

THE STUDY OF AN EDO KERNEL AND M_0 PARAMETER FOR A SI-SRR²

การศึกษาผลกระทบต่อประสิทธิภาพของค่าเคอร์เนลของ EDO และตัวแปร M_0
ที่มีผลต่อการสร้างคืนภาพความละเอียดสูงยิ่งแบบ SI-SRR²

Vorapoj Patanavijit

Vincent Mary School of Engineering, Assumption University

Abstract

Because of a run on high spatial resolution images, the fabulous analysis exertions in the field of Digital Image Processing (DSP), especially in single image Super Resolution Reconstruction (SI-SRR) algorithms, have ultimately inflated during this era. Hence, the uncomplicated and rapid SI-SRR algorithms have been dramatically intrigued for applying on commercial digital camera embedded equipment for instance, digital camera, smart phone, CCTV, etc. The SI-SRR based on high-frequency image prediction technique, one of the practical and effective SI-SRR algorithms, is the uncomplicated and powerful algorithm for increasing the image spatial resolution but this algorithm severely hinges upon two main factors: M_0 parameter and the Edge Detection Operator (EDO) kernel. Hence, this paper rigorously enquires into the performance of this SI-SRR algorithm for 14 standard tested images for the proposing of experimentally obtaining the value of two parameters (M_0 parameter and the EDO kernel), which give the highest PSNR under several environments: noiseless, several blurred environments at many blurred variances and several noisy environments at many Gaussian noise power levels.

Keywords: SI-SRR (Single Image Super Resolution Reconstruction), Digital Image Reconstruction, High-Frequency Image Prediction

บทคัดย่อ

เนื่องจากภาพที่มีความละเอียดสูงยังมีความต้องการในการประยุกต์ใช้งาน ดังนั้นจึงมีการวิจัยเกี่ยวกับการประมวลผลสัญญาณภาพดิจิทัลโดยเฉพาอย่างยิ่งเกี่ยวกับอัลกอริทึมการสร้างภาพความละเอียดสูงยิ่งที่สร้างขึ้นจากภาพความละเอียดต่ำ (SI-SRR) เพียงภาพเดียวอย่างแพร่หลายในช่วงเวลานี้ และเนื่องจากอัลกอริทึมการสร้างภาพความละเอียดสูงยิ่งแบบ SI-SRR จะมีความรวดเร็วในการคำนวณสูงและมีความซับซ้อนต่ำ ดังนั้นจึงเหมาะสำหรับประยุกต์ใช้งานกับอุปกรณ์ฝังตัวของกล้องดิจิทัลอย่างเช่น กล้องดิจิทัลทั่วไป โทรศัพท์มือถือ กล้องแบบ CCTV เป็นต้น อัลกอริทึมการสร้างภาพความละเอียดสูงยิ่งแบบ SI-SRR ที่กล่าวถึงในบทความนี้จะเป็นอัลกอริทึมที่ใช้เทคนิคการประมาณข้อมูลความถี่สูงของภาพ ถึงแม้ว่าอัลกอริทึมดังกล่าวจะมีประสิทธิภาพสูงและเหมาะสำหรับการประยุกต์ใช้งานแต่ประสิทธิภาพของอัลกอริทึมการสร้างภาพความละเอียดสูงยิ่งแบบ SI-SRR แบบนี้จะขึ้นอยู่กับตัวแปรหลักที่ใช้ในการคำนวณจำนวนสองตัวคือ ตัวแปร M_0 และค่าเคอร์เนลของ EDO ดังนั้นบทความนี้จะนำเสนอผลการศึกษาของอัลกอริทึมการสร้างภาพความละเอียดสูงยิ่งแบบ SI-SRR กับภาพทดสอบจำนวน 14 ภาพเพื่อหาค่าตัวแปร M_0 และค่าเคอร์เนลของ EDO ที่ทำให้ภาพที่สร้างขึ้นมีค่า PSNR สูงสุดภายใต้สภาวะแวดล้อมแบบภาพที่ความละเอียดต่ำที่บันทึกได้ไม่มีสัญญาณรบกวน ภาพที่ความละเอียดต่ำที่บันทึกได้ไม่คมชัด และภาพที่ความละเอียดต่ำที่บันทึกได้มีสัญญาณรบกวน

คำสำคัญ: การสร้างภาพความละเอียดสูงยิ่งแบบใช้ภาพเดียว (SI-SRR) การประมวลผลสัญญาณภาพดิจิทัล วิธีการประมาณข้อมูลความถี่สูงของภาพ

Introduction and Related Works

This section presents the related works of a SI-SRR based on high-frequency image prediction for enhancing a spatial resolution (Jeon, Park & Yang, 2006), which was introduced in 2006. Later, this SI-SRR algorithm is experimentally analyzed of its performance influence by both interpolation techniques (nearest interpolation techniques, bilinear interpolation techniques and bicubic interpolation techniques) and the number of gradient directions of sobel kernel edge detection under noiseless, blurred and noisy environments in 2013 (Patanavijit, Pirak & Ascheid, 2013). Moreover, the M_0 parameter, which is used in the control function, is also experimentally investigated for the proposing

of obtaining the maximum PSNR for each environment cases. In 2014, the SI-SRR performance influence by an edge detection kernels (such as Roberts kernel, Prewitt kernel, Sobel kernel, Laplacian kernel and Laplacian of Gaussian (LOG) kernel) has been experimentally investigated under noiseless, blurred and noisy environments (Patanavijit, Pirak & Ascheid, 2014). Hence, this paper presents a the unify framework of the a simulation performance influence of a number of gradient directions, M_0 parameter and the edge detection kernel for the SI-SRR based on the high-frequency image prediction under noiseless, blurred and noisy environments.

Framework Prospect of A SI-SRR Based on High Frequency Prediction with A Laplacian Pyramid

This section briefs the general idea of the SI-SRR based on high-frequency image prediction with a Laplacian Pyramid algorithm (Jeon, Park & Yang, 2006). The framework prospect of this SI-SRR is hinge upon the concept of a Laplacian pyramid algorithm (Jeon, Park & Yang, 2006), Burt & Adelson (1983), which can apply for divorcing the image $G_0(x, y)$ (the image dimension is $m \times n$ pixels), so called the input image, into high frequency part $L_0(x, y)$ (the image dimension is $m \times n$ pixels) and low frequency part $G_1(x, y)$ (the image dimension is $m \times n$ pixels). Because of the mathematical limitation of classical interpolations (Burt & Adelson, 1983; Gonzalez & Woods, 2002), the

upsampling image $G_{-1}(x, y)$ (the image dimension $2m \times 2n$ pixels), which is traditionally the desired reconstructed image, is generally loss high frequency part $L_{-1}(x, y)$ (the image dimension is $2m \times 2n$ pixels) and contains only a low frequency part $G_{-1}(x, y)$ (the image dimension is $2m \times 2n$ pixels). Thereby, the proposing of this SI-SRR algorithm is to reconstruct the high frequency part $L_{-1}(x, y)$ (the image dimension is $2m \times 2n$ pixels) for generating a desired reconstructed image $G_{-1}(x, y)$. As shown in Fig. 1 (Patanavijit, Pirak & Ascheid, 2014), this SI-SRR algorithm can be depicted into a unify framework block diagram, which comprises of 2 principle processes: the prediction of a high frequency image process and a control function process.

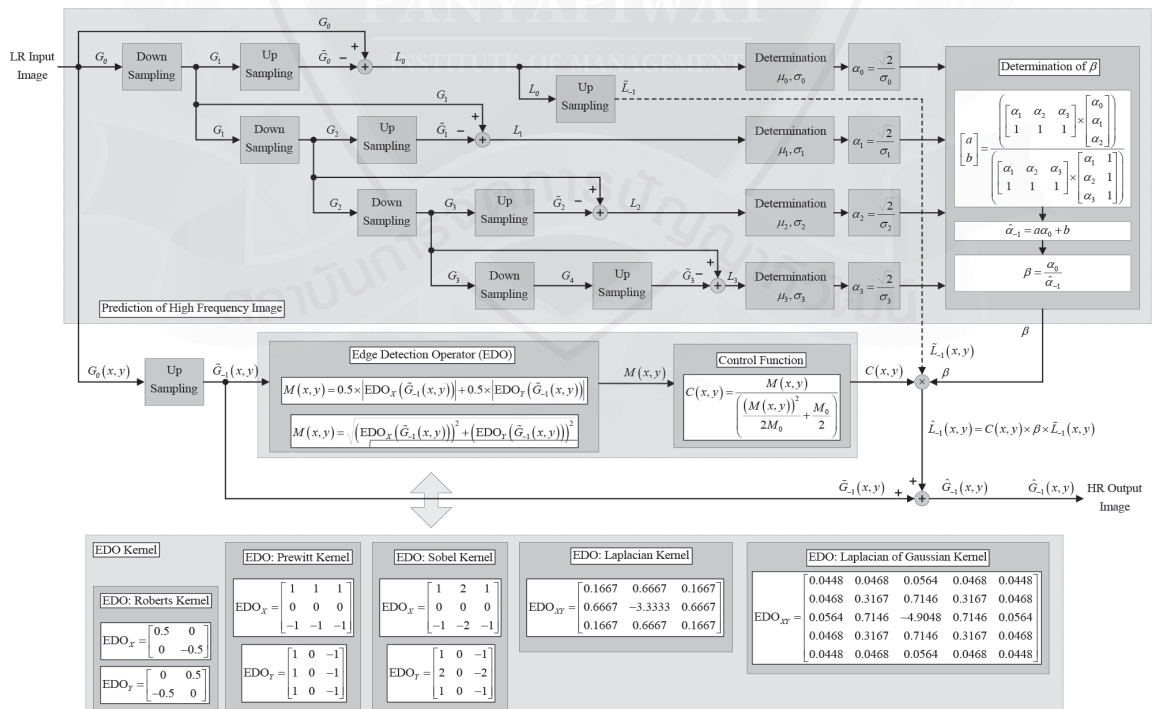


Figure 1 A unify framework block diagram of a SI-SRR algorithm (Patanavijit, Pirak & Ascheid, 2014)

Prediction Process

The proposing of the prediction of a high frequency image process is to determine $\tilde{L}_{-1}(x, y)$ and β .

1. G_i Generation of SI-SRR

The four resolutions of downsampling input images are first determined as following

$$G_1(x, y) = \text{DOWNSAMPLING}(G_0(x, y)) \quad (1.1)$$

$$G_2(x, y) = \text{DOWNSAMPLING}(G_1(x, y)) \quad (1.2)$$

$$G_3(x, y) = \text{DOWNSAMPLING}(G_2(x, y)) \quad (1.3)$$

$$G_4(x, y) = \text{DOWNSAMPLING}(G_3(x, y)) \quad (1.4)$$

2. G_i Generation of SI-SRR

Next, all downsampling input images are upsampling to generate low frequency parts of four resolutions as following

$$\tilde{G}_0(x, y) = \text{UPSAMPLING}(G_1(x, y)) \quad (2.1)$$

$$\tilde{G}_1(x, y) = \text{UPSAMPLING}(G_1(x, y)) \quad (2.2)$$

$$\tilde{G}_2(x, y) = \text{UPSAMPLING}(G_1(x, y)) \quad (2.3)$$

$$\tilde{G}_3(x, y) = \text{UPSAMPLING}(G_1(x, y)) \quad (2.4)$$

3. $\tilde{L}_i$ Generation of SI-SRR

Later, from framework prospect of Laplacian pyramid, the four resolutions of high frequency parts (so called Laplacian image data) $\tilde{L}_1(x, y)$, which are determined by upsampling process, are determined by subtraction between the image $G(x, y)$ and its low frequency part $\tilde{G}_i(x, y)$, which is determined by up as following.

$$L_0(x, y) = G_0(x, y) - \tilde{G}_0(x, y) \quad (3.1)$$

$$L_1(x, y) = G_1(x, y) - \tilde{G}_1(x, y) \quad (3.2)$$

$$L_2(x, y) = G_2(x, y) - \tilde{G}_2(x, y) \quad (3.3)$$

$$L_3(x, y) = G_3(x, y) - \tilde{G}_3(x, y) \quad (3.4)$$

4. Calculation μ_n and σ_n^2 of SI-SRR

Subsequently, each normalized histograms are determined from each high frequency parts ($L_0(x, y)$, $L_1(x, y)$, $L_2(x, y)$, $L_3(x, y)$) for the

proposing of using in the Gaussian fitting process.

The mean μ_n and variance σ_n^2 of each normalized histograms are determined from the previous process. Hence, four groups of statistical parameters $((\mu_0, \sigma_0^2), (\mu_1, \sigma_1^2), (\mu_2, \sigma_2^2), (\mu_3, \sigma_3^2))$ are determined as following equation.

$$\sigma_n^2 = \sum_{l=-\infty}^{+\infty} (l - \mu_n)^2 h(l) \quad (4)$$

where n denotes the level of the pyramid and $h(l)$ denotes the normalized histogram of each level Laplacian image.

5. Calculations α_n and β of SI-SRR

In general, the Laplacian pdf $f_p(p)$ (Jeon et al. (2006) can be specifically modeled from the Gaussian pdf for reducing the calculation complexity as following equation.

$$f_p(p) = 0.5\alpha e^{-\alpha|p|} \quad (5)$$

where p denotes the pixel intensity of the Laplacian image with zero mean and variance $\sigma^2 = 2/\alpha^2$ hence the group of Laplacian parameters α_n ($\alpha_0, \alpha_1, \alpha_2, \alpha_3$) can be specifically modeled as.

$$\alpha_n = \sqrt{2}/\sigma_n \quad (6)$$

Finally, the β can specifically modeled as following equation.

$$\begin{bmatrix} a \\ b \end{bmatrix} = \left(\begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ 1 & 1 & 1 \end{bmatrix} \times \begin{bmatrix} \alpha_0 \\ \alpha_1 \\ \alpha_2 \end{bmatrix} \right) / \left(\begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ 1 & 1 & 1 \end{bmatrix} \times \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} \right) \quad (7)$$

$$\hat{\alpha}_{-1} = a\alpha_0 + b \quad (8)$$

$$\beta = \alpha_0 / \hat{\alpha}_{-1} \quad (9)$$

Control Function Process

The control function process is shown in Fig. 1. The input image $G_0(x, y)$ is upsampling to reconstruct $\tilde{G}_{-1}(x, y)$ and, then, $M(x, y)$ can be specifically modeled by the following equation.

$$M(x, y) = 0.5 \left| \text{EDO}_x(\tilde{G}_{-1}(x, y)) \right| + 0.5 \left| \text{EDO}_y(\tilde{G}_{-1}(x, y)) \right| \quad (10.1)$$

$$M(x, y) = \sqrt{\left(\text{EDO}_x(\tilde{G}_{-1}(x, y)) \right)^2 + \left(\text{EDO}_y(\tilde{G}_{-1}(x, y)) \right)^2} \quad (10.2)$$

where Eq. (10.1) is usually applied for the purpose of accelerating the computational time and Eq. (10.2) is usually applied for the purpose of achieving the highest PSNR.

where $\text{EDO}(\cdot)$ denotes the Edge Detection Operator: Roberts kernel, Prewitt kernel, Sobel kernel, Laplacian kernel and Laplacian of Gaussian (LOG) kernel as shown in Fig. 1.

The $C(x, y)$ can be determined from the control function of $M(x, y)$, which can be specifically modeled by the following equation.

$$C(x, y) = (M(x, y) + b) / (k(M(x, y))^2 + h) \quad (11-1)$$

where $b = c_0 M_0 / 2(1 - c_0)$, $h = M_0 / 2(1 - c_0)$ and $k = 1/2M_0$

$$C(x, y) = M(x, y) / ((M(x, y))^2 / 2M_0 + 0.5M_0) \quad (11-2)$$

After β , and $\tilde{L}_{-1}(x, y)$ are $C(x, y)$ determined by the previous process, Later, the high frequency (Laplacian) part $\tilde{L}_{-1}(x, y)$ of the reconstructed image can be specifically modeled by the following equation.

$$\tilde{L}_{-1}(x, y) = C(x, y) \times \beta \times \tilde{L}_{-1}(x, y) \quad (12)$$

where $\tilde{L}_{-1}(x, y)$ is determined by upsampling the $L_0(x, y)$

The reconstructed image $\hat{G}_{-1}(x, y)$ can be specifically modeled by adding between the low frequency part $\tilde{G}_{-1}(x, y)$ and high frequency (Laplacian) part $\hat{L}_{-1}(x, y)$ as the following equation.

$$\hat{G}_{-1}(x, y) = \tilde{G}_{-1}(x, y) + \hat{L}_{-1}(x, y) \quad (13)$$

Experiment of Performance Exploration on Noiseless Environment

For experimental exploration of the performance of this SI-SRR algorithm, all 14 experimental images are down-sampled by a 2x2 factor from their origin images in both vertical and horizontal direction for the proposing of producing synthesized low resolution images. For the purpose of exploring the experimental performance, these low resolution images are used in both the SI-SRR algorithm based on nearest, bilinear and bicubic interpolation techniques and classical interpolation methods (such as nearest, bilinear and bicubic) to reconstruct the higher resolution image.

1. Experimental Performance Interpolation Techniques for the SI-SRR (Patanavijit, Pirak & Ascheid, 2013)

First, this simulation experimental section explores the optimal interpolation technique based on Sobel EDO, which makes the best performance of this SI-SRR algorithm under the noiseless environment. For the purpose of

accelerating the computational time, $M(x, y)$ is determined by Eq. (10.1) and experimental results (in PSNR) of both SRR algorithms and

classical interpolation techniques are illustrated in Table 1.

Table 1 Experimental result of interpolation technique (Nearest, Bilinear and Bicubic) influence on the performance of SI-SRR based on Sobel EDO under noiseless environment.

PSNR (dB)	Interpolation Technique			SI-SRR Algorithm Based on HF Prediction			
	nearest	bilinear	bicubic	nearest (4D)	bilinear (4D)	bicubic (2D)	bicubic (4D)
Lena 256	30.7847	30.7347	31.3214	30.7495	31.5311	31.6945	31.6936
Girl (Tiffany) 256	30.9354	31.4980	31.7950	31.2921	32.4923	32.6922	32.6842
Baboon 256	23.2556	22.9367	23.2961	23.2830	23.4064	23.5115	23.5144
House 128	29.5053	29.8193	30.3867	29.4662	30.8498	30.9812	30.9818
Resolution chart 128	19.5643	19.7281	20.4723	19.3622	21.1248	21.0611	20.9360
Peppers 256	30.9254	31.4634	32.0118	31.0780	32.9292	33.2031	33.2093
Airplane (F-16) 256	30.2861	31.2441	31.8386	30.6068	32.7622	33.0256	33.0238
Pentagon 512	28.8039	28.4625	28.9424	28.7798	29.1615	29.2991	29.3013
Aerial 512	25.6730	25.6624	26.4399	25.5599	26.7666	27.0678	27.0700
Tree 128	25.5058	25.8486	26.5660	25.4747	27.2875	27.4515	27.4706
Sailboat on lake 256	28.7881	28.8842	29.5903	28.7647	29.9330	30.1228	30.1374
Cameraman 128	25.4884	25.4579	26.1642	25.0816	26.5282	26.6526	26.6491
Stream & bridge 256	25.6787	25.5129	26.0307	25.5753	26.2325	26.3921	26.3918
Mobilcal Frame 10	22.0863	21.7225	22.3167	22.0512	22.5955	22.7310	22.7327

Under the noiseless environment, the experimental result of interpolation technique (Nearest, Bilinear and Bicubic) indicates that the SI-SRR algorithm using a bicubic (2D and 4D) interpolation technique gives the higher PSNR than the SI-SRR algorithm using bilinear interpolation technique about 0.12-0.30 dB and gives the higher PSNR than the SI-SRR algorithm using nearest interpolation technique about 0.23-2.41 dB. Furthermore, the SI-SRR algorithm

using a bicubic (2D and 4D) interpolation technique gives the higher PSNR than the classical interpolation using nearest, bilinear and bicubic about 0.26-2.74, 0.58-1.78 and 0.22-1.20 dB, respectively. Hence, from PSNR perspective, it can be inferred that the bicubic interpolation technique is an optimal interpolation technique for this SI-SRR algorithm under the noiseless environment. Nevertheless, a bicubic interpolation technique is more

complex and more implementing difficulty than a bilinear interpolation technique for real-time implementation hence the SI-SRR algorithm using bilinear interpolation technique is more suitable from the real-time perspective. Finally, this simulation experimental section explores the optimal M_0 parameter (from 0 to 1000) for this SI-SRR algorithm (the 2 gradient directional Sobel EOD), which gives the maximum PSNR under the noiseless environment. For the

purpose of analyze the performance influence M_0 parameter for this SI-SRR algorithm from PSNR perspective, the correlation of the simulation performance in PSNR and M_0 parameter is portrait in Fig. 2. From the simulation experimental result in Fig. 2, it can be inferred that an optimal value of M_0 is 400-600 for general images with non-strong or non-sharp edge and an optimal value of M_0 is 800-1000 for strong-edge.

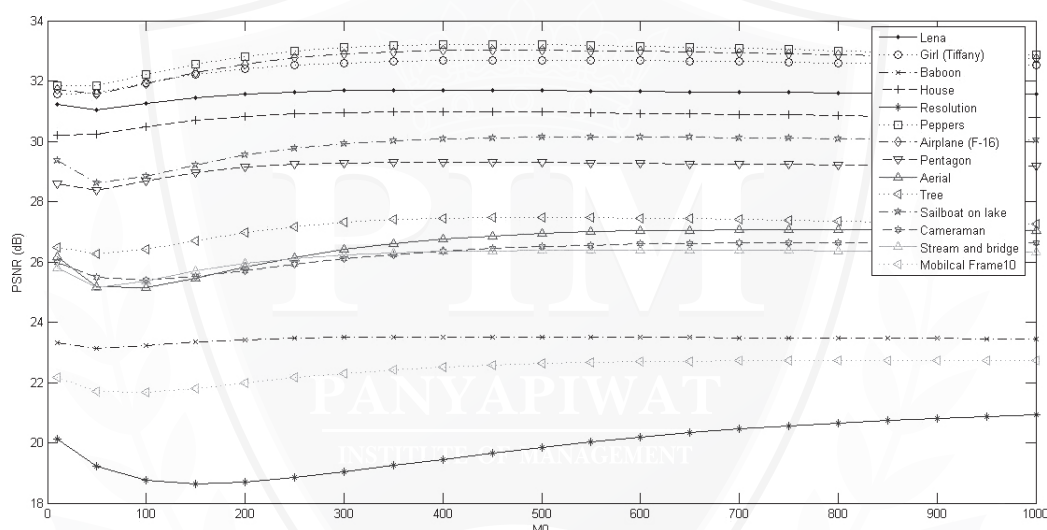


Figure 2 The correlation of the simulation performance in PSNR and M_0 parameter (using Sobel kernel [1]) under the noiseless environment.

Simulation Performance of An Edge EDO and M_0 parameter for The SI-SRR (Patanavijit, Pirak & Ascheid, 2014)

This section explores the EDO (Edge Detection Operator) for this SI-SRR algorithm, which gives the highest PSNR under the noiseless environments. In this experiment, Roberts kernel, Prewitt kernel, Sobel kernel (Jeon, Park & Yang, 2006; Patanavijit, Pirak & Ascheid, 2013) Laplacian kernel and Laplacian of Gaussian

(LOG) kernel are used in SI-SRR algorithm and $M(x, y)$ is determined by Eq. (10.2) for the purpose of achieving the highest PSNR, and the correlation results of the simulation performance in PSNR and M_0 parameter (which is varied from 0 to 2000) of the SI-SRR algorithm using Roberts kernel, Prewitt kernel, Sobel kernel, Laplacian kernel and Laplacian of Gaussian (LOG) kernel EDO are illustrated in Fig. 3(a) - Fig. 3 (e), respectively.

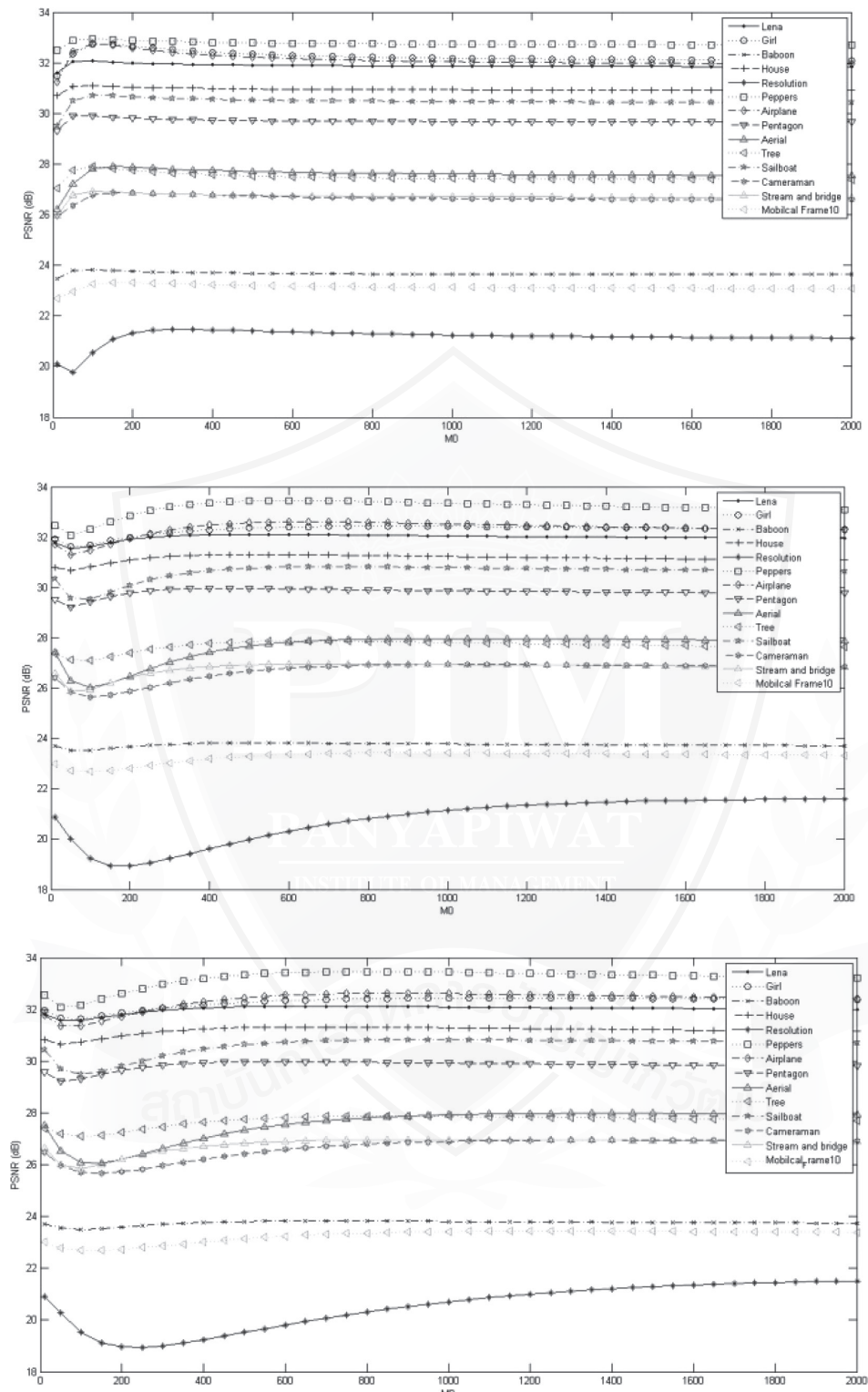


Figure 3 (a-c) The correlation of the simulation performance in PSNR and M0 parameter (based on Roberts (top), Prewitt (mid) and Sobel (bottom) under the noiseless.

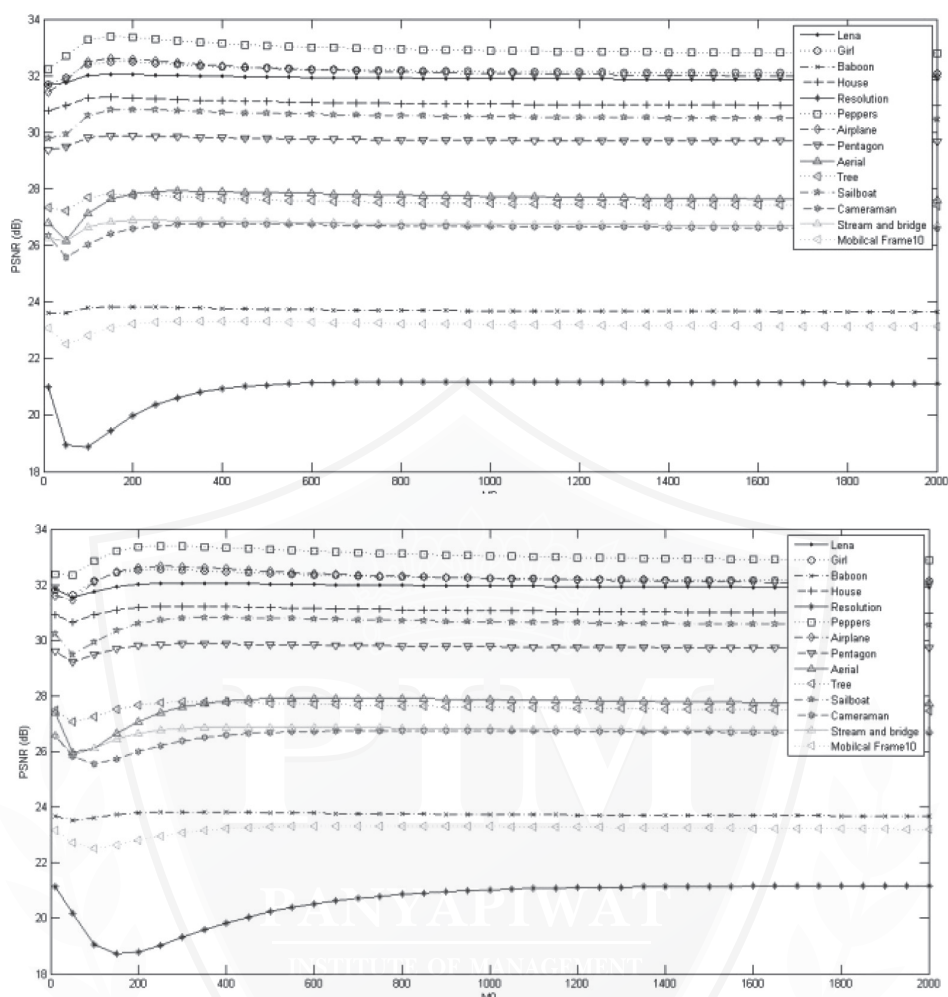


Figure 3 (d-e) The correlation of the simulation performance in PSNR and M_0 parameter (based on Laplacian (top) and Laplacian of Gaussian (LOG) kernel (bottom) under the noiseless.

From this simulation experimental result it can be inferred as following

- The best value of M_0 for Roberts kernel in Fig. 3(a) (top) is 100-150 for general images with both strong-edge and smooth texture.
- The best of M_0 for Prewitt kernel in Fig. 3(b) (mid) is 500-700 for common images with non-sharp edge and a best value of M_0 is 850-1050 for images with strong-edge.
- The best value of M_0 for Sobel kernel (Patanavijit, Pirak & Ascheid, 2013) in Fig. 3(c) (bottom) is 650-850 for common images with non-sharp edge and a best value of M_0 is 1250-1450 for images with sharpen-edge.
- The best value of M_0 for Laplacian kernel in Fig. 3(d) (top) is 150-200 for common images with non-sharp edge and a best value of M_0 is 300-400 for images with sharpen-edge.

- The best value of M_0 for LOG in Fig. 3(e) (bottom) is 250-400 for common images with non-sharp edge and a best value of M_0 is 650-800 for images with sharpen-edge.

Subsequently, the optimal M_0 for each EDO is experimentally picked for the purpose of

achieving the highest PSNR. The simulation experimental results of all EDO (Roberts kernel, Prewitt kernel, Sobel Kernel (Jeon et al. (2006), Laplacian kernel and Laplacian of Gaussian (LOG) kernel) under noiseless environment are illustrated in Table 2.

Table 2 Experimental result of EDO (Roberts kernel, Prewitt kernel, Sobel kernel, Laplacian kernel and Laplacian of Gaussian (LOG) kernel) influence on the performance of SI-SRR using Bicubic (2D) interpolation under noiseless environment.

PSNR (dB)	Interpolation			SI-SRR Algorithm Based on HF Prediction				
	nearest	bilinear	bicubic	Robert	Prew	Sobel	Lap	LOG
Lena 256	30.7847	30.7347	31.3214	32.0759	32.1122	32.1163	32.0560	32.0539
Girl 256	30.9354	31.4980	31.7950	32.7268	32.4364	32.4382	32.5056	32.5408
Baboon 256	23.2556	22.9367	23.2961	23.8215	23.8195	23.8230	23.8358	23.8275
House 128	29.5053	29.8193	30.3867	31.0975	31.3147	31.3150	31.2362	31.2196
Resolution chart 128	19.5643	19.7281	20.4723	21.4676	21.5889	21.5146	21.1809	21.1681
Peppers 256	30.9254	31.4634	32.0118	32.9523	33.4561	33.4564	33.3826	33.3963
Airplane 256	30.2861	31.2441	31.8386	32.7594	32.6116	32.6135	32.6180	32.6598
Pentagon 512	28.8039	28.4625	28.9424	29.8987	29.9670	29.9707	29.8708	29.8717
Aerial 512	25.6730	25.6624	26.4399	27.8944	27.9805	27.9839	27.9236	27.9179
Tree 128	25.5058	25.8486	26.5660	27.9077	27.8746	27.8764	27.8040	27.7830
Sailboat on lake 256	28.7881	28.8842	29.5903	30.7170	30.8236	30.8233	30.8099	30.8169
Cameraman 128	25.4884	25.4579	26.1642	26.8735	26.9445	26.9492	26.7553	26.7464
Stream & bridge	25.6787	25.5129	26.0307	26.9202	26.9636	26.9658	26.8851	26.8773
Mobilcal Frame	22.0863	21.7225	22.3167	23.3324	23.4330	23.4345	23.3255	23.3280

From this simulation experimental result in Table 2, it can be inferred that the best EDO from PSNR perspective is Sobel kernel because this SI-SRR using Sobel kernel gives the higher PSNR than PSNR than other kernel EDO in almost cases. Nevertheless, there are some

experimental cases that the SI-SRR using Roberts kernel, Prewitt kernel and Laplacian kernel gives the higher PSNR. Because of page constraint, some of virtual simulation experimental results of images, which are reconstructed by the SI-SRR algorithm, are illustrated in Fig. 4. (The left in

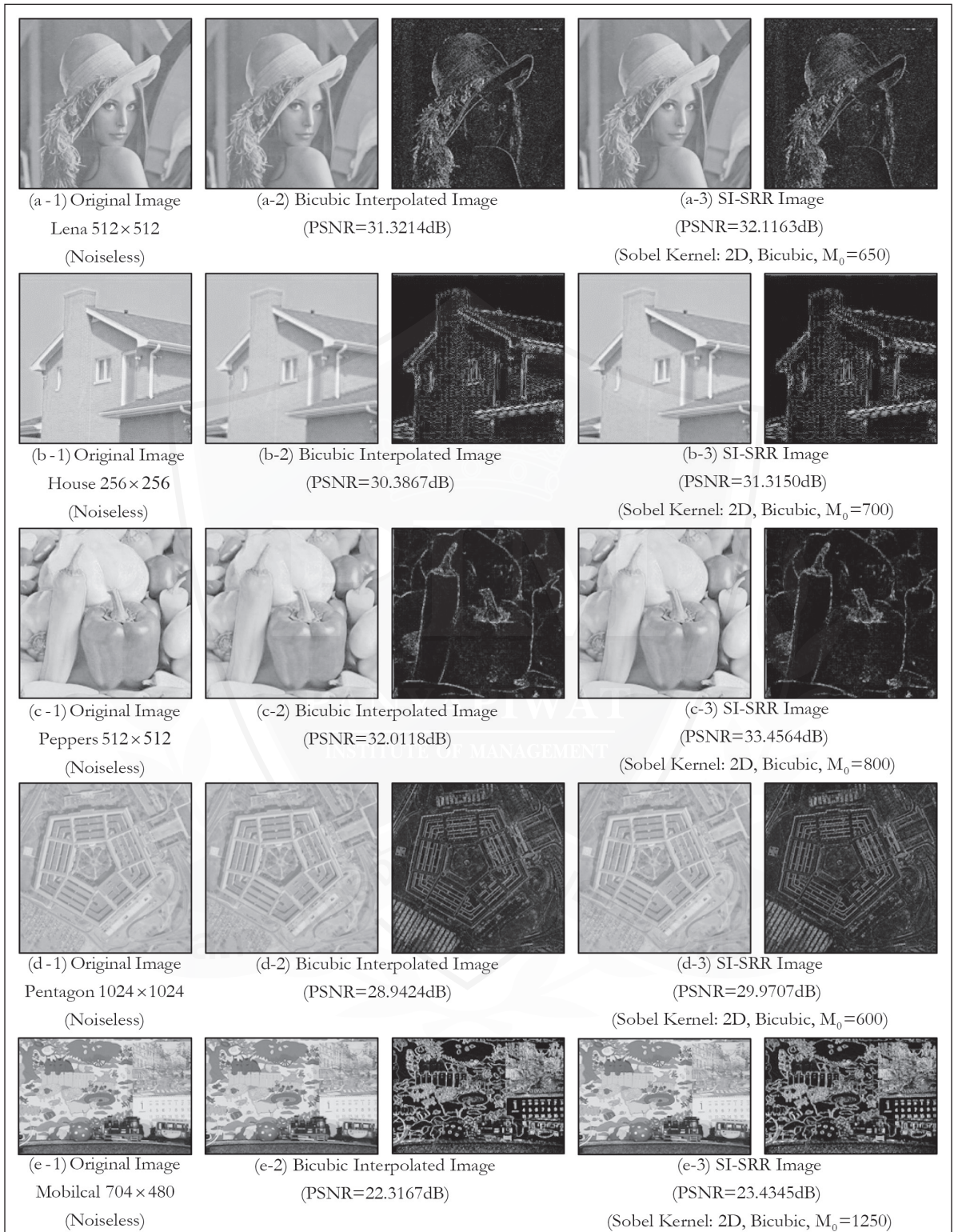


Figure 4 The simulation experimental results of the SI-SRR algorithm under the noiseless environment.

position portrait on our simulated result of each sub-portrait is the absolute difference between it's correspond the right in position (SR) and the original image, which are multiplied by five for the purpose of clearly virtualization.)

Experiment of Performance Exploration on Blurred Environment

This simulation experimental section explores the optimal EDO for the SI-SRR algorithm, which makes the best performance (in PSNR) under the six Gaussian blurred environments. In this experiment, each original image (12 tested

images) is first down-sampled by a factor 2x2 in both horizontal and vertical direction. Later, each down-sampled image is blurred by these six Gaussian blurred kernels (3x3 with sigma = 0.5, 3x3 with sigma = 1.0, 3x3 with sigma = 2.0, 5x5 with sigma = 0.5, 5x5 with sigma = 1.0 and 5x5 with sigma = 2.0.) for generating blurred down-sampled images. Because of page constraint, only PSNR results of these reconstructed images at 3x3 with sigma=0.5 and 5x5 with sigma = 2.0 are illustrated in Fig. 5(a)-Fig. 5(b) respectively.

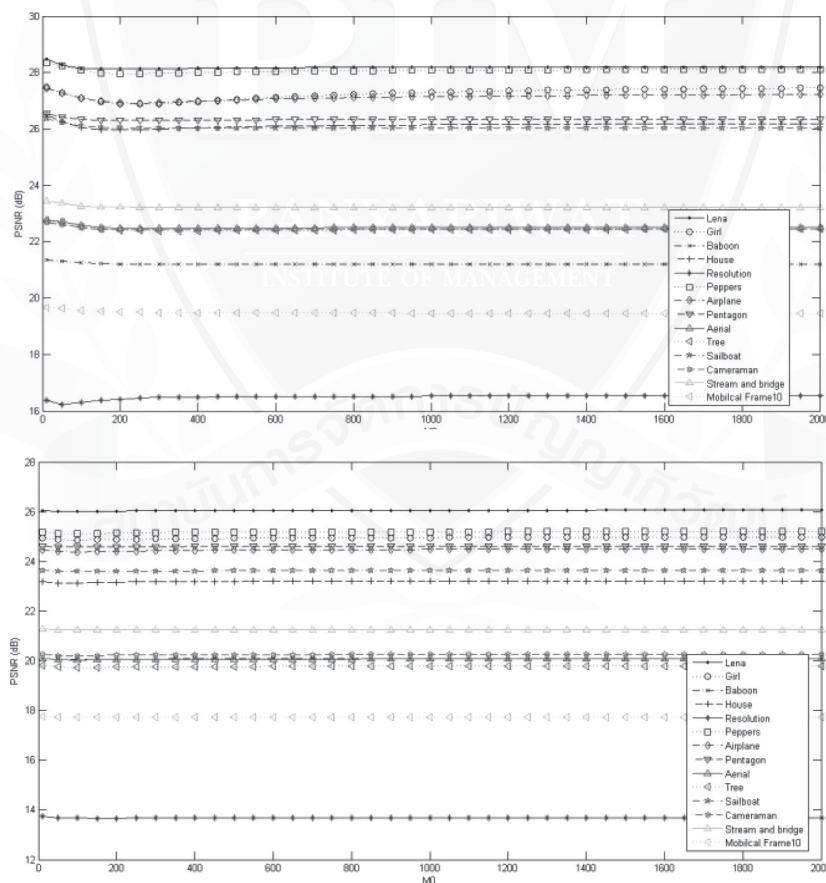


Figure 5 The correlation of the simulation performance in PSNR and M0 parameter (based on LOG kernel) under the blurred environments: 3x3 with sigma = 1.0 (left) and 5x5 with sigma = 2.0 (right).

From this simulation experimental result, it can be inferred that the best EDO from PSNR perspective is Laplacian of Gaussian (LOG) kernel because this SI-SRR using Laplacian of Gaussian (LOG) kernel give the higher PSNR than PSNR than other kernel EDO in almost cases, especially, under the high blurred environments (at 5x5 with sigma = 0.5-2.0). Nevertheless, there are some experimental cases that the SI-SRR using Sobel kernel and Laplacian kernel gives the higher PSNR under less blurred environments (at 3x3 with sigma = 0.5-2.0).

Later, the correlation results of the simulation performance in PSNR and M_0 parameter (which is varied from 0 to 2000) of the SI-SRR algorithm using LOG kernel are illustrated in Fig 5. For the less blurred environments (at 3x3 with sigma = 1.0) in Fig. 5(a) (Left), it can be inferred that the best value of M_0 is 10-250 for general images with both strong-edge and smooth texture. For the high blurred environments (at 5x5 with sigma = 2.0) in Fig. 5(b) (Right), it can be inferred that the best of M_0 is 10-250 for general images with both strong-edge and smooth texture.

Experiment of Performance Exploration on Noisy Environment

This simulation experimental section explores

the optimal EDO for the SI-SRR algorithm, which makes the best performance (in PSNR) under the five AWGN environments. In this experiment, the original image (all 12 tested images) is first down-sampled by a factor 2x2 in both horizontal and vertical direction. Later, each down-sampled image is corrupted by these AWGN (SNR=15dB, 20dB, 25dB, 30dB and 35dB) for generating noisy down-sampled images. Because of page constraint, only PSNR results of these reconstructed images at SNR = 30dB and 35dB are illustrated in Fig. 6(a) - Fig. 6(b) respectively.

From this simulation experimental results, it can be inferred that the best EDO from PSNR perspective is Sobel kernel because this SI-SRR using Sobel kernel give the higher PSNR than other kernel EDO in almost cases under the low noisy environments (at SNR = 30dB and 35dB) and this SI-SRR using Prewitt kernel give the higher PSNR than other kernel EDO in almost cases under the medium noisy environments (at SNR = 25dB). Nevertheless, this classical interpolation techniques give the higher PSNR than SI-SRR under the severe noisy environments (at SNR = 15dB and SNR = 20dB) because this SI-SRR enhances, reconstructs and enlarges the high frequency component (including noise) hence the noise component is enlarged.

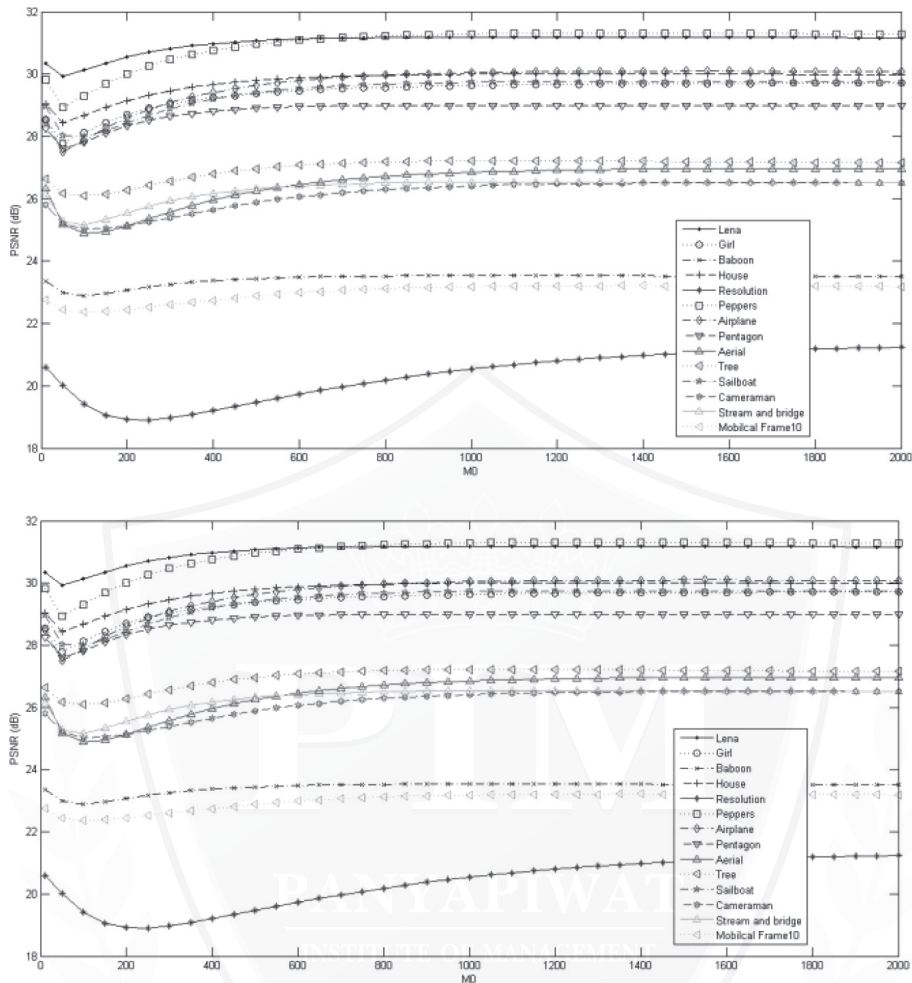


Figure 6 The correlation of the simulation performance in PSNR and M_0 parameter (based on Sobel kernel) under the noisy environments: SNR30dB (left) and SNR35dB (right).

Conclusion and Discussion

This paper rigorously enquires into the impact of an interpolation technique, EDO kernel (such as Roberts kernel, Prewitt kernel, Sobel kernel, Laplacian kernel and LOG kernel) and M_0 parameter for the SI-SRR algorithm based on high-frequency prediction for 14 standard tested images under 3 main environments: noiseless environment (1 case), Gaussian blurred envi-

ronments (2 cases: 3×3 with $\sigma = 0.5$ and 5×5 with $\sigma = 2.0$) and noisy environment (5 cases: SNR = 15dB, 20dB, 25dB, 30dB and 35dB). The optimal EDO for this SI-SRR algorithm are concluded for each environment. Moreover, the turning range of M_0 parameter is clearly concluded for each environment for future implementation.

References

- Burt, P. J. & Adelson, E. H. (1983). The Laplacian pyramid as a compact image code. *IEEE Transactions on Communications*, 31(4), 532-540.
- Gonzalez, R. C. & Woods, R. E. (2002). *Digital Image Processing*. NJ, USA: Prentice-Hall.
- Jeon, B., Park, R. & Yang, S. (2006). Resolution Enhancement by Prediction of the High-Frequency Image Based on the Laplacian Pyramid, Hindawi Co., EURASIP JASP. 1-11
- Patanavijit, V., Pirak, C. & Ascheid, G. (2013). Experimental Performance Analysis of Image High-frequency image prediction reconstruction Based on the High-Frequency Image Prediction under Several Blurred and Noisy Environments. *Proceeding of IEEE International Symposium on Communications and Information Technologies 2013 (ISCIT 2013)*, ECTI Association, Samui Island, Thailand. (pp. 469-474)
- Patanavijit, V., Pirak, C. & Ascheid, G. (2014). A Performance Impact of An Edge Kernel for The High-Frequency Image Prediction Reconstruction. *Proceeding of IEEE International Symposium on Communications and Information Technologies 2014 (ISCIT 2014)*, Incheon, Korea. (pp. 484-488)



Name and Surname: Vorapoj Patanavijit

Highest Education: Ph.D. in Electrical Engineering,
Chulalongkorn University

University or Agency: Assumption University

Field of Expertise: He works in the field of signal processing and multidimensional signal processing, specializing, in particular, on Image/Video Reconstruction, SRR, CS, Enhancement, Fusion, Denoising, Inverse Problems, Motion Estimation, Optical Flow Estimation and Registration. He has authored and co-authored over 110 peer-reviewed publications in DSP and DIP

Address: Assumption University (AU), VME Bldg., 2nd Flr., 88 Moo 8, Bang Na-Trad Km. 26, Samuthprakarn 10540