An Extra-Rate Spatial Enhancement Constructed by MSRR using Regularized Technique and SSRR using High-Frequency Pre-Forecasting

Vorapoj Patanavijit[1] and **Kornkamol Thakulsukanant**[2], Members

ABSTRACT

Under many circumstances, a high spatial resolution image (HR) is greatly needed for modern applications nevertheless the HR image captured device is usually overpriced cost. Hence, Super Resolution Reconstruction (SRR) technique, which can reconstruct a HR image from a single LR image or many LR images by using algebraic formulation, is one of the modern research fields in digital image processing (DIP) and Computer Vision (CV). In this paper, an extra-rate spatial enhancement constructed by MSRR (Multi-frame Super Resolution Reconstruction) using regularized technique and SSRR (Single-frame Super Resolution Reconstruction) using high-frequency pre-forecasting is presented in order to enlarge up to 16x ratio rate. Initially, a group of captured images with low spatial resolution are mathematically fused by MSRR using regularized technique established on a recursive Maximum Likelihood (ML) and Tukey's Biweight norm in order to enlarge up to 4x ratio rate. Next, this 4x enhanced image is enlarged to be 16x spatial resolution image by SSRR established on the high-frequency pre-forecasting. In the verification experimentation section, the verification outcome demonstrates that the proposed spatial enhancement is successful for enlarging HR image with 16x ratio rate with finer quality.

Keywords: MSRR (Multi-frame Super Resolution Reconstruction), SSRR (Single-Super Resolution Reconstruction), Digital Image Reconstruction, Regularized ML (Maximum Likelihood), Tukey's Biweight Function

Manuscript received on August 2, 2017 ; revised on May 17, 2018.

The Portions of this research work were presented at the 14th Annual International Conference of Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON 2017), Thailand, June 2017, as "A Novel Resolution Enhancement Established on An Iterative Regularized ML MSRR and High-Frequency Pre-Determining SSRR for Ultra-Magnification Rate", (IEEE Xplore) [15]"

Final manuscript received on May 18, 2018.

[1] The author is with Faculty of Engineering, Assumption University,Thailand, E-mail: Patanavijit@yahoo.com

[2] The author is with The author is with School of Management and Economics, Assumption University, Thailand, E-mail: kthakulsukanan@yahoo.com

1. THE RESEARCH PROBLEM AND MOTIVATION

In DIP and CV, SRR technique [2,6,8,9,11-12], which can reconstruct a HR image from a single LR image or many LR images by using algebraic formulation, is one of the modern research fields in digital image processing because a high spatial resolution image (HR) is greatly needed for modern applications. Nevertheless MSRR, constructed on an iterative ML regularized technique, has the capability to increase the spatial resolution while eliminate the noise, the spatial enhance ratio rate of this MSRR is limited to 5.7x for theoretical case and to 1.6x for real case because of the algebraic limitation of this reconstruction MSRR [3,16]. The SSRR, constructed on high-frequency pre-forecasting [1], has the capability to increase the spatial resolution from a single captured image however the SSRR has less efficiency in the noisy case [13]. In order to bring the superiority of both MSRR for increasing the spatial resolution while eliminating the noise and SSRR for increasing the spatial resolution from a single captured image, this paper presents an extra-rate spatial enhancement constructed by MSRR [10] and SSRR [1,13] for spatial enhancing up to 16x ratio rate.

In this research article, there is arranged as 4 sections. Section 1 initially briefs the problem of this super resolution research and the inspiration of this super resolution research. Next, Section 2 proposes the algebraic formulation of the extra-rate resolution enhancement constructed on MSRR and SSRR. In Section 3, two standard tested images (Foreman: 110th Frame (352×288) and Lena (512×512)) are initially used to create a collection of corrupted images with low spatial resolution (Foreman: 110th Frame (88×72) and Lena (128×128)) under many noisy cases with several powers. Subsequently, these corrupted LR images are processed by using the proposed spatial enhancement for constructing the finer quality image with 16x spatial resolution magnification rate (Foreman: 110th Frame (352×288) and Lena (512×512)) for testing the proposed combined technique in both objective and subject measurements. The summary is presented in the last section.

2. THE ALGEBRAIC THEORY OF THE NOVEL RESOLUTION ENHANCEMENT ESTABLISHED ON MSRR METHOD AND SSRR METHOD

This section introduces the algebraic theory of the extra-rate spatial enhancement, which is unified on MSRR [10] and SSRR [1] and the overall computed diagram of the spatial enhancement is illustrated in Fig. 1.

Initially, for restoring the fine image information while suppressing the noise, a group of captured LR images is processed by using MSRR using a regularized technique constructed on a recursive ML and Tukey's Biweight norm [10], which is comprehensively presented in section 2.1, to build the finer quality image with 4x ratio rate. Subsequently, the 4x enlarged image is processed to build the 16x enlarge image by using SSRR constructed on the high-frequency pre-forecasting [1], which is comprehensively presented in section 2.2.

2.1 THE ALGEBRAIC THEORY OF THE MSRR CONSTRUCTED ON AN TUKEY'S BIWEIGHT REGULARIZED ML TECHNIQUE

Initially, for restoring the fine image information while suppressing the noise, a group of captured LR images is processed by using MSRR using a regularized technique constructed on a recursive ML and Tukey's Biweight norm [10] to build the finer quality image with 4x rate. The MSRR is traditionally classified as an ill-posed condition because the MSRR algebraic theory faults to satisfy many Hadamard Theory conditions hence an additional information (so called regularized function) is algebraic unavoidable required for stability perspective and convergent rate perspective. In lexicographic configuration, the finer quality image $\hat{\underline{X}}_{4x}$ (2m×2n pixels) with 4x spatial rate can be explicated in the algebraic equation of a group of captured LR images $\underline{Y}_k$ (m×n pixels) as following expression.

$$\hat{\underline{X}}_{4x} = \underset{\underline{X}_{4x}}{\text{ArgMin}} \left\{ \sum_{k=1}^{N} \rho\left(D_k H_k F_k \underline{X}_{4x} - \underline{Y}_k\right) + \lambda \cdot \left(\Gamma \underline{X}_{4x}\right)^2 \right\} \quad (1)$$

F_k is wrapped matrix of the k^{th} captured LR images with respect to the reference captured LR images; H_k is the defocused matrix due to blurring effect; is down-side spatial resolution matrix due to down sampling effect; D_k is a adjusting parameter for turning regularized function [14]; λ is the Regularization matrix, which is algebraically computed from Tikhonov regularization [14]; $\rho(\cdot)$ is the fidelity function [10]. By applying the nonlinear optimized technique [14] for determining this minimized problem, the former algebraic expression can be written

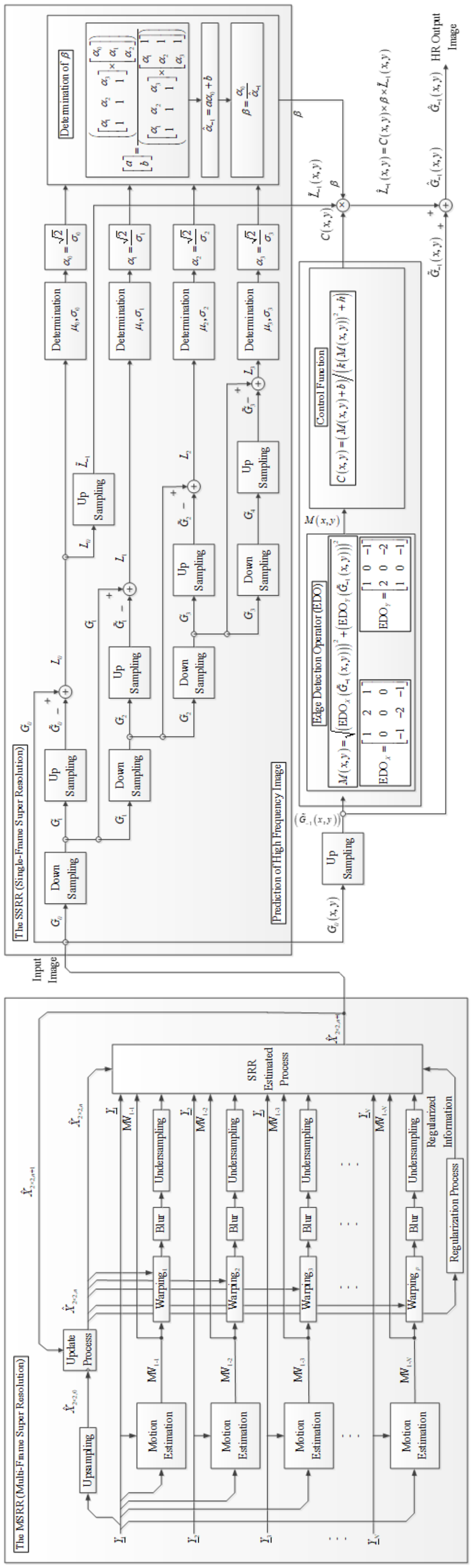

Fig.1: *The computed diagram of the proposed spatial enhancement constructed on MSRR and SSRR.*

as upcoming algebraic expression.

$$\underline{\hat{X}}_{4x,n+1} = \underline{\hat{X}}_{4x,n} + \beta \cdot \left\{ \begin{array}{l} \sum_{k=1}^{N} F_k^T H_k^T D_k^T \cdot \psi\left(\underline{Y}_k - D_k H_k F_k \underline{\hat{X}}_{4x,n}\right) \\ -\left(\lambda \cdot \left(\Gamma^T \Gamma\right) \underline{\hat{X}}_{4x,n}\right) \end{array} \right\} \quad (2)$$

where $\psi(\cdot)$ is the gradient function of $\rho(\cdot)$, which is $\psi_{TUKEY}(x) = x\left[1-(x/T)\right]^2$ for $|x| \le T$ or 0 for $|x| > T$ [10] and β is the step-size constant in the nonlinear optimized technique.

2.2 THE ALGEBRAIC THEORY OF THE SSRR CONSTRUCTED ON THE HIGH-FREQUENCY PRE-FORECASTING

The primary goal of the second subsystem of the proposed spatial enhancement, which is constructed on a high-frequency pre-forecasting, is to spatially enhance to magnification rate from the only one 4x image $\underline{\hat{X}}_{4x}$ to be 16x image $\hat{X}_{16x}$. Like the MSRR, the SSRR is classified as ill-posed inverse problem because of the SSRR algebraic theory faults to satisfy many Hadamard Theory conditions. Hence, an additional information (so called synthesized high-frequency data, which is algebraically processed by pre-forecasting technique) is algebraic unavoidable required for building the finer quality image $\hat{X}_{16x}$. In general, although the traditional interpolation technique [5] can spatially enhance the image $\underline{\hat{X}}_{4x}$, which is built in the previous MSRR, to be finer resolution image $\hat{X}_{16x}$, this finer resolution image $\hat{X}_{16x}$ is comprised of only low frequency data ($\underline{\hat{X}}_{16x,L}$) because the traditional interpolation technique cannot synthesize the high frequency part ($\underline{\hat{X}}_{16x,H}$). By using the algebraic digital image processing theory of Laplacian pyramid [4], this theory states that an image $\underline{\hat{X}}_{4x}$ can be classified into a high frequency data ($\underline{\hat{X}}_{4x,H}$) and low frequency data ($\underline{\hat{X}}_{4x,L}$).

The first sub-process of the proposed spatial enhancement, which is shown in Fig. I, is a high frequency pre-forecasting, which is constructed on Laplacian pyramid theory [4], for synthesizing a high frequency data of a finer spatail image $\hat{X}_{16x}$ from the high frequency part of an input image $\underline{\hat{X}}_{4x,H}$ (2m×2n pixels), the 1st downsizing input image $\underline{\hat{X}}_{1x,H}$ (m×n pixels), the 2nd downsizing input image $\underline{\hat{X}}_{0.25x,H}$ (0.5m×0.5n pixels) and the 3rd downsizing input image $\underline{\hat{X}}_{0.0625x,H}$ (0.25m×0.25n pixels). Subsequently, the image histogram is processed from the high frequency data of all level downsizing input images and, then, the normal mean (μ_n) and normal variance (σ_n) is processed by modeling normal distribution. Later, the Laplacian parameter (α_n) of all level downsizing input images is processed from the normal mean (μ_n) and normal variance (σ_n) by modeling the Laplacian distribution for complexity reduction perspective. By using the linear least squares (LS) for overdetermined case, the Laplacian parameter of an finer spatial image $\hat{\alpha}_{-1}$ (of $\underline{\hat{X}}_{16x,H}$) can be processed from the Laplacian parameter (α_n) of all level downsizing input images: α_0)(of $\underline{\hat{X}}_{4x,H}$), α_1)(of $\underline{\hat{X}}_{1x,H}$), α_2)(of $\underline{\hat{X}}_{0.25x,H}$) and α_3)(of $\underline{\hat{X}}_{0.0625x,H}$).

The second sub-process of the SSRR constructed on a high frequency pre-forecasting is comprised by an edge detection and a control function [1], for bounding the outlier value of intensity magnitude. The edge detection operator (EDO) [1], which is constructed on Sobel kernel [13], is used to process the edge info $M(x,y)$ (4m×4n pixels) as following expression.

$$\text{M(x,y)}=\sqrt{\left(\text{EDO}_X(\tilde{G}_{-1}(x,y))\right)^2 + \left(\text{EDO}_Y(\tilde{G}_{-1}(x,y))\right)^2} \quad (3.1)$$

$$\text{EDO}_X = \left[\begin{array}{ccccccccccc} 1 & 2 & 1 & ; & 0 & 0 & 0 & ; & -1 & -2 & -1 \end{array}\right] \quad (3.2)$$

$$\text{EDO}_Y = \left[\begin{array}{ccccccccccc} 1 & 0 & -1 & ; & 2 & 0 & -2 & ; & 1 & 0 & -1 \end{array}\right] \quad (3.3)$$

where $G_{-1}(x,y)$ is the a low frequency component of HR image and $L_{-1}(x,y)$ is the a high frequency component of HR image.

For bounding the outlier value of intensity magnitude, the bounded edge $C(x,y)$ is processed by the control function [1,7] as following expression

$$C(x,y) = \left(M\left(x,y\right)+b\right) \Big/ \left(k(M\left(x,y\right))^2 + h\right) \quad (4.1)$$

$$b = (0.5)\ c_0 M_0 (1-c_0)^{-1} \quad (4.2)$$

$$k = (0.5)\ (M_0)^{-1} \quad (4.3)$$

$$h = (0.5)\ M_0 (1-c_0)^{-1} \quad (4.4)$$

The b, k and h is constant parameter, which is defined for bounding the image modeling in both the edge intensity and smooth areas. The constant M_0 is used to suppress the unbound intensity at edge areas, whereas c_0 is used to suppress the outlier intensify at smooth areas.

The finer spatial enhanced image ($\underline{\hat{X}}_{16x}$) is processed by adding the low frequency data ($\underline{\hat{X}}_{16x,L}$), which is synthesized from the bicubic interpolation process with the high frequency ($\underline{\hat{X}}_{16x,H}$), which is multiplied by $C \times (\alpha_0/\hat{\alpha}_{-1})$.

$$\hat{X}_{16x} = \hat{X}_{16x,L} + C \times (\alpha_0/\hat{\alpha}_{-1}) \times \hat{X}_{16x,H} \quad (5)$$

3. VERIFICATION EXPERIMENTATION

For verifying the efficiency of the proposed spatial enhancement, this section does not present only the result of the spatial enhanced image, which is processed by the proposed spatial enhancement, but also the other spatial enhanced images, which are processed by the traditional interpolation technique [5], the SSRR [1] and the MSRR [10], are used to compare with the proposed spatial enhancement.

Two group of captured images (Foreman (10th Frame) and Lena) with low spatial resolution (Foreman: 88×72 and Lena: 128×128) are synthesized from the original image (Foreman: 352×288 and Lena: 512×512) by down-sizing the original standard image for building the coarser image (Foreman: 176x144 and Lena: 256×256) and, then, this coarser image is shifted in horizontal direction with one-pixel. Subsequently, this shifted coarser image is processed by Gaussian low-pass filter and down-sizing by 4 times, next, is processed by several noisy case (five Gaussian noise circumstance, one Poisson noise circumstance, three Salt and Pepper noise circumstance, and three Speckle noise circumstance) for building the captured coarser image (Foreman: 88×72 and Lena: 128×128). The identical synthesized process is repeated for building another three captured coarser images (Foreman: 88×72 and Lena: 128×128) at other shifting on horizontal and vertical direction.

The ideal for turning parameters in this verification experiment is to turn parameters that make the proposed spatial enhancement the highest performance (in PSNR and visual perspective) and each experiment is repeated several times with several parameters for verification integrity. The finest enhanced image with highest PSNR and visual perspective is selected.

In order to simplify turning process of the control function [13], the parameter c_0 is set to be zero in all experiment (resulting $c_0 = 0$, $h = M_0/2$, $k = 1/2M_0$, $b = 0$) therefore the control function $C(x, y)$ in Eq.(4) is a function that depend on only one parameter M_0. The control function $C(x, y)$ can be algebraic simplified as following expression

$$C(x,y) = M(x,y)\left(0.5(M_0)^{-1}(M(x,y))^2 + 0.5M_0\right)^{-1} \quad (6)$$

From the experimental results in PSNR of verification testing of Foreman (10th Frame) and Lena as shown in Table I and II, the finer enhanced image, which is computed by the proposed spatial enhancement, can be portrayed in Fig. 2 and Fig. 3, respectively. Thereby, the proposed spatial enhancement (for spatial enhancing 16x ratio rate) has the highest PSNR and best visual quality in all noise models and noise power levels, compared with traditional interpolation technique [5], the SSRR [1] and the MSRR [10]. From these results, the SSRR has the lowest PSNR because the SSRR cannot be effectively work under noisy cases [13] however the proposed resolution enhancement, which is constructed by MSRR using regularized ML technique and SSRR using high-frequency pre-forecasting, can be reconstructed the enhanced image effectively.

4. CONCLUSION

This paper proposed a new resolution enhancement constructed by the mathematical combination of MSRR, which is constructed by the regularized ML technique and stochastic Tukey's Biweight function, and SSRR, which is constructed by the high-frequency pre-forecasting technique and an outlier control function, spatially enhancing up to 16x ratio rate and the verification outcome demonstrates that the proposed spatial enhancement has is successful for reconstructing HR image with 16x spatial resolution rate and noise suppressing.

ACKNOWLEDGEMENT

The research project was funded by Assumption University.

References

[1] B.W. Jeon, R.H. Park and S. Yang, "Resolution Enhancement by Prediction of the High-Frequency Image Based on the Laplacian Pyramid," *EURASIP Journal on Advances in Signal Processing*, Hindawi Publishing Corp., Dec. 2006.

[2] D. Rajan, S. Chaudhuri and M. V. Joshi, "Multi-objective super resolution: concepts and examples," in *IEEE Signal Processing Magazine*, vol. 20, no. 3, pp. 49-61, May 2003.

[3] D. Robinson and P. Milanfar, "Statistical performance analysis of super-resolution," in *IEEE Transactions on Image Processing*, vol. 15, no. 6, pp. 1413-1428, June 2006.

[4] P. J. Burt and E. H. Adelson, "The Laplacian pyramid as a compact image code," *IEEE Transactions on Communications*, vol. 31, 1983.

[5] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, Prentice-Hall,Upper Saddle River,NJ, USA, 2nd edition, 2002.

[6] M. G. Kang and S. Chaudhuri, "Super-resolution image reconstruction," in *IEEE Signal Processing Magazine*, vol. 20, no. 3, pp. 19-20, May 2003.

[7] M. J. Black and A. Rangarajan, "On The Unification Of Line Processes, Outlier Rejection and Robust Statistics with Applications in Early Vision," *International Journal of Computer Vision*, vol. 19, pp. 57-91, Jul. 1996.

[8] M. K. Ng and N. K. Bose, "Mathematical analysis of super-resolution methodology," in *IEEE Signal Processing Magazine*, vol. 20, no. 3, pp. 62-74, May 2003.

[9] S. C. Park, M. K. Park and M. G. Kang, "Super-resolution image reconstruction: a technical overview," in *IEEE Signal Processing Magazine*, vol. 20, no. 3, pp. 21-36, May 2003.

[10] V. Patanavijit and S. Jitapunkul, "A Robust Iterative Multiframe Super-Resolution Re-

Table 1: *Verification result of Foreman (10^{TH} frame) (for creating HR:352×288 from LR:88×72).*

Reconstruction Algorithms	Noisy Case (dB)													
	SNR 25dB	*SNR 22.5dB*	*SNR 20dB*	*SNR 17.5dB*	*SNR 15dB*	*Poisson*	*S&P D=0.005*	*S&P D=0.010*	*S&P D=0.015*	*Speckle V0.01*	*Speckle V0.02*	*Speckle V0.03*	*Speckle V0.04*	*Speckle V0.05*
16xBicubic Interpolation	23.1467	22.5289	21.7653	20.5286	19.2089	22.5658	23.0177	22.4868	21.6279	21.6770	20.3726	19.2574	18.6165	17.9815
16xSSRR	23.1461	22.5267	21.7620	20.5261	19.2963	22.5639	23.0191	22.4842	21.6221	21.6733	20.3702	19.3337	18.7747	18.3173
16xT-MSRR	24.5258	23.9990	23.4771	22.7293	22.0671	24.0015	25.9945	25.1942	25.9444	23.2609	22.6054	21.8555	21.7373	21.3067
16xT-MSRR and SSRR	**24.6033**	**24.0343**	**23.4835**	**22.7412**	**22.0721**	**24.0564**	**26.1927**	**25.3547**	**26.1336**	**23.2872**	**22.6126**	**21.8561**	**21.7406**	**21.3093**

Table 2: *Verification result of Lena (for creating HR:512×512 from LR:128×128).*

Reconstruction Algorithms	Noisy Case (dB)													
	SNR 25dB	*SNR 22.5dB*	*SNR 20dB*	*SNR 17.5dB*	*SNR 15dB*	*Poisson*	*S&P D=0.005*	*S&P D=0.010*	*S&P D=0.015*	*Speckle V0.01*	*Speckle V0.02*	*Speckle V0.03*	*Speckle V0.04*	*Speckle V0.05*
16xBicubic Interpolation	26.5665	25.8919	25.2750	24.4520	23.3072	25.4444	25.6542	24.6671	23.9309	25.3347	24.2845	23.4244	22.7176	22.0720
16xSSRR	26.5892	25.7798	25.0565	24.0805	22.5130	25.2699	25.5566	24.3565	23.5019	25.1275	23.8900	22.7369	20.1180	23.0535
16xT-MSRR	27.0313	26.5769	25.9796	25.2532	24.7041	26.1199	28.1310	28.0388	28.1139	25.6100	25.0576	24.6990	24.4381	24.2429
16xT-MSRR and SSRR	**27.0491**	**26.5892**	**25.9831**	**25.2532**	**24.7065**	**26.1177**	**28.3407**	**28.2375**	**28.3225**	**25.6339**	**25.0660**	**24.7003**	**24.4381**	**24.2429**

construction using a Bayesian Approach with Tukey's Biweigth," *Proceeding of IEEE International Conference on Signal Processing 2006 (ICSP 2006)*, Guilin, China, Nov. 2006.

[11] V. Patanavijit, "Super-Resolution Reconstruction and its Future Research Direction," *AU Journal of Technology (AU J.T.)*, Assumption University, Thailand, Jan. 2009.

[12] V. Patanavijit, "Mathematical Analysis of Stochastic Regularization Approach for Super-Resolution Reconstruction, *AU Journal of Technology (AU J.T.)*, Assumption University, Thailand, Apr. 2009.

[13] V. Patanavijit, C. Pirak and G. Ascheid, "A Performance Impact of An Edge Kernel for The High-Frequency Image Prediction Reconstruction," *ISCIT 2014*, Incheon, Korea, Sep. 2014.

[14] V Patanavijit, "Comparative Experimental Exploration of Robust Norm Functions for Iterative Super Resolution Reconstructions under Noise Surrounding," *ECTI Transactions on EEC, ECTI Association*, Thailand, vol.13, no.2, August 2015.

[15] K. Thakulsukanant and V. Patanavijit, "A Novel Resolution Enhancement Established on An Iterative Regularized ML MSRR and High-Frequency Pre-Determining SSRR for Ultra-Magnification Rate," *Proceeding of The 14th Annual International Conference of Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON 2017)*, Phuket, Thailand, pp.115-118, June 2017.

[16] Z. Lin and H.Y. Shum, "Fundamental Limits of Reconstruction-Based Superresolution Algorithms under Local Translation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 26, no.1, pp. 83-97, Jan. 2004.

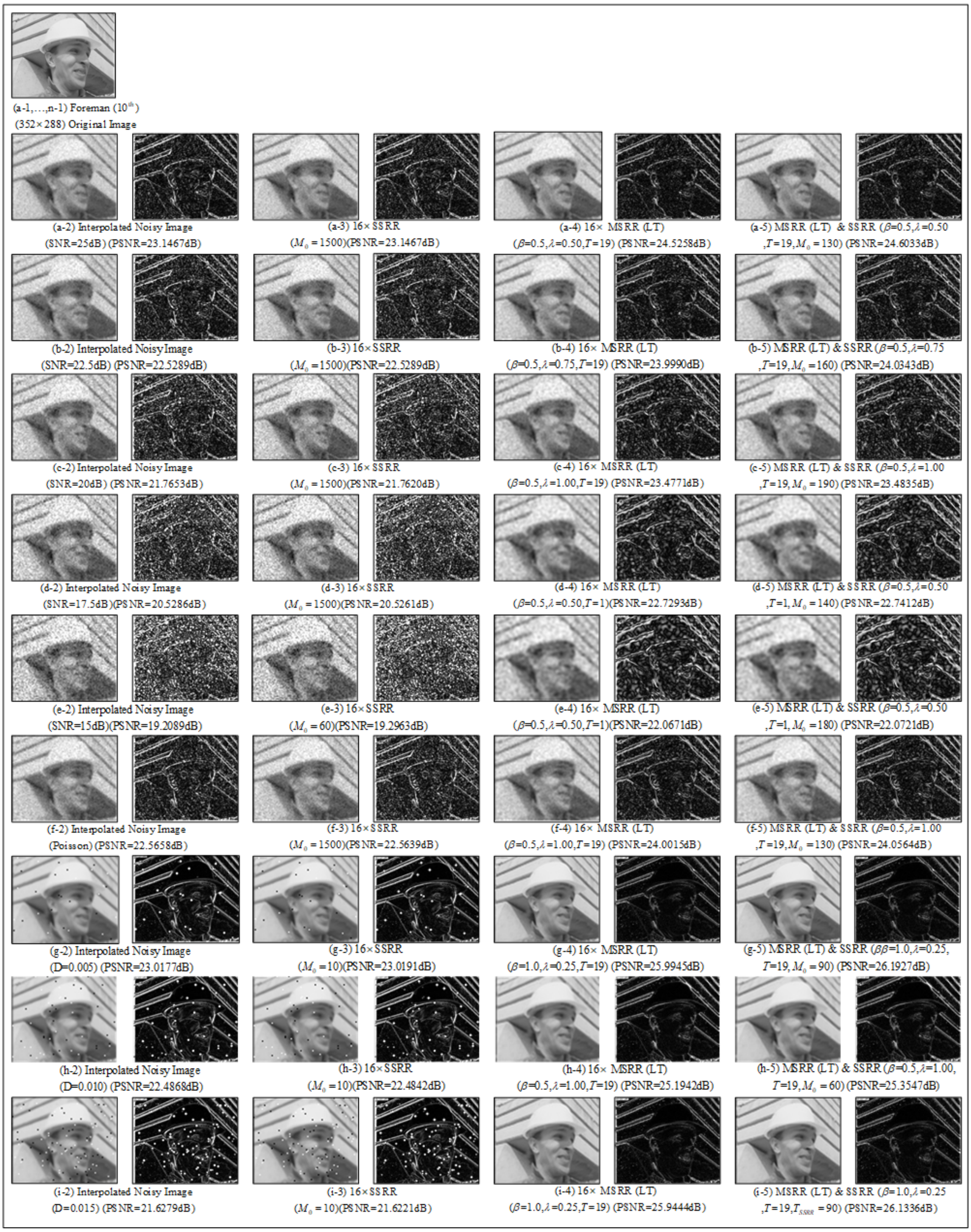

Fig.2: *The experimental results of verification testing of Foreman (10th Frame) (for enhancing HR:352×288 from LR:88×72) (Each sub-figure (which is right-hand-side position at each enlarged image) is the absolute subtraction of that enlarged image and the ordinary image and, then, the result is expanded by five for the observing point of view).*

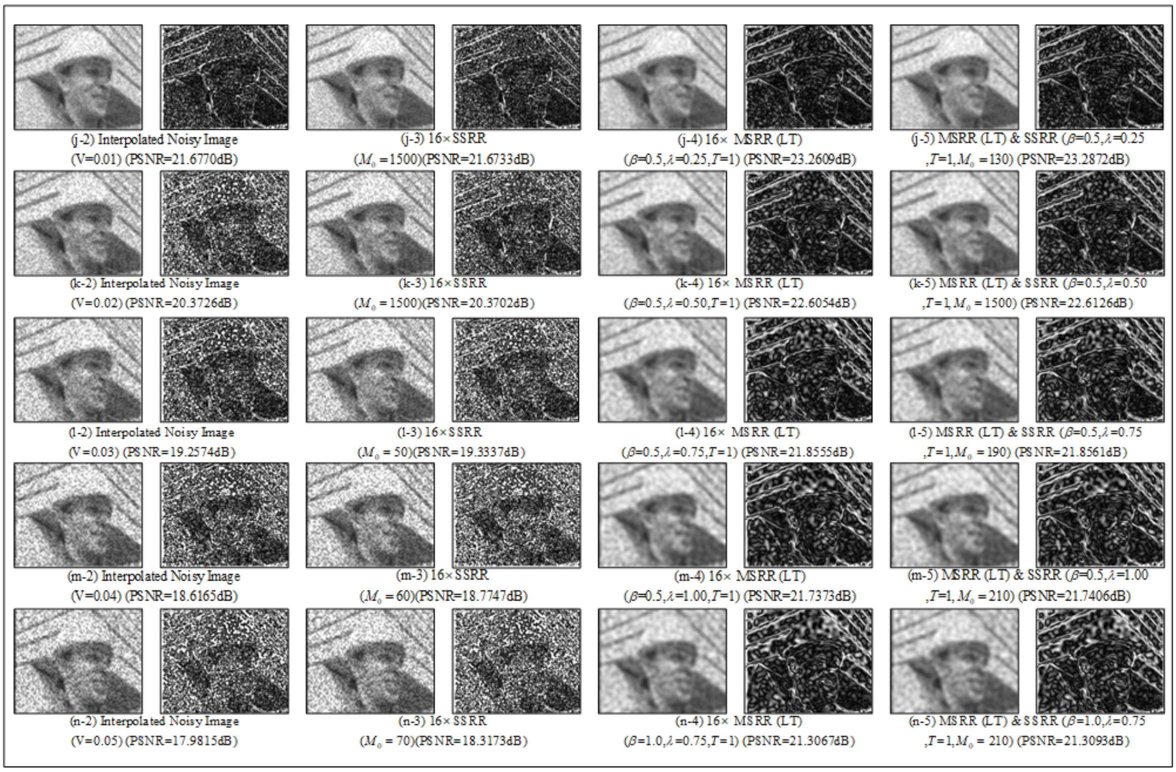

Fig.2: *The experimental results of verification testing of Foreman (10th Frame) (for enhancing HR:352×288 from LR:88×72) (Each sub-figure (which is right-hand-side position at each enlarged image) is the absolute subtraction of that enlarged image and the ordinary image and, then, the result is expanded by five for the observing point of view)(Cont.).*

Fig.3: *The experimental results of verification testing of Lena (for enhancing HR:512×512 from LR:128×128) (Each sub-figure (which is right-hand-side position at each enlarged image) is the absolute subtraction of that enlarged image and the ordinary image and, then, the result is expanded by five for the observing point of view) .*

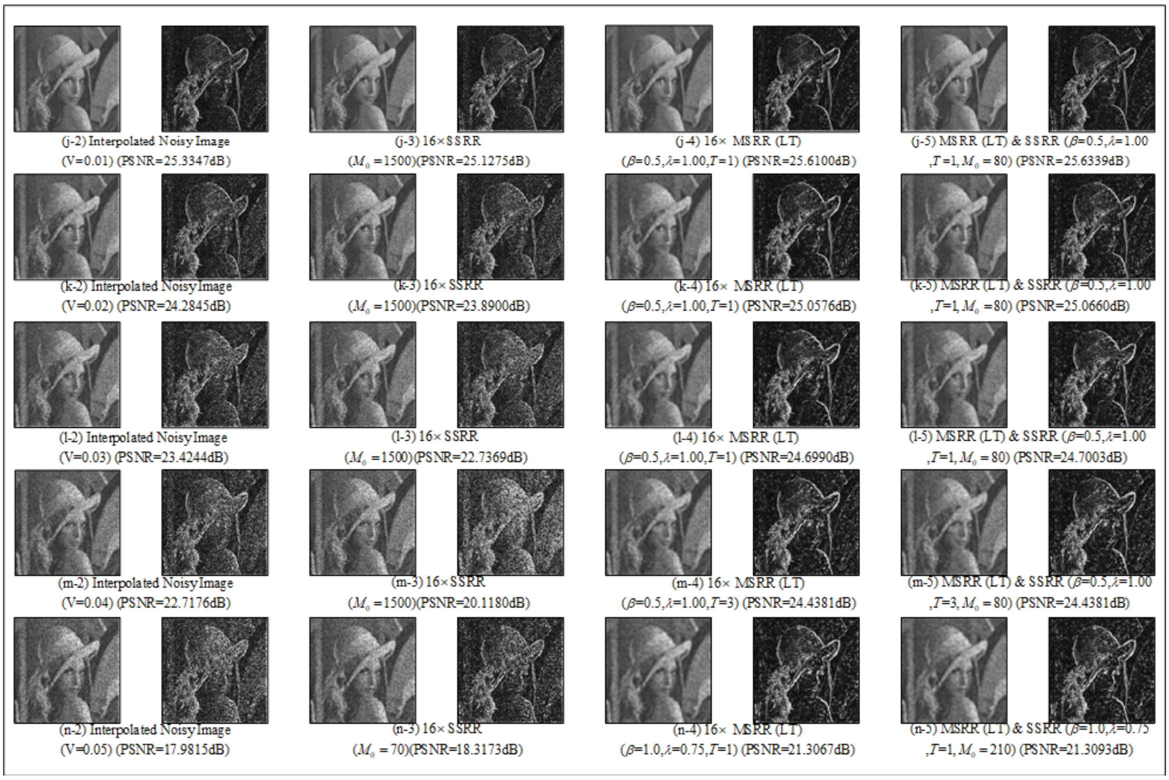

Fig.3: *The experimental results of verification testing of Lena (for enhancing HR:512×512 from LR:128×128) (Each sub-figure (which is right-hand-side position at each enlarged image) is the absolute subtraction of that enlarged image and the ordinary image and, then, the result is expanded by five for the observing point of view)(Cont.).*

Vorapoj Patanavijit received the B.Eng., M.Eng. and Ph.D. degrees from the Department of Electrical Engineering at the Chulalongkorn University, Bangkok, Thailand, in 1994, 1997 and 2007 respectively. He has served as a full-time lecturer at Department of Electrical and Electronic Engineering, Faculty of Engineering, Assumption University since 1998 where he is currently an Associate Professor.

He has authored and co-authored over 135 national/international peer-reviewed publications in Digital Signal Processing (DSP) and Digital Image Processing (DIP). He has served as a Technical Program Committees (TPC) on Signal Processing of ECTI (Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology) Association, Thailand since 2012 to 2015.

As a technical reviewer of international journals since 2006, he has been assigned to review over 60 journal papers (indexed by ISI). As a technical reviewer of over 40 international/national conferences since 2006, he has been assigned to review over 130 proceeding papers. He has participated in more than 8 projects and research programmed funded by public and private organizations.

He works in the field of signal processing and multidimensional signal processing, specializing, in particular, on Image/Video Reconstruction, SRR (Super-Resolution Reconstruction), Compressive Sensing, Enhancement, Fusion, Digital Filtering, Denoising, Inverse Problems, Motion Estimation, Optical Flow Estimation and Registration.

Kornkamol Thakulsukanant received the B.Eng. (Electrical Engineering) from Assumption University, Thailand in 1994, MSc. (Telecommunications and Computer Network Engineering) from London South Bank University, United Kingdom in 1997 and Ph.D. (in Electronic and Electrical Engineering) from Bristol University, United Kingdom in 2009 respectively.

She served as a full-time lecturer at Faculty of Science and Technology, Assumption University since 1998 until 2014 and she has served as full-time lecturer at School of Management and Economics, Assumption University where she has been currently an Assistance Professor (in ICT) since 2014.

She works in the field of Digital Signal Processing (DSP) and Digital Image Processing (DIP), specializing, in particular, on Digital Image Reconstruction/Enhancement.