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An innovative vigorous outlier recognition placed on LROAD for fix-amplitude impulsive noise

Vorapoj Patanavijit, Kornkamol Thakulsukanant
Faculty of Engineering, Assumption University of Thailand, Bangkok, Thailand

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ABSTRACT

Due to large current applications on digital images in these recent years, outlier suppression is one of the primary stages for modern computer vision implementations thereupon there are tremendously invented for creating an efficient and practical outlier suppression, which ordinarily are composed of outlier recognition stage and outlier rebuilt stage. The localised rank ordered difference (LROAD) approach, which is progressed from rank-ordered absolute differences (ROAD), has been invented since 2016. Later, the LROAD approach evolved to be one of the efficient outlier recognition stages from its eminent effectiveness. The paper focus to propose the innovative vigorous outlier recognition placed on localised rank-ordered logarithmic differences (LROLD) approach, which is progressed from LROAD and (ROLD), which is higher effectiveness than the ordinary LROAD, for applying on FAIN. From the computer experiments, which are examined on many depictions such as Girl, Pepper F16 and Lena, the innovative vigorous outlier recognition placed on LROLD approach has higher eminent effectiveness then the stage-of-art approach such as LROAD and ROAD approaches at numerous consistencies of FAIN.

Corresponding Author:

Vorapoj Patanavijit
Faculty of Engineering, Assumption University of Thailand
VME Bldg., 2nd Flr., 88 Moo 8 Bang Na-Trad Km. 26, Bangsaothong, 10540 Samuthprakarn Thailand
Email: patanavijit@gmail.com

1. INTRODUCTION

In computer vision and digital image processing [1], there are large current applications on digital images [2]-[4] in this recent years thereupon one of the primary stages for modern computer vision implementations [5] such as MF-SR [6], [7], SF-SR [8], face classification [9] is the outlier suppression because the sophisticated image processing approaches [5]-[9] are ordinarily sensitive on outlier. As a result, outlier suppression is one of the primary stages for modern computer vision implementations thereupon there are tremendous invented for creating practical outlier suppression approaches, which ordinarily are composed of outlier recognition stage and outlier rebuilt stage. Initially, the standard median filter (SMF) [10] was invented for FAIN in 1975 and, later, has been evolved to be one of the ordinary outlier suppression approach. For suppressing FAIN on color illustrations, the vector median filter (VMF) [11], which is progressed from ordinary SMF, was invented in 1990 and has been evolved to be one of the standard outlier suppression approach for color illustrations. Next, an adaptive median filter (AMF) [12], which was progressed from the SMF where the calculating window is self-regulating changing, was invented to be the noise suppressing algorithm for FAIN in 1994 and later, has been evolved to be one of the ordinary outlier suppression approach with superior effectiveness. In 2017, The outlier suppression approach [13] placed on both amplitude preserving cast elimination and swarm optimization was invented for exploiting color illustrations. Thereupon, self-regulating computer-abetment investigation approach [14] placed on SVM designation for MRI brain illustrations was invented in 2017. Next, the outlier suppression approach [15] placed on outlier consistency evaluation by local statistics was invented for illustrations in 2018. Succeeding, the outlier suppression approach [16] placed on a powerful filtering approach was invented for color illustrations in 2018. Subsequently, the ordinary outlier suppression approach placed on the Gaussian filtering and Wiener filtering [17] been examined its effectiveness by changeable kernel dimension in 2019. Later, the outlier suppression approach placed on filter approach [18] been examined its effectiveness on medical illustrations in 2019. Charmouti *et al.* [19] revises tremendous outlier suppression approaches placed on different ordinary approaches and relatively reexamines this effectiveness on outlier suppression point of view in 2019. In 2020, the revised outlier suppression approach placed on an apparitional wavelet approach [20], which is the progressed from Haar wavelet as apparitional order by a LP filtering generalization with the apparitional delay process, has been invented. For underwater acoustic outlier, the outlier suppression approach placed on DWT [21] with noise density estimation was invented in 2020.

Tremendous present outlier suppression approaches [22]-[25], which are ordinarily composed of outlier recognition stage and outlier rebuilt stage, have been developed as following. In 2017, the outlier suppression approach placed on hybrid statistic method [22] is developed for suppressing impulse outlier. For high consistency of FAIN, alternative outlier suppression approach, so called adaptive decision based inverse distance weighted interpolation (DBIDWI) approach [23]-[24], which was developed for by Kishorebabu *et al.* [23] in 2017, is examined its effectiveness [24] under almost consistency of FAIN in 2019. Many present outlier recognition approaches [25] placed on rank-ordered absolute differences (ROAD), rank-ordered logarithmic differences (ROLD) and rank-ordered relative differences (RORD) are relatively reexamines for recognizing impulse outlier in 2019. Next, the outlier suppression approach placed on the triple threshold statistical detection (TTSD) filter [26] was developed for RAIN in 2018. Subsequently, the outlier suppression approach placed on the localised rank ordered absolute differences (LROAD) filter [27], which is progressed from the ordinary ROAD approach, initially was developed for RAIN in 2016 and these approach provides superior effectiveness. Consequently, the paper focus to propose the innovative vigorous outlier recognition placed on localised rank-ordered logarithmic differences (LROLD) approach [28], which is progressed from LROAD and rank-ordered logarithmic differences (ROLD), which is higher effectiveness than LROAD for FAIN.

2. THE PROPOSED LROLD ALGORITHM

Under FAIN situation, especially the salt-and-pepper outlier, the outlier illustration $\underline{Y}$, which is ordinarily characterized from the outlier-less illustration $\underline{X}$, is scientifically indicated in the successive algebraic testimony.

$$\underline{Y} = \underline{X} + \underline{N} \tag{1}$$

The analytical data processing of the proposed LROLD algorithm approach for outlier recognition stage as successive:

a. For each processed illustration component $y(i,j)$ in the anormaly illustration $\underline{Y}$, the 5×5 local neighbornood group of the processed illustration component is scientifically indicated in the successive algebraic testimony as $\boldsymbol{\Omega}_{5\times5}$ where this local neighbornood group $\boldsymbol{\Omega}_{5\times5}$ is detached into nine 3×3 local neighbornood groups as $\{\boldsymbol{\Omega}_{1x}, \boldsymbol{\Omega}_{2x}, \boldsymbol{\Omega}_{3x}, \dots, , \boldsymbol{\Omega}_{9x}\}$ as indicating in the Figure 1.

b. The absolute value of the subtraction between the processed illustration component $y(i,j)$ and each illustration component in each 3×3 local neighbornood groups ($\{\boldsymbol{\Omega}_{1x}, \boldsymbol{\Omega}_{2x}, \boldsymbol{\Omega}_{3x}, \dots, , \boldsymbol{\Omega}_{9x}\}$) is scientifically indicated in the successive algebraic testimony.

$$d_{x,y}^{k} = \left| y_{\boldsymbol{\Omega}_{3\times3}} - y(i,j) \right|, \quad y_{\boldsymbol{\Omega}_{3\times3}} \in \boldsymbol{\Omega}_{kx} \tag{2}$$

Next, the logarithmic distance value of each processed absolute value $d_{x,y}^{k}$ is scientifically indicated in the successive algebraic testimony.

$$d_{x,y}^{k} = 1 + \tfrac{1}{5}\left(max\left(log_2\left(d_{x,y}^{k} \right), -5 \right) \right) \tag{3}$$

Later, each processed logarithmic absolute value $d_{x,y}^{k}$ is ascendingly categorized as the successive algebraic testimony.

$$\underset{\text{ascending}}{Sort}\left(d_{x,y}^{k} \right) = d_{x,y}^{k}(1) \le d_{x,y}^{k}(2) \le d_{x,y}^{k}(3) \le \dots \le d_{x,y}^{k}(8) \tag{4}$$

c. Each ascendingly categorized values is used to process the LROLD for each 3×3 local neighbornood group ($\{\boldsymbol{\Omega}_{1x}, \boldsymbol{\Omega}_{2x}, \boldsymbol{\Omega}_{3x}, \dots, , \boldsymbol{\Omega}_{9x}\}$) as the successive algebraic testimony.

$$\mathrm{LROLD}_m^k(x) = \sum_{i=1}^{m} d_{x,y}^k(i) \tag{5}$$

d. Next, each 3×3 local neighbornood group $\boldsymbol{\Omega}_{kx}$ is recognized as identification to each processed illustration component $y(i,j)$ where the value $\mathrm{LROLD}_m^k(x)$ of 3×3regional window $\boldsymbol{\Omega}_{kx}$ is lower than the preset value (d_T) otherwise that 3×3 local neighbornood group $\boldsymbol{\Omega}_{kx}$ is recognized as non-identification.

e. Each processed illustration component $y(i,j)$ is recognized as an outlier illustration component where the total 3×3 local neighbornood group $\boldsymbol{\Omega}_{kx}$ is recognized as identification lower than 3 group otherwise the processed illustration component $y(i,j)$ is recognized as a outlier-less illustration component.

The comprehensive analytical data processing of the LROLD approach for outlier recognition is indicated as Figure 2 (see in appendix).

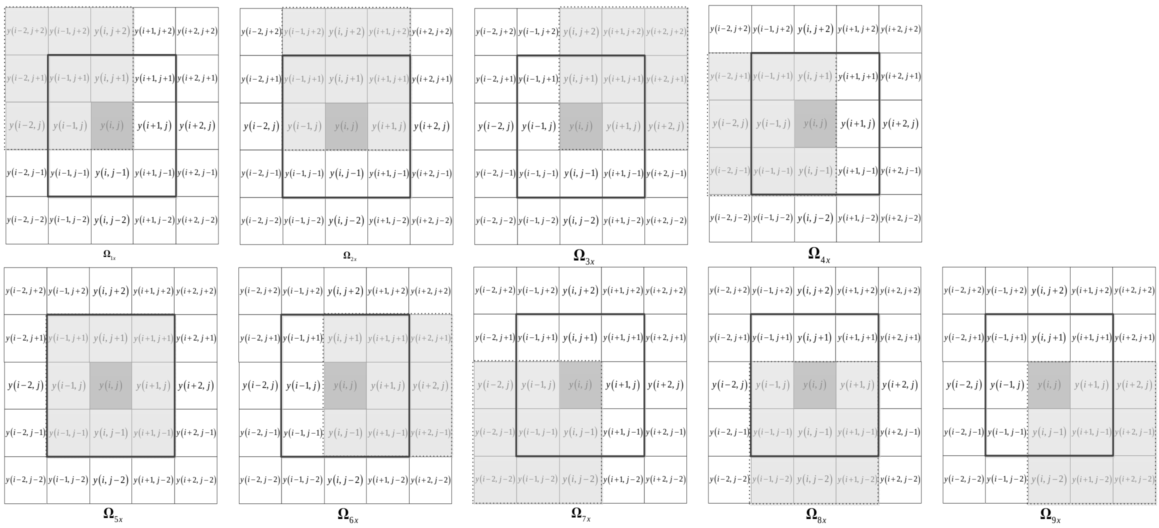

Figure 1. The organization of 3×3 local neighbornood group of LROLD

3. THE SCIENTIFIC PROCESS EXAMPLES OF LROLD APPROACH

This scientific part focuses to the detail process of LROLD approach. This example of LROLD approach process is indicated as Figure 3 (see in appendix) where the processed illustration component $y(i,j) = 255$ is outlier. First, the processed illustration is separatedly processed only on 5×5 local neighbornood group and, later, separately processed on nine 3×3 local neighbornood groups to be the similarity index and the processed illustration component $y(i,j)$ is recognized as outlier illustration component.

4. THE SCIENTIFIC RESULTS AND DISCUSSIONS

For this scientific part, the analytical computer program is the MATLAB software, which is performed on tremendous microcomputers with hardware blueprint: MPU is i7-6700HQ and primary data storage is 16 GB. Each microcomputers performs on these many illustrations (such as Girl, Lena, Pepper and F16), which are degraded by incorporating with FAIN at numerous consistency. In the first scientific experiment, the first and second moment statistical specifications of the outlier-less illustration components and outlier illustration components (from 90% to 5%) are performed by the ordinary LROAD outlier recognition approach of Girl, Lena, Pepper and F16 as indicating in the Figure 4(a), 4(c), 4(e) and 4(g) , respectively, which is compared with, the proposed LROLD outlier recognition approach of Girl, Lena, Pepper and F16 as indicating in the Figure 4(b), 4(d), 4(f) and 4(h), respectively (see in appendix). From these results, the proposed LROLD distribution of the outlier-less illustration components and outlier illustration components can remarkably recognize whether illustration components are outlier or outlier-less during the outlier consistency 5% - 60% but the proposed LROLD distribution cannot recognize when the outlier consistency is more than 70%. In the second scientific experiment, the LROLD outlier recognition effectiveness, which is performed by (6), of Girl, Lena and Pepper (from 5% to 60%) are indicated in the Tables 1-3, respectively. Moreover, the ordinary AMF and LROAD outlier recognition effectiveness are used to compare the recognition effectiveness. From these results, the proposed LROLD distribution provides the superior recognition effectiveness at all outlier consistency between 5% - 60%. In the third scientific experiment, for exploring the overall proposed outlier suppression effectiveness, the ordinary GF, SMF, BF, AMF and LROAD outlier suppression effectiveness are used to compare the reconstruction effectiveness of Girl, Lena and Pepper (during the outlier consistency 5% - 60%) are indicated in the Tables 4-6, respectively. From these results in the Tables 4-6, the proposed LROLD outlier reconstruction provides the superior effectiveness for quantitative measurement index (PSNR) than other previouse compared outlier suppression algorithms (GF, SMF, BF, AMF and LROAD).

$$Accuracy = \frac{1}{2}\left(\left(\frac{\text{number of estimated noisy pixels}}{\text{number of noisy pixels}}\right) + \left(\frac{\text{number of estimated noiseless pixels}}{\text{number of noiseless pixels}}\right)\right) \quad (6)$$

Table 1. The outlier recognition effectiveness: Girl

Outlier recognition	Outlier consistency (%)											
	5	10	15	20	25	30	35	40	45	50	55	60
AMF	0.7363	0.6910	0.6558	0.6209	0.5880	0.5632	0.5381	0.5217	0.5021	0.4827	0.4677	0.4516
LROAD	0.8532	0.8498	0.8413	0.8391	0.8383	0.8285	0.8181	0.8004	0.7839	0.7566	0.7319	0.7053
LROLD	0.8573	0.8538	0.8455	0.8450	0.8441	0.8379	0.8316	0.8209	0.8091	0.7927	0.7728	0.7496

Table 2. The outlier recognition effectiveness: Lena

Outlier recognition	Outlier consistency (%)											
	5	10	15	20	25	30	35	40	45	50	55	60
AMF	0.8395	0.8133	0.7896	0.7650	0.7428	0.7233	0.7049	0.6920	0.6773	0.6624	0.6486	0.6373
LROAD	0.9978	0.9960	0.9942	0.9853	0.9761	0.9604	0.9420	0.9219	0.8838	0.8422	0.7868	0.7157
LROLD	0.9979	0.9949	0.9915	0.9851	0.9796	0.9682	0.9492	0.9258	0.8874	0.8445	0.7993	0.7419

Table 3. The outlier recognition effectiveness: Pepper

Outlier recognition	Outlier consistency (%)											
	5	10	15	20	25	30	35	40	45	50	55	60
AMF	0.8550	0.8189	0.7893	0.7638	0.7368	0.7191	0.7002	0.6819	0.6653	0.6539	0.6411	0.6263
LROAD	0.9926	0.9913	0.9816	0.9734	0.9642	0.9556	0.9374	0.9108	0.8749	0.8266	0.7727	0.7002
LROLD	0.9941	0.9912	0.9856	0.9802	0.9672	0.9577	0.9407	0.9123	0.8794	0.8359	0.7916	0.7328

Table 4. The comparison consequences of the proposed outlier recognition algorithm (PSNR): Girl

Outlier recognition	PSNR (dB)											
	5	10	15	20	25	30	35	40	45	50	55	60
Outlier image	16.4490	13.6890	11.9287	10.6567	9.5498	8.8677	8.0984	7.5798	7.0728	6.5712	6.2085	5.8609
GF (3x3)	20.0454	17.2530	15.3515	13.9593	12.7248	11.9599	11.0501	10.4543	9.8471	9.2367	8.7895	8.3590
SMF (3x3)	32.4867	31.5583	27.6179	25.5153	22.9614	20.7738	18.441	16.5146	14.8145	13.0319	11.8226	10.4981
BF (bilateral filter)	25.0465	21.6288	18.649	16.4313	14.4659	13.2611	11.9108	11.0055	10.1288	9.2885	8.6809	8.1088
AMF (5x5)	37.5895	36.9197	34.4478	31.1837	28.4091	26.2925	23.532	21.7295	19.9573	17.8279	16.5229	14.9128
LROAD	39.4510	36.9332	35.2214	31.4844	28.5135	24.7323	21.4113	18.5755	16.5495	14.1005	12.5879	11.0750
LROLD	39.9704	37.5537	35.8474	33.4131	31.7502	28.7866	26.1867	23.1084	20.7034	18.2121	16.3151	14.3784

Table 5. The comparison consequences of the proposed outlier recognition algorithm (PSNR): LENA

Outlier recognition	PSNR (dB)											
	5	10	15	20	25	30	35	40	45	50	55	60
Outlier image	18.7139	15.6564	13.8274	12.6389	11.6783	10.8971	10.224	9.6481	9.0745	8.6553	8.2118	7.7813
GF (Gausian filter)	22.4181	19.3812	17.5385	16.3208	15.3526	14.5829	13.8785	13.2479	12.6598	12.2146	11.7609	11.2939
SMF (median filter)	31.6421	30.7076	29.2982	27.6257	25.4101	23.6811	20.8127	19.008	16.8389	15.4758	13.8573	12.328
BF (Bilateral filter)	27.5253	25.8091	24.2271	22.5517	20.9944	19.5225	18.0901	16.8416	15.5293	14.5831	13.5378	12.525
AMF (5x5)	36.0907	35.3032	33.7454	32.1558	29.8105	27.8658	25.6654	23.7869	21.5949	20.5710	19.4658	18.0481
LROAD	41.2463	37.6146	35.5349	32.3949	29.3816	26.9173	23.1573	20.7286	17.5746	15.8325	13.8569	12.1018
LROLD	41.6609	37.4668	35.1803	33.4546	30.9454	28.8877	25.7819	23.3168	20.3925	18.4624	16.5733	14.588

Table 6. The comparison consequences of the proposed outlier recognition algorithm (PSNR): Pepper

Outlier recognition	PSNR (dB)											
	5	10	15	20	25	30	35	40	45	50	55	60
Outlier image	18.4752	15.3798	13.5570	12.3593	11.3929	10.6242	9.9742	9.3998	8.8599	8.3843	7.9930	7.6189
GF (Gausian filter)	22.1408	19.0677	17.2234	15.9804	14.9986	14.1748	13.5209	12.9076	12.3275	11.8117	11.3720	10.9563
SMF (Median filter)	32.2578	30.6116	28.847	26.5888	24.2073	22.0663	20.3774	18.4321	16.6168	14.8506	13.4655	12.0128
BF (Bilateral filter)	26.9352	25.0013	23.1364	21.4752	19.8178	18.2898	17.0781	15.9051	14.7393	13.6826	12.8287	11.9777
AMF (5x5)	37.1145	36.0387	33.6096	31.6485	29.4205	26.7650	25.5160	23.3923	21.4867	19.8454	18.3435	16.8082
LROAD	40.5977	37.8928	34.8313	32.4239	28.0055	25.6055	22.8024	20.0982	17.6646	15.3078	13.5889	11.8527
LROLD	40.3878	37.5492	34.8666	32.7106	29.3443	27.2038	25.7138	22.8715	20.4449	18.0574	16.2879	14.4357

Finally, to demonstate the visionalization effectiveness, some scientific results of Pepper images are illustrated in Figures 5(a) to (c). The ordinary SMF, AMF and LROAD outlier reconstruction effectiveness are used to compare the reconstruction effectiveness where the ordinary SMF at 20%, 25% and 30% outlier reconstruction effectiveness are indicated in the figure 5(a-2), 5(b-2), 5(c-2), respectively and the ordinary AMF at 20%, 25% and 30% outlier reconstruction effectiveness are indicated in the figure 5(a-3), 5(b-3), 5(c-3), respectively and the ordinary LROAD at 20%, 25% and 30% outlier reconstruction effectiveness are indicated in the figure 5(a-4), 5(b-4), 5(c-4), respectively. From these results, the proposed LROLD outlier reconstruction provides the superior effectiveness for both perceptional quality and engineering measured quality (PSNR and SSIM).

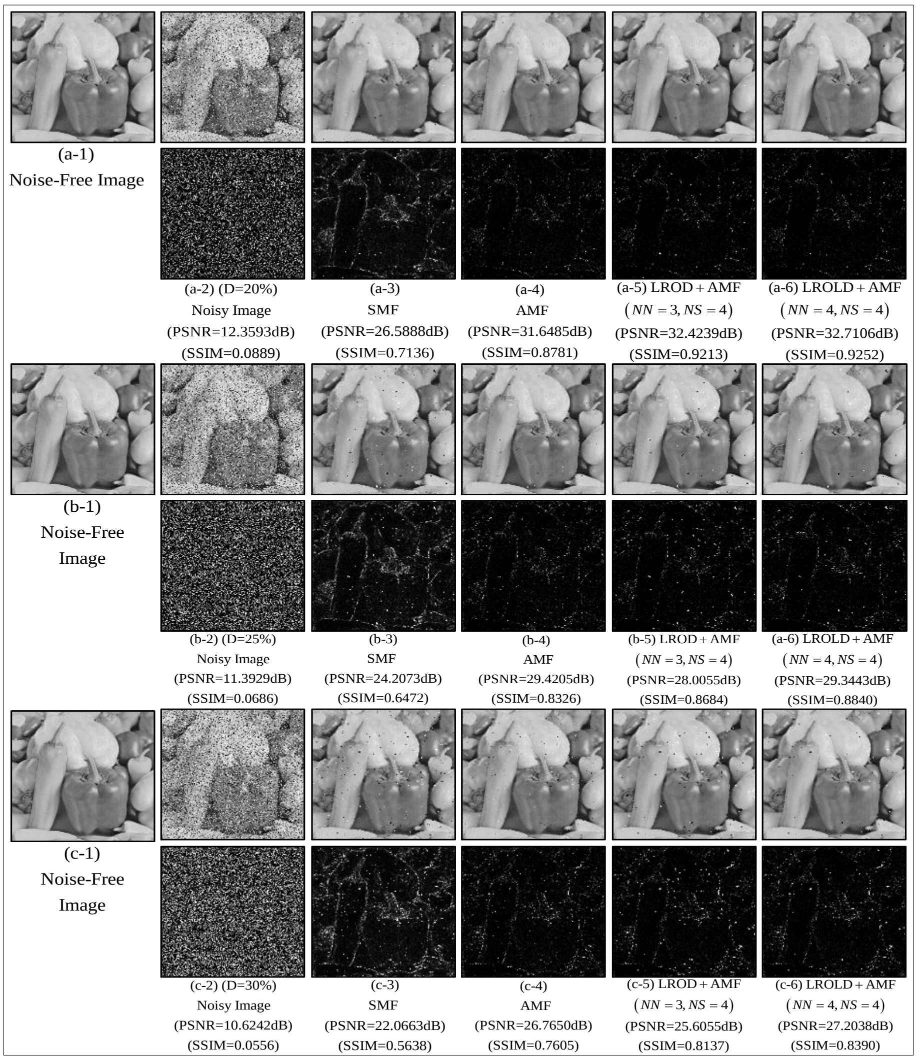

Figure 5. The comparison consequences of the scientific outlier illustrations (Pepper)

5. CONCLUSION

The paper focus to propose the innovative vigorous outlier recognition placed on LROAD approach, which is progressed from LROAD and ROLD, which is higher effectiveness than LROAD for FAIN. From this experimental results, the proposed LROAD outlier recognition can provide the superior effectiveness for recognizing whether illustration components are outlier or outlier-less. Therefore, the proposed LROLD outlier reconstruction provides the superior effectiveness than SMF, AMF and LROAD for both perceptional quality and engineering measured quality (PSNR and SSIM).

APPENDIX

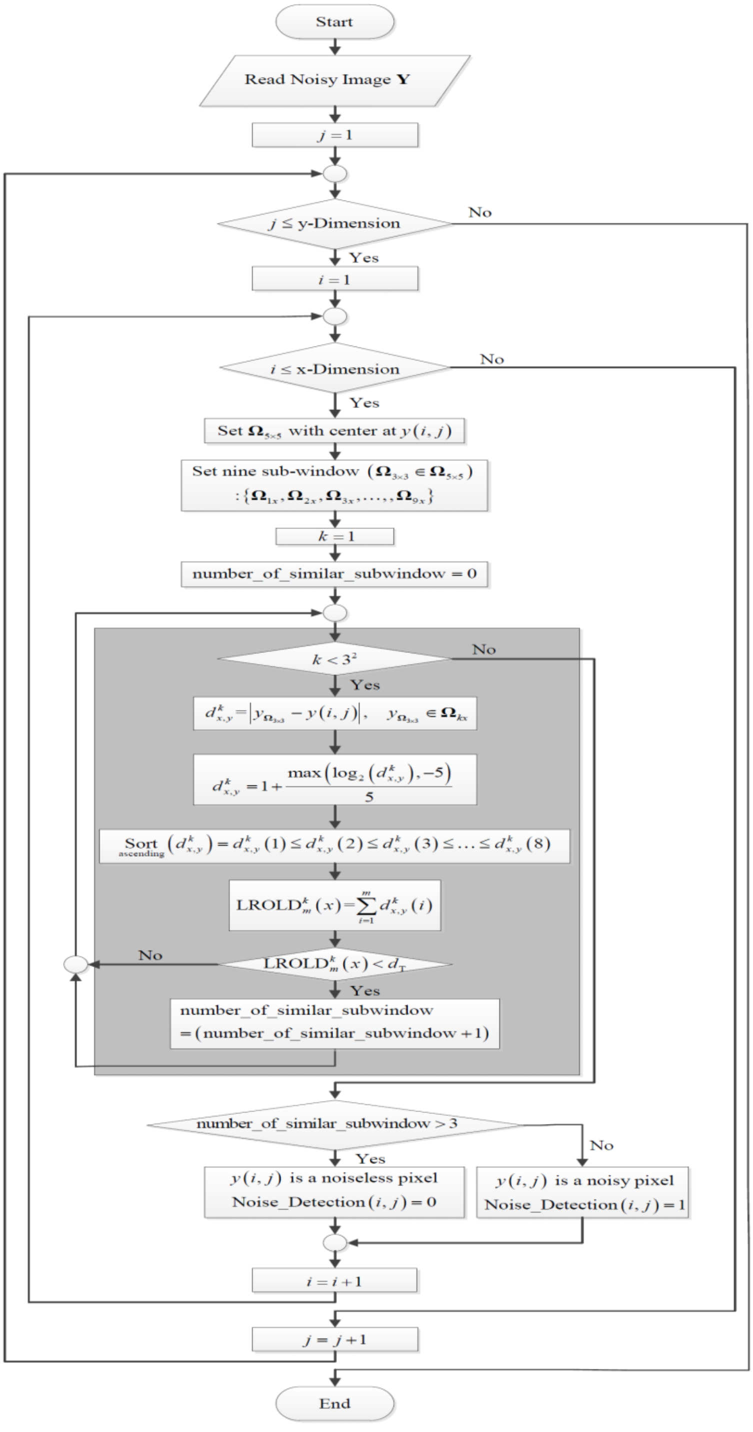

Figure 2. The scientific processing of LROLD approach

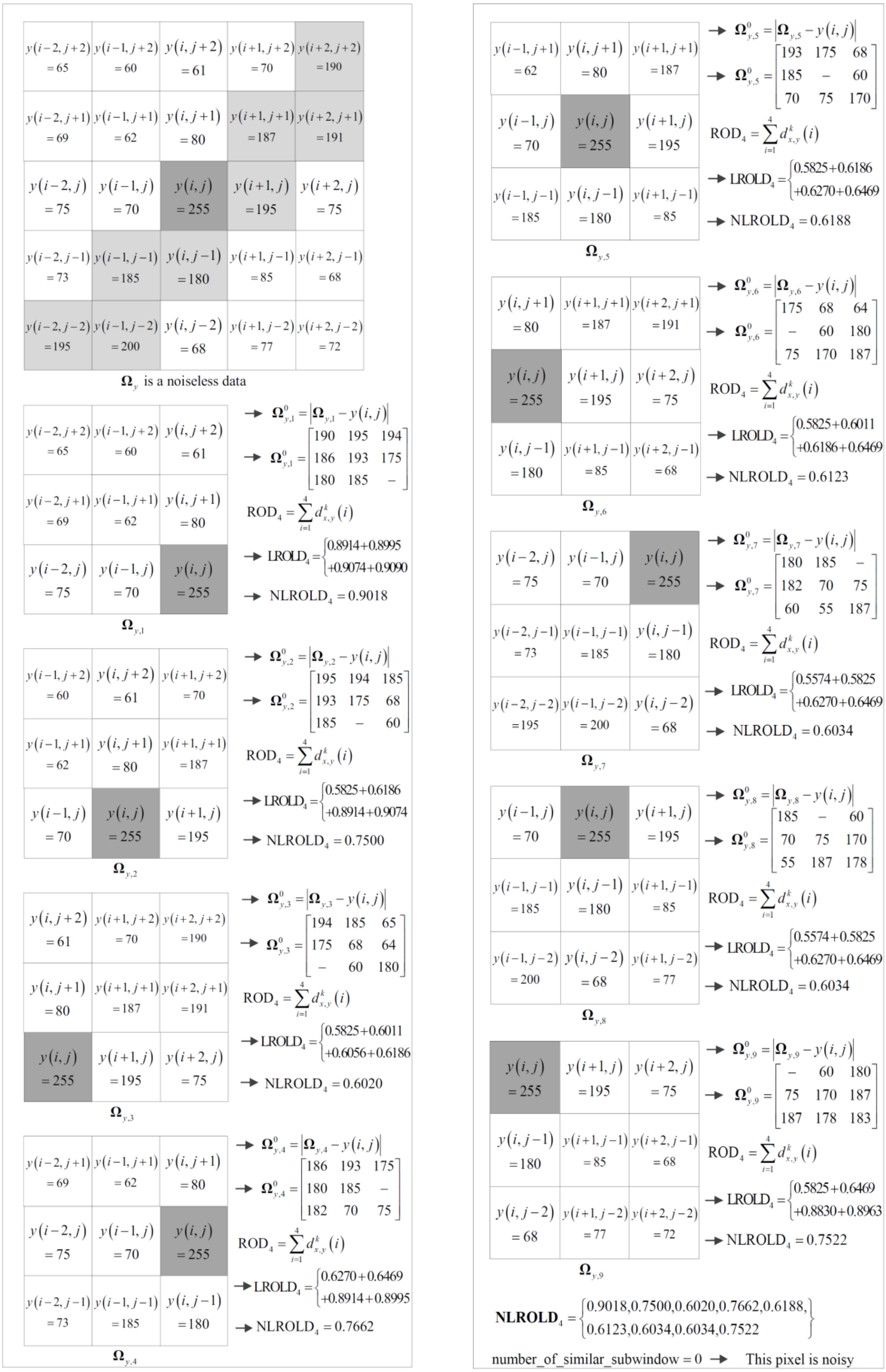

Figure 3. The example of LROLD approach process where $y(i,j) = 255$ is outlier

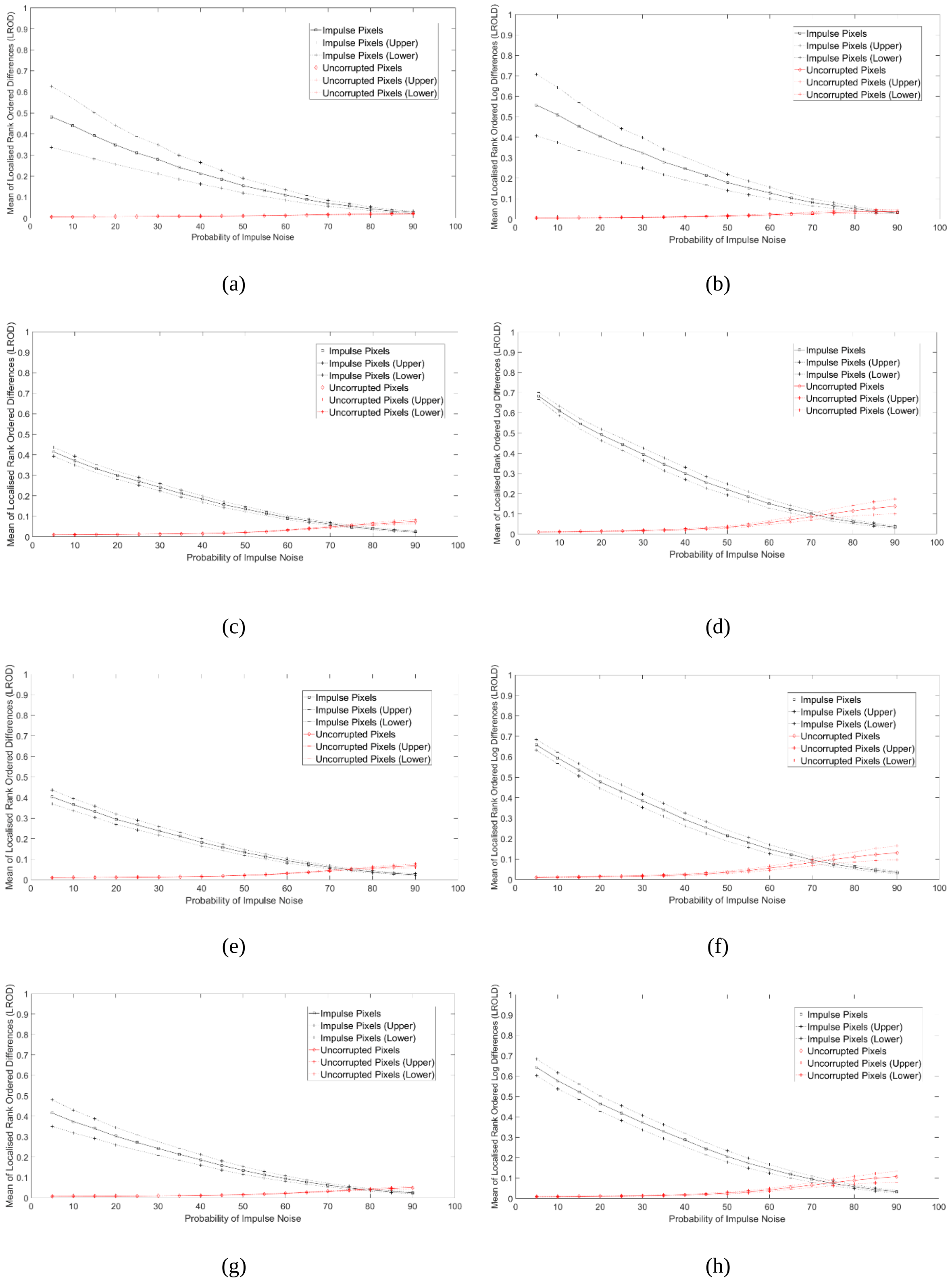

Figure 4. The scientific result of the first and second moment statistical specifications (a) The LROAD of mean and SD: Girl, (b) The LROLD of mean and SD: Girl, (c) The LROAD of mean and SD: Lena, (d) The LROLD of mean and SD: Lena, (e) The LROAD of mean and SD: Pepper, (f) The LROLD of mean and SD: Pepper, (g) The LROAD of mean and SD: F16, and (h) The LROLD of mean and SD: F16

REFERENCES

[1] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 2nd edition, New Jersey: Prentice-Hall, Upper Saddle River, 2002.

[2] A. S. M. Shafi and M. M. Rahman, “Decomposition of color wavelet with higher order statistical texture and convolutional neural network features set based classification of colorectal polyps from video endoscopy,” *International Journal of Electrical and Computer Engineering*, vol. 10, no. 3, pp. 2986-2996, 2020, doi: 10.11591/ijece.v10i3.pp2986-2996.

[3] S. Bagchi, K. G. Tay, A. Huong, and S. K. Debnath, “Image processing and machine learning techniques used in computer-aided detection system for mammogram screening - a review,” *International Journal of Electrical and Computer Engineering*, vol. 10, no. 3, pp. 2336-2348, 2020, doi: 10.11591/ijece.v10i3.pp2336-2348.

[4] N. D. Abdullah, U. R. Hashim, S. Ahmad, and L. Salahuddin, “Analysis of texture features for wood defect classification,” *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 1, 2020, pp. 121-128, doi: 10.11591/eei.v9i1.1553.

[5] A. J. Qasim, R. Din, and F. Q. A. Alyousuf, “Review on techniques and file formats of image compression,” *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 2, pp. 602-610, 2020, doi: 10.11591/eei.v9i2.2085.

[6] V. H. Patil, G. K. Kharate, S. M. Kamlapur, “Super resolution imaging needs better registration for better quality results,” *Bulletin of Electrical Engineering and Informatics*, vol. 1, no. 1, pp. 43-50, 2012, doi: 10.11591/eei.v1i1.225.

[7] C. Deng, J. Liu, W. Tian, S. Wang, H. Zhu, and S. Zhang, “Image Super-Resolution Reconstruction Based On $L_{1/2}$ Sparsity,” *Bulletin of Electrical Engineering and Informatics*, vol. 3, no. 3, pp. 155-160, 2014, doi: 10.11591/eei.v3i3.284.

[8] D. Kesrarat, K. Thakulsukanant, and V. Patanavijit, “A novel elementary spatial expanding scheme form on SISR method with modifying Geman&McClure function,” *TELKOMNIKA (Telecommunication, Computing, Electronics and Control)*, vol. 17, no. 5, pp. 2554-2560, 2019, doi: 10.12928/TELKOMNIKA.v17i5.12799.

[9] P. R. Srinivasa, R. K. Nadesh, and K. N. C. Senthil, “Robust Face Recognition Using Enhanced Local Binary Pattern,” Bulletin of Electrical Engineering and Informatics, vol. 7, no. 1, pp. 96-101, 2018, doi: 10.11591/eei.v7i1.761.

[10] W. K. Pratt, “Median filtering,” Tech. Rep., Image Proc. Inst., Univ. Southern California, Los Angeles, Sep. 1975.

[11] J. Astola, P. Haavisto and Y. Neuvo, “Vector median filters,” in *Proceedings of the IEEE*, vol. 78, no. 4, pp. 678-689, April 1990, doi: 10.1109/5.54807.

[12] H. Hwang and R. A. Haddad, “Adaptive median filters: new algorithms and results,” *IEEE Transactions on Image Processing*, vol. 4, no. 4, pp. 499-502, April 1995, doi: 10.1109/83.370679.

[13] O. P. Verma and N. Sharma, “Intensity Preserving Cast Removal in Color Images UsingParticle Swarm Optimization,” *International Journal of Electrical and Computer Engineering*, vol. 7, no. 5, pp. 2581-2595, 2017, doi: 10.11591/ijece.v7i5.pp2581-2595

[14] M. Hamiane and F. Saeed, “SVM Classification of MRI Brain Images for Computer-Assisted Diagnosis,” *International Journal of Electrical and Computer Engineering*, vol. 7, no. 5, pp. 2555-2564 2017, doi: 10.11591/ijece.v7i1.pp2555-2564.

[15] A. Khmag, S. Ghoul, S. A. R. Al-Haddad, and N. Kamarudin, “Noise Level Estimation for Digital Images Using Local Statistics and Its Applications to Noise Removal,” *TELKOMNIKA (Telecommunication, Computing, Electronics and Control)*, vol. 16, no. 2, pp. 915-924, 2018, doi: 10.12928/TELKOMNIKA.v16i2.9060.

[16] K. A. Sai and K. Ravi, “An Efficient Filtering Technique for Denoising Colour Images,” *International Journal of Electrical and Computer Engineering*, vol. 8, no. 5, 2018, pp. 3604-3608, doi: 10.11591/ijece.v8i5.pp3604-3608.

[17] Z. M. Ramadan, “Effect of kernel size on Wiener and Gaussian image filtering,” *TELKOMNIKA (Telecommunication, Computing, Electronics and Control)*, vol. 17, no. 3, pp.1455-1460, 2019, doi: 10.12928/TELKOMNIKA.v17i3.11192.

[18] J. Na`am, J. Harlan, R. Syelly, and A. Ramadhanu, “Filter technique of medical image on multiple morphological gradient (MMG) method,” *TELKOMNIKA (Telecommunication, Computing, Electronics and Control)*, vol. 17, no. 3, pp.1317-1323, June 2019, doi: 10.12928/TELKOMNIKA.v17i3.9722.

[19] B. Charmouti *et al.*, “An overview of the fundamental approaches that yield several image denoising techniques,” *TELKOMNIKA (Telecommunication, Computing, Electronics and Control)*, vol. 17, no. 6, pp. 2959-2967, 2019, doi: 10.12928/TELKOMNIKA.v17i6.11301.

[20] L. Abderrahim, M. Salama, and D. Abdelbaki, “Novel design of a fractional wavelet and its application to image denoising,” *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 1, pp. 129-140, 2020, doi: 10.11591/eei.v9i1.1548.

[21] Y. Y. Al-Aboosi, R. S. Issa, and A. K. Jassim, “Image denosing in underwater acoustic noise using discrete wavelet transform with different noise level estimation,” *TELKOMNIKA Telecommunication, Computing, Electronics and Control*, vol. 18, no. 3, pp. 1439-1446, 2020, doi: 10.12928/TELKOMNIKA.v18i3.14381.

[22] S. Rajkumar and G. Malathi, “An Efficient Image Denoising Approach for the Recovery of Impulse Noise,” *Bulletin of Electrical Engineering and Informatics*, vol. 6, no. 3, pp. 281-286, 2017, doi: 10.11591/eei.v6i3.680.

[23] V. Kishorebabu, G. Packyanathan, H. Kamatham, and V. Shankar, “An adaptive decision based interpolation scheme for the removal of high density salt and pepper noise in images,” *EURASIP Journal on Image and Video Processing*, p. 67, 2017, doi: 10.1186/s13640-017-0215-0.

[24] V. Patanavijit, “Denoising performance analysis of adaptive decision based inverse distance weighted interpolation (DBIDWI) algorithm for salt and pepper noise,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 15, no. 2, pp. 804-813, 2019, doi: 10.11591/ijeecs.v15.i2.pp804-813.

[25] V. Patanavijit and K. Thakulsukanant, “The statistical analysis of random-valued impulse noise detection techniques based on the local image characteristic: ROAD, ROLD and RORD,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 15, no. 2, pp. 794-803, 2019, doi: 10.11591/ijeecs.v15.i2.pp794-803,

[26] N. Singh and U. Oorkavalan, “Triple Threshold Statistical Detection filter for removing high density random-valued impulse noise in images,” *EURASIP Journal on Image and Video Processing*, p. 22, 2018, doi: 10.1186/s13640-018-0263-0.

[27] B. Roig and V. D. Estruch, “Localised rank-ordered differences vector filter for suppression of high-density impulse noise in colour images,” *IET Image Process.*, vol. 10, no. 1, pp. 24-33, 2016, doi: 10.1049/iet-ipr.2014.0838.

[28] V. Patanavijit, D. Kesrarat, K. Thakulsukanant and W. Lee, “A Novel Robust Outlier Classification Founded On Localised Rank-Ordered Logarithmic Differences For Fix-Value Impulsive Noise,” *2021 9th International Electrical Engineering Congress (iEECON)*, 2021, pp. 369-372, doi: 10.1109/iEECON51072.2021.9440380.

BIOGRAPHIES OF AUTHORS

Vorapoj Patanavijit 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 180 national/international peer-reviewed publications in Digital Signal Processing (DSP) and Digital Image Processing (DIP). He received the best paper awards from many conferences such as ISCIT2006 (2006), NCIT2008 (2008), EECON-33 (2010), EECON-34 (2011), EECON-35 (2012), EECON-43 (2020) and etc. Moreover, he is invited to be the guest speaker at IWAIT2014 and contributed the invited paper at iEECON 2014. As a technical reviewer of international journals since 2006, he has been assigned to review over 100 journal papers (indexed by SCI and Scopus). As a technical reviewer of over 40 international/national conferences since 2006, he has been assigned to review over 175 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. He can be contacted at email: patanavijit@gmail.com.

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 works in the field of Digital Signal Processing (DSP) and Digital Image Processing (DIP), specializing, in particular, on Digital Image Reconstruction/Enhancement. She can be contacted at email: kthakulsukanant@yahoo.com.