the best computational time in post processing based algorithms. Proposed algorithm takes only 1.06(s) with Inter(R) Core(TM) i7-2600 CPU @ 3.40GHz and 4.0GB Ram, which is 2% comparing with flooding based bit-depth expansion algorithm. We use well known OpenCV library for the easy implementing the proposed algorithm, computational time can be reduced if we don't use that library for memory access. The detailed computational time is summarized in table 2.

6. Conclusion

In this paper, we propose new bit-depth expansion algorithm for displaying legacy LBD contents to the HBD display by using the estimation of LSB's expectation value. We formulate bit-depth expansion algorithm as MAP problem and approximate the solution as expectation in the proposed method. Proposed algorithm is compared its performance in computational time and quantitative quality with other bit-depth expansion algorithms. It shows the best performance, when computational complexity and image quality are considered at the same time.

Proposed algorithm can be used as an application which converts legacy contents to HBD contents for displaying in HDR display.

References

[1] Scott J. Daly and Xiaofan Feng, "De-contouring: prevention and removal of false contour artifacts", Proc. SPIE 5292, Human Vision and Electronic Imaging IX, 130 (June 7, 2004).

[2] Chun Hung Liu at el., "Bit-depth expansion by adaptive filter", Circuits and Systems, 2008. ISCAS 2008. IEEE International Symposium on, On page(s): 496 - 499.

[3] Cheuk-Hong Cheng; Au, O.C.; Chun-Hung Liu; Ka-Yue Yip "Bit-depth expansion by contour region reconstruction", Circuits and Systems, 2009. ISCAS 2009. IEEE International Symposium on, On page(s): 944 - 947.

[4] Cheuk-Hong Cheng; Au, O.C.; Ngai-Man Cheung; Chun-Hung Liu; Ka-Yue Yip "Low color bit-depth image enhancement by contour-region dithering", Communications, Computers and Signal Processing, 2009. PacRim 2009. IEEE Pacific Rim Conference on, On page(s): 666 - 670.

[5] Min-Ho M.-H. Park, J. W. Lee, Rae-Hong R.-H. Park, and J.-S. Kim, "False contour reduction using neural networks and adaptive bi-directional smoothing," IEEE Transactions on Consumer Electronics, vol. 56, no. 2, pp. 870.878, 2010.

[6] X. Jin, S. Life and K. N. Ngan, "Composite Model-Based DC Dithering for Suppressing Contour Artifacts in Decompressed Video," IEEE Transactions on Image Processing, vol. 20, no. 8, Aug. 2011.

[7] Mittal, G.; Jakhetiya, V.; Jaiswal, S.P.; Au, O.C.; Tiwari, A.K.; Dai Wei "Bit-depth expansion using Minimum Risk Based Classification", Visual Communications and Image Processing (VCIP), 2012 IEEE, On page(s): 1 - 5.

[8] Pengfei Wan; Au, O.C.; Ketan Tang; Yuanfang Guo; Lu Fang "From 2D Extrapolation to 1D Interpolation: Content Adaptive Image Bit-Depth Expansion", Multimedia and Expo (ICME), 2012 IEEE International Conference on, On page(s): 170 - 175.

[9] Pengfei Wan; Cheung, G.; Florencio, D.; Cha Zhang; Au, O.C. "Image bit-depth enhancement via maximum-a-posteriori estimation

DOI: 10.2352/ISSN.2470-1173.2016.14.IPMVA-383

of graph AC component", Image Processing (ICIP), 2014 IEEE International Conference on, On page(s): 4052 - 4056.

[10] Pengfei Wan; Au, O.C.; Ketan Tang; Yuanfang Guo "Image de-quantization via spatially varying sparsity prior", Image Processing (ICIP), 2012 19th IEEE International Conference on, On page(s): 953 - 956.

[11] Seyun Kim, Sungkwon Choo, Nam Ik Cho, "Removing False Contour Artifact for Bit-depth Expansion", IEEK Transactions on Smart Processing & Computing Vol.2 No.2, 2013.4, 97-101.

Author Biography

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Table 1. Result for various bit-depth expansion algorithms in PSNR

	ZP	BR	MIG	Daly's	Adaptive Filter based	Minimum Risk based	Flooding based	Proposed
1	43.40	43.72	43.32	44.30	41.95	44.99	45.64	**47.77**
2	43.25	43.43	42.94	44.00	43.68	45.00	46.28	**48.22**
3	43.49	43.62	43.56	44.03	44.31	45.05	46.32	**45.13**
4	42.72	43.66	42.08	44.07	39.80	44.53	46.33	**47.89**
5	42.82	43.95	42.78	43.79	42.89	43.59	46.53	**48.40**
6	43.89	44.02	43.60	45.03	39.33	44.38	44.85	**47.80**
7	42.66	43.59	42.11	44.04	42.09	45.79	46.47	**47.97**
8	42.42	43.22	42.48	43.57	42.71	43.61	46.77	**47.52**
9	42.90	42.43	42.40	43.42	44.67	43.91	46.60	**44.79**
10	42.68	44.07	42.40	43.64	41.60	43.89	46.94	**47.33**
11	42.48	40.22	39.60	44.65	46.09	44.04	45.52	**46.97**
12	42.72	43.85	42.38	43.66	37.89	39.86	47.27	**46.31**
13	42.88	44.66	42.42	43.63	42.36	43.36	46.76	**47.61**
14	43.03	44.35	42.62	44.04	43.14	44.00	46.42	**46.57**
15	42.72	43.97	42.63	44.14	42.00	43.50	45.86	**46.87**
16	42.78	44.18	42.55	44.14	39.70	43.12	46.22	**47.05**
17	42.89	44.61	42.55	43.59	42.66	43.60	46.50	**46.54**
18	42.69	43.71	42.34	43.67	42.73	43.24	46.85	**47.61**
19	42.20	44.39	42.22	44.23	39.90	44.34	43.97	**47.50**
Avg	42.87	43.67	42.47	43.98	42.08	43.61	46.22	**47.15**

Table 2. Result for various bit-depth expansion algorithms in Computational Time (s)

	ZP	BR	MIG	Daly's	Adaptive Filter based	Minimum Risk based	Flooding based	Proposed
1	0.07	0.18	0.17	0.21	10.95	2.57	31.83	**0.67**
2	0.07	0.18	0.17	0.21	11.55	2.56	33.22	**0.67**
3	0.069	0.18	0.17	0.21	11.55	2.56	37.54	**0.67**
4	0.068	0.18	0.17	0.21	9.27	2.59	24.75	**0.72**
5	0.07	0.17	0.18	0.21	11.30	2.60	29.58	**0.67**
6	0.07	0.18	0.17	0.21	10.51	2.58	35.62	**0.67**
7	0.07	0.18	0.18	0.21	11.47	2.56	28.06	**0.67**
8	0.07	0.17	0.18	0.21	11.69	2.58	30.37	**0.67**
9	0.07	0.18	0.17	0.21	11.91	2.57	32.25	**0.67**
10	0.15	0.41	0.39	0.47	19.58	2.57	60.62	**1.51**
11	0.13	0.34	0.33	0.40	23.12	5.74	81.00	**1.29**
12	0.06	0.15	0.14	0.17	7.03	4.86	23.17	**0.56**
13	0.31	0.83	0.91	0.96	51.19	2.14	147.78	**3.10**
14	0.15	0.40	0.39	0.47	19.84	11.69	63.74	**1.52**
15	0.16	0.45	0.43	0.53	14.37	5.72	43.10	**1.81**
16	0.07	0.18	0.18	0.22	6.63	6.37	19.99	**0.72**
17	0.12	0.32	0.31	0.38	13.70	2.64	45.60	**1.26**
18	0.15	0.40	0.39	0.47	24.33	4.57	68.46	**1.56**
19	0.07	0.19	0.19	0.23	8.22	5.72	26.44	**0.75**
Avg	0.10	0.28	0.27	0.33	15.17	3.23	45.43	**1.06**

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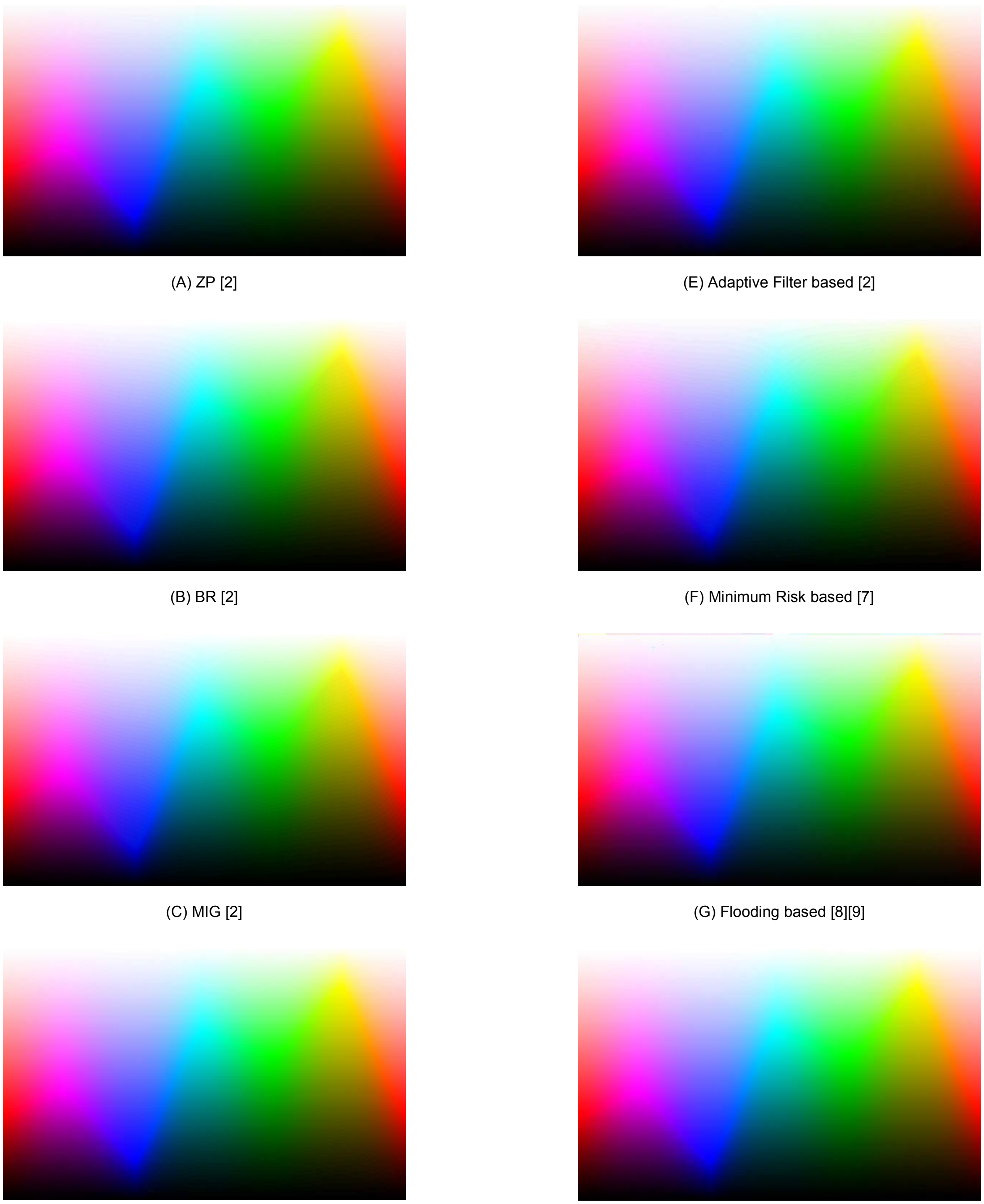

(A) ZP [2]

(E) Adaptive Filter based [2]

(B) BR [2]

(F) Minimum Risk based [7]

(C) MIG [2]

(G) Flooding based [8][9]

(D) Daly's [1]

(H) Proposed

Figure 4. Comparison of different bit-depth expansion algorithm

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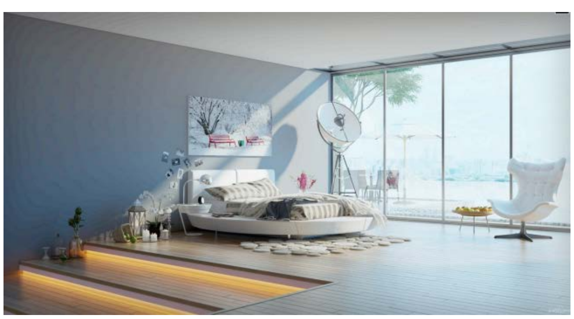
(A) ZP [2]

(B) BR [2]

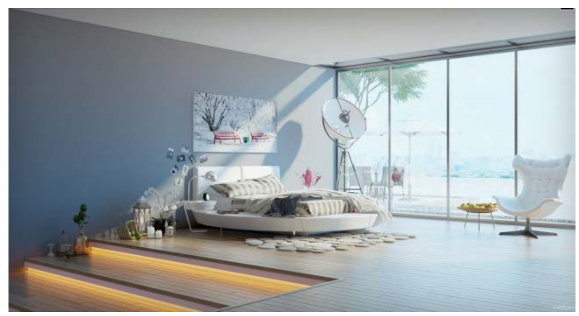
(C) MIG [2]



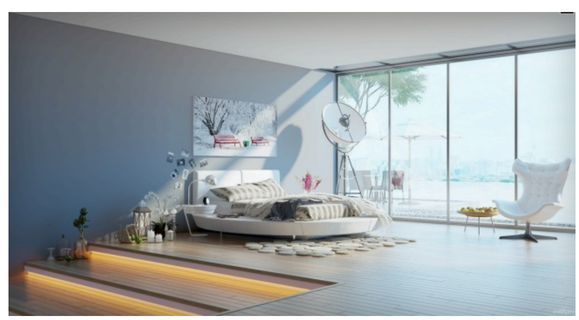
(D) Daly's [1]

(E) Adaptive Filter based [2]

(F) Minimum Risk based [7]



(G) Flooding based [8][9]



(H) Proposed

Figure 5. Comparison of different bit-depth expansion algorithm