Experimental Analysis of Performance Comparison on Both Linear Filter and Bidirectional Confidential Technique for Spatial Domain Optical Flow Algorithm

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ABSTRACT

Optical flow is a method for classifying the density velocity or motion vector (MV) in a degree of pixel basis for motion classification of image in video sequences. In actual situation, many unpleasant situations usually generate noises over the video sequences. These unpleasant situations corrupt the performance in efficiency of optical flow. In turn to increase the efficiency of the MV, this research work proposes the performance comparison on linear filter and bidirectional confidential technique for spatial domain optical flow algorithms. Our experiment concentrates on the 3 classical spatial based optical flow algorithms (such as spatial correlation-based optical flow (SCOF), Horn-Schunk algorithm (HS) and Lucas-Kanade algorithm (LK)). Different standard video sequences such as AKIYO, CONTAINER, COASTGUARD, and FOREMAN are comprehensively evaluated to demonstrate the effectiveness results. These video sequences have differences in aspect of action and speed in foreground and background. These video sequences are also debased by the Additive White Gaussian Noise (AWGN) at different noise degree (such as AWGN at 25 dB, 20 dB, and 15 dB consequently). Peak Signal to Noise Ratio (PSNR) is utilized as the performance index in our observation.

Keywords: Spatial Based Optical Flow, AWGN, Motion Classification, and PSNR

1. INTRODUCTION

The spatial based optical flow approaches are utilized in various areas to classify MV such as video reconstruction, video coding, object segmentation, super image resolution reconstruction, and motion tracing. Under the ordinary view of optical flow, the image velocities of every pixel are valued by utilizing the movement between two images in sequence which are picked. Various classifications of optical flow are proposed but this research work concentrates on spatial bases intensity gradient optical flow (such as SCOF [1], HS [2] and LK [3]).

SCOF is classical spatial based intensity gradient optical flow that using block-based for motion classification in a level of pixel where minimum sum of absolute difference (SAD) is considered as the error estimation in mean filter (L2). This algorithm presents simple in algorithm and high accuracy in MV but requires high computation time. HS was proposed by B.K.P. Horn and B.G. Schunck in 1981 by using the technique of gradient intensity and minimization for motion classification in mean filter (L2) as a result. This algorithm presents high accuracy in MV but the appropriate value of smoothness weighting should be applied otherwise it may presents low accuracy in a result.

LK was proposed by B.D. Lucas and T. Kanade in 1981 by using the technique of gradient intensity and weight least-square for motion classification in mean filter (L2) as a result. Basically, this algorithm presents fast computation but the accuracy is low when comparing with SCOF and HS (under appropriate smoothness weight).

However, the performance in efficiency of these classical spatial based intensity gradient optical flow decreases under the noisy environments. Various algorithms have been introduced to improve the efficiency in performance over the unpleasant situations or noisy domains. For example, Barron, Fleet, and Beauchemin (BFB) [4] modified the ideal matter for performance evolution over HS and LK al-

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The Portions of this work were presented at The 2011 IEEE Intelligent Signal Processing and Communication Systems (ISPACS) as "A Novel Robust and High Reliability Spatial Correlation Optical Flow Algorithm Based on Median Motion Estimation and Bidirectional Symmetry Flow Technique" [9], The 8th IEEE Workshops of International Conference on Advanced Information Networking and Applications (WAINA 2012) as "A Novel Robust and High Reliability for Lucas-Kanade Optical Flow Algorithm Using Median Filter and Confidence Based Technique" [10], and The 2012 IEEE Electrical Engineering / Electronics, Computer, Telecommunications and Information Technology (ECTI) as "An Alternative Robust and High Reliability Optical Flow based on Horn-Schunck Algorithm Using Median Filter and Confidence Based Technique" [11].

gorithms by balancing the intensity assessment for gradient constraint in 1994. The result is the increasing of the accuracy in MV from the original algorithm of HS and LK. In 2008, R. Li and S. Yu presented a confidence-based optical flow algorithm for high reliability (CHR) [5]. In accordance with the results of performance evaluation from D. Kesrarat and V. Patanavijit in 2010 [7], CHR produced an improvement in the quality over many domains of video sequences. Bidirectional symmetry of forward and backward technique was utilized to determine the reliability rate of the MV as a result. But under the model of bidirectional, it required double computation times in approximately.

In 2009, T. Kondo and W. Kongprawechnon presented the robust motion estimation methods using gradient orientation information (RGOI) [6]. In accordance with the results of a performance evaluation from D. Kesrarat and V. Patanavijit in 2011 [8], RGOI produced effectively outcome over noisy domain and presented better result in MV under high noise level especially on slow movement sequence. But under low noise level, the original algorithm still presented better result in MV. Median filter (L1) was utilized over the MV of original gradient-based algorithm in RGOI. In 2012, D. Kesrarat and V. Patanavijit presented an alternative robust and high reliability spatial based optical flow algorithms using median filter and confidence based technique (RHR). They regarded on local intensity gradient optical flow on the traditional spatial optical flow algorithms that the MV was calculated for higher reliability over noisy environments by using bidirectional symmetry in combination with median filter (L1). This RHR algorithm was applied over SCOF [9], LK [10], and HS [10] respectively with the positive result from the experiment over noisy environments but double computation time based on the model of bidirectional is required.

In our experiment, we study the performance of SCOF, SCOF on RGOI, SCOF on CHR, SCOF on RHR, HS, HS on RGOI, HS on CHR, HS on RHR, LK, LK on RGOI, LK on CHR, and LK on RHR by using PSNR as an indicator in comparison when they are applied in a level of sub-pixel translation on various video sequences that are debased with AWGN (25 dB, 20 dB, and 15 dB).

This research work is organized as follow. Section 2 explains the motion classification algorithms based on inspected optical flow algorithms. Section 3 explains the experimental analysis of performance comparison. Section 4 introduces the experiment results to identify the efficiency of the reference algorithms. Section 5 concludes the experiment result.

2. OPTICAL FLOW MOTION CLASSIFICATION ALGORITHMS

This section states optical flow algorithms for motion classification that we simulate on our experiment.

2.1 Spatial Correlation-Based Optical Flow (SCOF) [1]

SCOF is the traditional spatial based optical flow algorithm for motion classification that utilizes basic block matching technique in a level of pixel based. The best candidate MV is the minimum SAD of the block over the determining area.

This algorithm presented high efficiency under clear sequence but it utilized much of processing time and less noise tolerance in accordance with the outcomes of performance evaluation from D. Kesrarat and V. Patanavijit [7-8].

2.2 Horn - Schunck Algorithm (HS) [2]

In 1981, B.K.P. Horn and B.G. Schunck proposed HS algorithm. HS is spatial temporal gradient based technique. The image intensity (I_x, I_y, I_t) is determined by image velocity from spatiotemporal of image gradient is defined as:

$$\begin{aligned} I_x = {}^1/_4\{ & I(x,y+1,t) - I(x,y,t) + I(x+1,y,1,t) \\ & - I(x+1,y,t) + I(x,y+1,t+1) - I(x,y,t+1) \\ & + I(x+1,y+1,t+1) - I(x+1,y,t+1)\} \end{aligned} \quad (1.1)$$

$$\begin{aligned} I_y = {}^1/_4\{ & I(x+1,y,t) - I(x,y,t) + I(x+1,y+1,t) \\ & - I(x,y+1,t) + I(x+1,y,t+1) - I(x,y,t+1) \\ & + I(x+1,y+1,t+1) - I(x,y+1,t+1)\} \end{aligned} \quad (1.2)$$

$$\begin{aligned} I_t = {}^1/_4\{ & I(x,y,t+1) - I(x,y,t) + I(x+1,y,t+1) \\ & - I(x+1,y,t) + I(x,y+1,t+1) - I(x,y+1,t) \\ & + I(x+1,y+1,t+1) - I(x+1,y+1,t)\} \end{aligned} \quad (1.3)$$

Where $I(x, y, t)$ denotes the gradient intensity (brightness) of point (x, y) in the images at time t.

Then, minimization process is took in iterative by weighted average [1/12 1/6 1/12 ; 1/6 -1 1/6 ; 1/12 1/6 1/12] of the value at neighbouring points where the relevant smoothness weight (α) should be regarded to minimize the sum of error and obtain MV (u, v) as follow:

$$u^{k+1}(x,y,t) = \bar{u}^k(x,y,t) - \frac{I_x(x,y,t)\begin{bmatrix} I_x(x,y,t)\bar{u}^k(x,y,t) \\ +I_y(x,y,t)\bar{v}^k(x,y,t) \\ +I_t(x,y,t) \end{bmatrix}}{\alpha^2 + I_x^2(x,y,t) + I_y^2(x,y,t)} \quad (2.1)$$

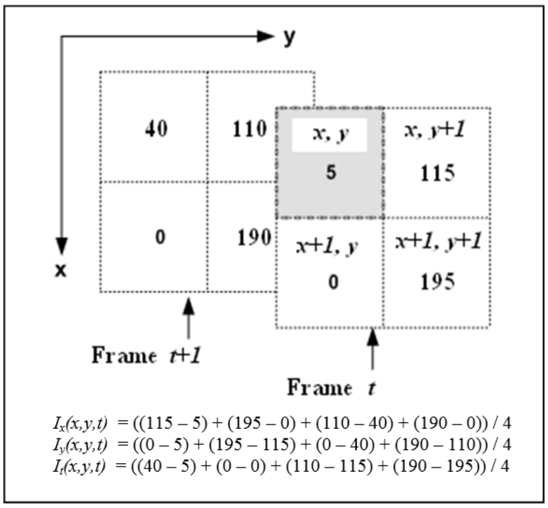

Fig.1: *Example of gradient computation of image brightness at point (x, y).*

$$v^{k+1}(x,y,t)=\bar{v}^k(x,y,t)-\frac{I_y(x,y,t)\begin{bmatrix}I_x(x,y,t)\bar{u}^k(x,y,t)\\+I_y(x,y,t)\bar{v}^k(x,y,t)\\+I_t(x,y,t)\end{bmatrix}}{\alpha^2+I_x^2(x,y,t)+I_y^2(x,y,t)} \quad (2.2)$$

Where $\bar{u}^k(x,y,t)$ and $\bar{v}^k(x,y,t)$ denote neighbourhood average of horizontal and vertical ($u^k(x,y,t)$ and $v^k(x,y,t)$) which first are set to 0 and k is the number of iterative calculation.

In accordance with the outcomes of performance evaluation from D. Kesrarat and V. Patanavijit [7-8], this algorithm presented fast computation but the quality was varying under different smoothness weight (α). The relevant value of α should be regarded for the best performance

2.3 Lucas - Kanade Algorithm (LK) [3]

This algorithm was proposed in 1981 by B.D. Lucas and T. Kanade. Differential technique is derived like HS by using intensity for gradient constraint based on Eqs.(1.1)-(1.3) but utilizes a weight least-square as a regular model in each small spatial neighbourhood for obtaining MV instead of minimization process in HS is defined as:

$$\begin{bmatrix}u(x,y,t)\\v(x,y,t)\end{bmatrix}=\begin{bmatrix}\sum I_x^2(x,y,t) & \sum I_x(x,y,t)I_y(x,y,t)\\ \sum I_x(x,y,t)I_y(x,y,t) & \sum I_y^2(x,y,t)\end{bmatrix}^{-1}\times\begin{bmatrix}-\sum I_x(x,y,t)I_t(x,y,t)\\-\sum I_y(x,y,t)I_t(x,y,t)\end{bmatrix} \quad (3)$$

The initial MV is obtained by a linear system based on matrix in Eq.(3). Then, the iterative process is utilized for final MV.

This algorithm presents fast computation with acceptable quality.

2.4 Barron, Fleet and Beauchemin Ideal Matter for Gradients Estimation (BFB) [4]

In 1994, J.L Barron, D.J. Fleet and S.S. Beauchemin presented performance evaluation over various optical flow algorithms and proposed the ideal matter of mask coefficient to compute image intensity which has been applied in the primary part over HS and LK algorithms. The gradient estimation ideal mater of BFB uses 4-point central differences for determining image intensity.

1/12	-1	8	0	-8	1

Fig.2: *The ideal matter coefficient of BFB.*

The image intensity for gradient constraint on ideal matter of BFB is defined as:

$$I_x(x,y,t)=1/12\{-1\times I(x,y-2,t)+8\times I(x,y-1,t)+ 0\times I(x,y,t)+-8\times I(x,y+1,t)+1\times I(x,y+2,t)\} \quad (4.1)$$

$$I_y(x,y,t)=1/12\{-1\times I(x-2,y,t)+8\times I(x-1,y,t)+ 0\times I(x,y,t)+-8\times I(x+1,y,t)+1\times I(x+2,y,t)\} \quad (4.2)$$

$$I_t(x,y,t)=1/12\{-1\times I(x,y,t-2)+8\times I(x,y,t-1)+ 0\times I(x,y,t)+-8\times I(x,y,t+1)+1\times I(x,y,t+2)\} \quad (4.3)$$

In accordance with the performance evaluation from J.L Barron, D.J. Fleet and S.S. Beauchemin [4], it showed the better performance in reliability of the MV over traditional HS and LK algorithms.

2.5 Confidence Based Optical Flow Algorithm for High Reliability (CHR) [5]

In 2008 by R. Li and F. Yu proposed this algorithm to enhanced the efficiency of MV by applied the bidirectional symmetry approach to presented forward MV (frame $t \rightarrow t+1$) and backward MV (frame $t+1 \rightarrow t$) with confidence assessment model. Both of MVs in forward and backward is computed by HS with extra computation on confidence assessment in reliability.

Early, this algorithm was implemented over HS [2] only, but we also utilized this model in our experiment over SCOF [1] and LK [3] for performance evaluation. The reliability rate of MV is described as:

$$Ru_l(x,y,t)=\exp\left(-\frac{|u_l(x,y,t)+u_{l^-}(x+u_l(x,y,t),y,t+1)|}{\begin{bmatrix}|u_l(x,y,t)|\\+|u_{l^-}(x+u_l(x,y,t),y,t+1)|\end{bmatrix}/2+\beta}\right) \quad (5.1)$$

$$Rv_l(x,y,t) = \exp\left(-\frac{|v_l(x,y,t) + v_{l^-}(x+v_l(x,y,t), y, t+1)|}{\left[\begin{array}{c}|v_l(x,y,t)| \\ +|v_{l^-}(x+v_l(x,y,t), y, t+1)|\end{array}\right]/2+\beta}\right) \quad (5.2)$$

Where $Ru(x, y, t)$ is the reliability rate of MV in horizontal axis and $Rv(x, y, t)$ is the reliability rate of MV in vertical axis. u and v are the MV in vertical and horizontal on forward direction (l) and backward direction (l^-) that are calculated by traditional optical flow algorithm. β is a parameter that it is set to avoid divined by 0 in the equation. Then, the average MV in horizontal ($\bar{u}(x, y, t)$) and vertical ($\bar{v}(x, y, t)$) axis based on reliable rate and pre-defined neighbourhood ($N(s_0)$) over each pixel base on frame t of the location $s_0 = (x, y, t)$ is defined as:

$$\bar{u}_l(s_0) = \left(\sum_{s_i \in N(s_0)} Ru_l(s_i) u_l(s_i)\right) / \left(\sum_{s_i \in N(s_0)} Ru_l(s_i)\right) \quad (6.1)$$

$$\bar{v}_l(s_0) = \left(\sum_{s_i \in N(s_0)} Rv_l(s_i) v_l(s_i)\right) / \left(\sum_{s_i \in N(s_0)} Rv_l(s_i)\right) \quad (6.2)$$

The final optimum MV is obtained by using the $\bar{u}(x, y, t)$ and $\bar{v}(x, y, t)$ as the center on reliable area.

This algorithm presented an improvement of the quality in MV under clear and noisy domains in accordance with the outcomes of performance evaluation from D. Kesrarat and V. Patanavijit [7-8].

2.6 Robust Motion Estimation Methods Using Gradient Orientation Information (RGOI) [6]

In 2009, T. Kondo and W. Kongprawechnon proposed this algorithm to enhance the performance in efficiency in changing of light conditions by utilized gradient orientation information of L1 median over MV of traditional algorithm described as:

$$(u_{L1}(x,y,t), v_{L1}(x,y,t)) = \left(\frac{u(x,y,t)}{|u(x,y,t)|}, \frac{v(x,y,t)}{|v(x,y,t)|}\right) \quad (7)$$

Where $u(x, y, t)$ and $v(x, y, t)$ are the MV from tradition optical flows in horizontal and vertical axis (such as SCOF, HS, or LK) and ($u_{L1}(x, y, t)$, $v_{L1}(x, y, t)$) are indicated by 2 scalars (-1 to 1) and zero value is assigned when the magnitude is zero as a result.

Early, this algorithm was implemented over HS [2] only, but we also utilized the model in our experiment over SCOF [1] and LK [3] for performance evaluation.

This algorithm presented an improvement of the quality in MV under noisy environments especially on slow movement sequence and presented high deviation in improvement of the result in accordance with the outcomes of performance evaluation from D. Kesrarat and V. Patanavijit [9-11].

3. EXPERIMENTAL ANALYSIS OF PERFORMANCE COMPARISON

In this research work, we summarize the optical flow research framework as shown in Fig.4. In accordance with the classical spatial based optical flow algorithms (such as SCOF [1], HS [2], and LK [3]) as shown in Fig.4, these algorithms concentrate on gradient intensity which is widely applied in many areas. In general, the unidirectional symmetry with mean filter (L2) is presented as the result for MV from original algorithm of motion classification. From performance testing, sometime the result of MV presents wrong direction from the experiment cases. Then, we cannot conclude the accuracy in the result of MV that is really correct or not because the estimation process is very sensitive to many conditions such as light changing or noise contaminating.

The model of confidence based algorithm for high reliability (CHR) [5] presents bidirectional symmetry that brings the result of MV from original algorithm using mean filter (L2) in forward direction as usual in comparison with the result of MV in backward direction. The objective of CHR is to ensure that the results of MV when they are calculated in forward and backward are really the same by rating the value base on Eqs. (5.1)-(5.2) for reliability rate. Then, the average MV base on pre-defined neighborhood is calculated as the final result of MV. From the experiment's outcome of D. Kesrarat and V. Patanavijit [7-8], it presented an improvement in the accuracy of MV.

The model of robust motion estimation (RGOI) [6] presents the using of median filter (L1) over the result of MV from original algorithm. The objective of this algorithm is to increase the accuracy of motion classification under the noisy environments. In motion classification, when the sequence is interfered by noise, it presents the wrong result of MV in both direction and magnitude. The objective of RGOI is to limit the distance of wrong direction or magnitude in MV to ?1. From the experiment's outcome of D. Kesrarat and V. Patanavijit [7-8], it presented better performance of MV under the increasing of noise.

In accordance with the performance evaluation of D. Kesrarat and V. Patanavijit [7-8] over the model of CHR and RGOI, we combined the model of median filter (L1) together with bidirectional symmetry and reliability of confidence based as an alternative robust and high reliability spatial based optical flow algorithms using median filter and confidence based technique (RHR). The RHR algorithm is described in Fig.3

The traditional spatial based optical flow (such as SCOF, HS, or LK) is utilized to determine the forward MV in horizontal axis ($u_l(x,y,t)$) and vertical axis ($v_l(x,y,t)$) and backward MV in horizontal axis ($u_l^-(x,y,t+1)$) and vertical axis ($v_l^-(x,y,t+1)$) by mean filter (L2) on the focus sequence based on predefine approach of bidirectional symmetry in CHR. Then, the gradient orientation (median filter) from the model of RGOI on Eq.(7) is utilized over the ($u_l(x,y,t)$, $v_l(x,y,t)$) and ($u_l^-(x,y,t+1)$, $v_l^-(x,y,t+1)$) respectively to obtain the unit vector orientation in forward ($u_{L1}, l(x,y,t)$, $v_{L1}, l(x,y,t)$) and backward ($u_{L1,l^-}(x,y,t+1)$, $v_{L1,l^-}(x,y,t+1)$) as a result. Afterwards, reliability rate based on Eqs.(5.1)-(5.2) is applied by using unit vector orientation on forward ($u_{L1}, l(x,y,t)$, $v_{L1}, l(x,y,t)$) and backward ($u_{L1,l^-}(x,y,t+1)$, $v_{L1,l^-}(x,y,t+1)$) MV to calculate instead of traditional MV ($u_l(x,y,t)$, $v_l(x,y,t)$) and ($u_{l^-}(x,y,t+1)$, $v_{l^-}(x,y,t+1)$). Then, the final optimum MV is obtained base on Eqs.(6.1)-(6.2) as the process step in CHR which is represented as the final result in RHR algorithm.

4. EXPERIMENTAL RESULTS

We implement the experiment by using different 100 frames on 4 standard video sequences (AKIYO, CONTAINER, COASTGUARD and FOREMAN) of QCIF (176?144) which are original video sequence, AWGN 25dB (low noise), 20dB (medium noise), and 15dB (high noise) consequently (totally 16 video sequences). In the experiment, we utilize 0.5 bilinear interpolations for all proposed algorithms.

For SCOF algorithm, we set ±3 for neighbors block size and set ±7 for window search area for an experiment. The experiment's outcomes of SCOF, CHR on SCOF, and RGOI on SCOF are used in comparison with the RHR on SCOF.

For HS algorithm, we set global smoothness and use the ideal matter of BFB mask coefficient for gradient estimation with smoothness weight (?) = 0.5 as same as the domain in the performance evaluation of Barron, Fleet, and Beauchemin [4] at 100 iterations. The experiment's outcome in efficiency of HS, CHR on HS, and RGOI on HS are used in comparison with RHR on HS.

For LK algorithm, we set global smoothness and use the ideal matter of BFB mask coefficient for gradient estimation with spatial neighborhoods window (5×5) without pyramid at 5 iteration loops. The experiment's outcome in efficiency of LK, CHR on LK, and RGOI on LK are used in comparison with RHR on LK.

For confidence base model, we set $\beta = 0.0001$, and pre-defined neighbourhood $(s_i) = \pm 1$.

Finally, the performances evaluations over the enhancement in PSNR are inspected on our experiment by confront these rebuild image frames with their original sequence define as:

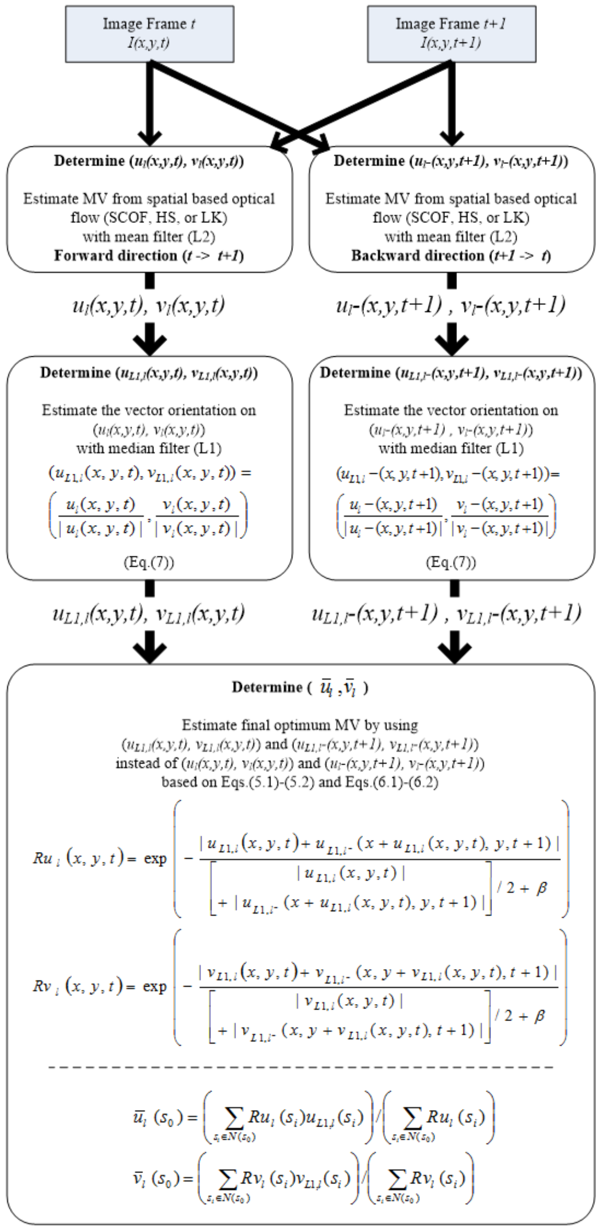

Fig.3: *Overall Process sequence of the proposed algorithm.*

$$E = \frac{1}{mn} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} [A(x,y,t) - B(x,y,t)]^2 \qquad (8)$$

$$PSNR = 10 \cdot \log_{10} \left(\frac{M_I^2}{E} \right) \qquad (9)$$

Where E is mean squared error of two m?n gray scale 8 bits image A and B. M_I is the maximum pixel value of the image equal to 255 (8 bits image).

In Fig. 4 shows the structure of the research framework of this experiment. In Fig.5 illustrates the image frame no. 21 of AKIYO, CONTAINER, COASTGUARD, and FOREMAN sequence when they are debased with AWGN 25 dB, 20dB, and 15dB respectively. Due to page limitation, this paper presents only some of results in Fig. 6-8 by indicate the value of PSNR of the rebuild image from the outcome of MV on each algorithm under different degree of AWGN and sequences. In Fig. 6 focuses on the performance of PSNR on SCOF based algorithm. In Fig. 7 focuses on the performance of PSNR on HS based algorithm. And in Fig. 8 focuses on the performance of PSNR on LK based algorithm.

5. CONCLUSIONS

In accordance with the experiment's outcome, we conclude our experiments into 3 main groups. There are SCOF, HS and LK.

In SCOF (including SCOF, CHR on SCOF, RGOI on SCOF, and RHR on SCOF), we conclude as:-

- Under the clear condition, SCOF and CHR produce greatest outcome while RGOI produces least outcome with slightly better in RHR-SCOF.
- Under the noisy domain, RHR-SCOF produces greatest outcome.
- Under strong noise domain, RHR-SCOF gains dramatically in higher performance.
- In accordance with the references sequences where slow sequence (AKIYO and CONTAINER) and fast movement sequence (COASTGUARD and FOREMAN), we conclude that RHR-SCOF produces greater efficiency from low noise domain and increasing in higher deviation on higher noise domain on slow sequence while produces higher efficiency on medium to high noise domain on fast sequence.

In HS (including HS, CHR on HS, RGOI on HS, and RHR on HS), we conclude as:-

- Under the clear domain, RHR-HS produces marginally lower efficiency when confronts with the HS, CHR-HS, and RGOI-HS.
- Under the noisy domain, RHR-HS produces greatest outcome.
- Under slow sequence, RHR-HS produces high deviation in better outcome when confronts with HS, CHR-HS, and RGOI-HS on increasing of noise while produces low deviation but still presents the greatest outcome under the increasing of noise on fast sequence.

In LK (including LK, CHR on LK, RGOI on LK, and RHR on LK), we conclude as:-

- Under the noisy domain, RHR-LK produces greatest outcome.
- Under slow sequence, RHR-LK produces dramatically higher efficiency than other algorithms. It produces higher performance on increasing of noise.
- Under fast sequence, RHR-LK produces higher efficiency but stabilizes in deviation on increasing of noise.

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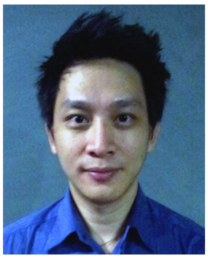

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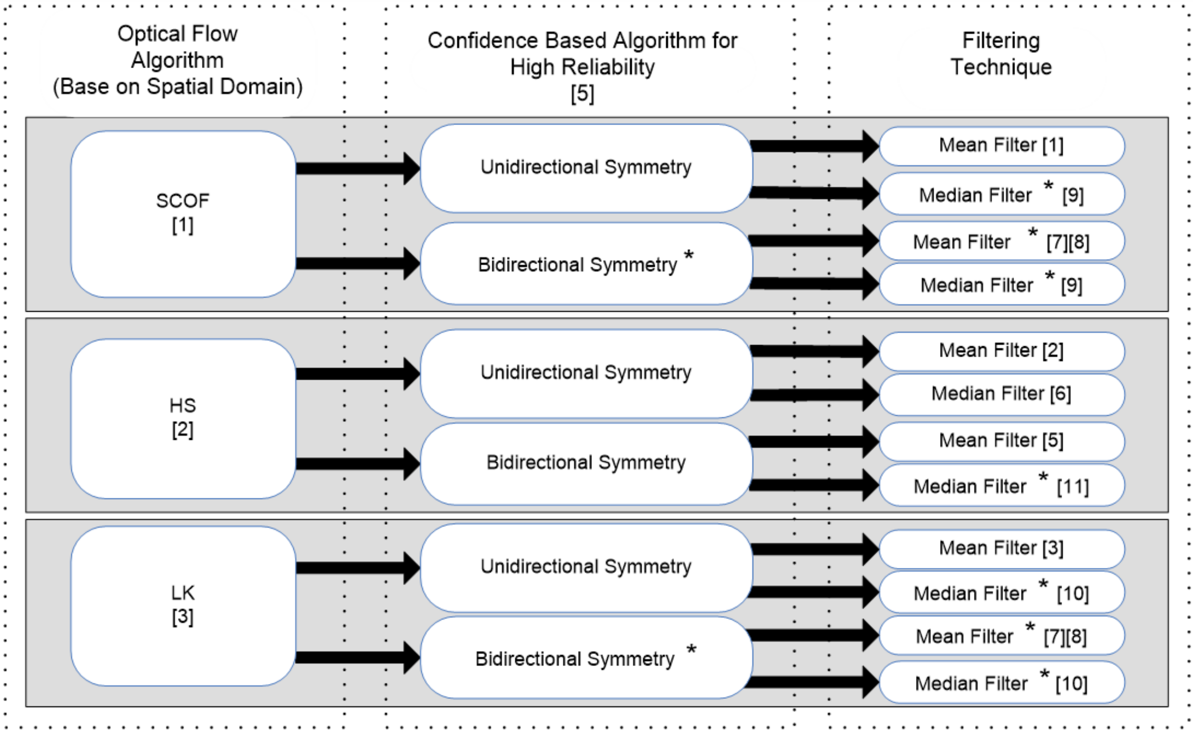

Fig.4: *Optical flow research framework. (where "*" is our research framework).*

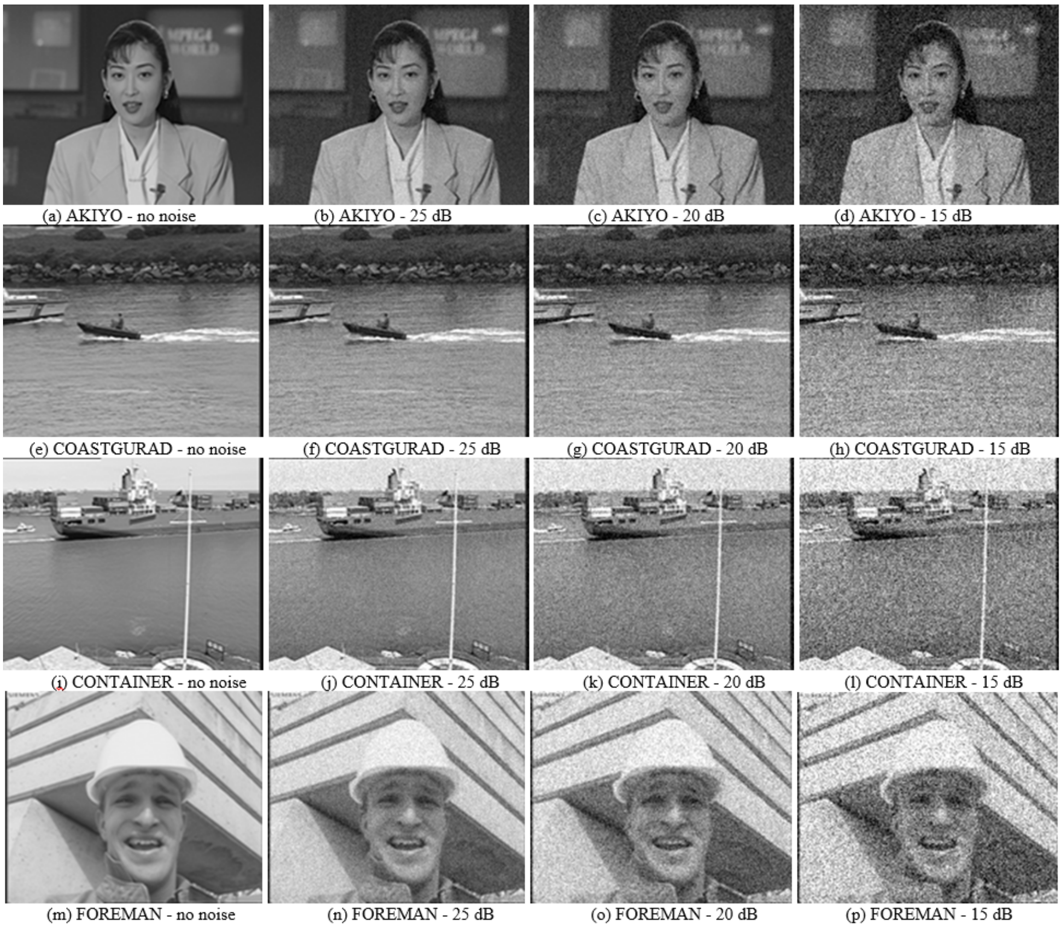

Fig.5: *Example of image frame that contaminated by AWGN.*

Table 1: *Average PSNR, standard deviation and deviation in average PSNR of several AWGN sequence with original (no noise) sequence (100 frames each). .*

	AKIYO			**COASTGUARD**			**CONTAINER**			**FOREMAN**		
	AVG PSNR (dB)	**SD of PSNR**	**AVG Diff (dB)**	**AVG PSNR (dB)**	**SD of PSNR**	**AVG Diff (dB)**	**AVG PSNR (dB)**	**SD of PSNR**	**AVG Diff (dB)**	**AVG PSNR (dB)**	**SD of PSNR**	**AVG Diff (dB)**
SCOF – No Noise	46.280	2.723	-	34.093	2.384	-	43.692	0.337	-	36.332	2.393	-
CHR-SCOF – No Noise	46.281	2.724	-	34.067	2.371	-	43.562	0.845	-	35.906	2.185	-
RGOI-SCOF – No Noise	45.778	3.527	-	30.322	3.856	-	43.807	0.308	-	31.765	2.899	-
RHR-SCOF – No Noise	45.802	3.518	-	30.339	3.877	-	43.814	0.304	-	31.747	2.898	-
SCOF – 25 dB	37.554	0.493	8.726	30.831	2.624	3.261	34.982	0.226	8.710	31.178	1.342	5.154
CHR-SCOF – 25 dB	39.118	0.544	7.163	31.596	2.870	2.471	36.450	0.192	7.112	32.328	1.588	3.577
RGOI-SCOF – 25 dB	41.035	1.380	4.744	29.691	3.505	0.631	39.265	0.215	4.542	30.762	2.292	1.003
RHR-SCOF – 25 dB	41.246	1.430	4.556	29.736	3.549	0.602	39.653	0.234	4.161	30.819	2.342	0.929
SCOF – 20 dB	33.596	0.278	12.684	28.158	1.879	5.935	30.720	0.212	12.973	28.512	0.800	7.820
CHR-SCOF – 20 dB	35.452	0.276	10.829	29.234	2.164	4.833	32.514	0.181	11.048	30.061	1.086	5.845
RGOI-SCOF – 20 dB	38.323	0.773	7.455	28.916	3.128	1.406	35.818	0.186	7.988	30.056	2.002	1.709
RHR-SCOF – 20 dB	38.585	0.811	7.217	28.975	3.182	1.364	36.150	0.214	7.664	30.157	2.041	1.591
SCOF – 15 dB	29.950	0.198	16.331	25.415	1.296	8.678	26.317	0.207	17.376	25.604	0.473	10.728
CHR-SCOF – 15 dB	31.929	0.199	14.352	26.682	1.594	7.386	28.112	0.202	15.450	27.242	0.663	8.664
RGOI-SCOF – 15 dB	35.682	0.461	10.096	27.833	2.699	2.489	32.008	0.173	11.798	29.106	1.690	2.659
RHR-SCOF – 15 dB	36.003	0.499	9.799	27.929	2.780	2.410	32.317	0.191	11.498	29.234	1.733	2.514
HS – No Noise	44.326	3.684	-	28.780	3.082	-	42.986	0.441	-	30.366	2.392	-
CHR-HS – No Noise	45.089	3.755	-	30.072	3.519	-	43.834	0.307	-	31.320	2.420	-
RGOI-HS – No Noise	44.906	3.446	-	29.752	3.346	-	43.115	0.360	-	31.387	2.659	-
RHR-HS – No Noise	45.109	3.813	-	29.919	3.831	-	43.851	0.291	-	31.403	2.712	-
HS – 25 dB	33.929	0.413	10.397	26.610	2.001	2.170	29.561	0.220	13.425	27.473	0.853	2.893
CHR-HS – 25 dB	37.167	0.663	7.922	28.334	2.539	1.738	33.333	0.276	10.501	29.955	1.243	1.365
RGOI-HS – 25 dB	36.747	0.527	8.159	28.362	2.697	1.390	32.475	0.159	10.64	30.096	1.816	1.291
RHR-HS – 25 dB	38.669	0.996	6.440	28.833	3.241	1.086	35.917	0.215	7.934	30.572	2.090	0.831
HS – 20 dB	30.760	0.232	13.566	25.216	1.515	3.564	26.424	0.193	16.562	25.707	0.562	4.659
CHR-HS – 20 dB	34.166	0.341	10.923	26.984	2.013	3.088	29.558	0.252	14.276	28.218	0.910	3.102
RGOI-HS – 20 dB	34.758	0.292	10.148	27.509	2.423	2.243	29.908	0.120	13.207	29.041	1.510	2.346
RHR-HS – 20 dB	36.618	0.637	8.491	27.738	3.039	2.181	32.622	0.174	11.229	29.627	1.780	1.776
HS – 15 dB	28.419	0.160	15.907	23.830	1.232	4.950	24.034	0.135	18.952	24.106	0.407	6.260
CHR-HS – 15 dB	31.423	0.232	13.666	25.431	1.608	4.641	26.442	0.209	17.392	26.192	0.675	5.128
RGOI-HS – 15 dB	33.205	0.238	11.701	26.594	2.213	3.158	28.068	0.095	15.047	27.827	1.255	3.560
RHR-HS – 15 dB	34.917	0.461	10.192	27.179	2.644	2.740	30.168	0.136	13.683	28.437	1.498	2.966
LK – No Noise	37.413	3.384	-	24.228	2.051	-	35.159	0.471	-	24.869	1.932	-
CHR-LK – No Noise	38.433	4.011	-	24.606	2.182	-	38.207	0.520	-	25.043	2.000	-
RGOI-LK – No Noise	38.247	3.109	-	25.143	2.315	-	35.983	0.296	-	26.525	1.765	-
RHR-LK – No Noise	39.193	3.757	-	25.341	2.414	-	38.800	0.470	-	26.594	1.846	-
LK – 25 dB	33.311	1.077	4.102	24.341	2.067	-0.113	29.645	0.294	5.514	24.766	1.544	0.103
CHR-LK – 25 dB	34.241	1.323	4.192	24.753	2.215	-0.147	31.017	0.336	7.189	24.974	1.638	0.068
RGOI-LK – 25 dB	34.396	1.046	3.852	25.212	2.337	-0.069	30.609	0.256	5.374	26.281	1.468	0.243
RHR-LK – 25 dB	35.154	1.273	4.039	25.435	2.446	-0.094	31.787	0.312	7.012	26.361	1.546	0.233
LK – 20 dB	32.265	0.743	5.149	24.332	2.085	-0.103	27.915	0.232	7.245	24.726	1.352	0.143
CHR-LK – 20 dB	33.147	0.894	5.286	24.754	2.229	-0.149	27.694	0.242	10.513	25.150	1.291	-0.108
RGOI-LK – 20 dB	33.613	0.780	4.634	25.223	2.361	-0.080	29.170	0.191	6.813	26.190	1.425	0.335
RHR-LK – 20 dB	34.283	0.944	4.910	25.463	2.481	-0.122	30.086	0.227	8.714	26.302	1.513	0.292
LK – 15 dB	31.330	0.505	6.084	24.290	2.057	-0.062	26.669	0.212	8.490	24.781	1.160	0.088
CHR-LK – 15 dB	32.233	0.614	6.210	24.754	2.229	-0.149	27.694	0.242	10.513	25.150	1.291	-0.108
RGOI-LK – 15 dB	33.036	0.620	5.211	25.222	2.366	-0.079	28.305	0.158	7.679	26.200	1.392	0.325
RHR-LK – 15 dB	33.654	0.732	5.540	25.469	2.484	-0.128	29.114	0.185	9.686	26.382	1.492	0.212

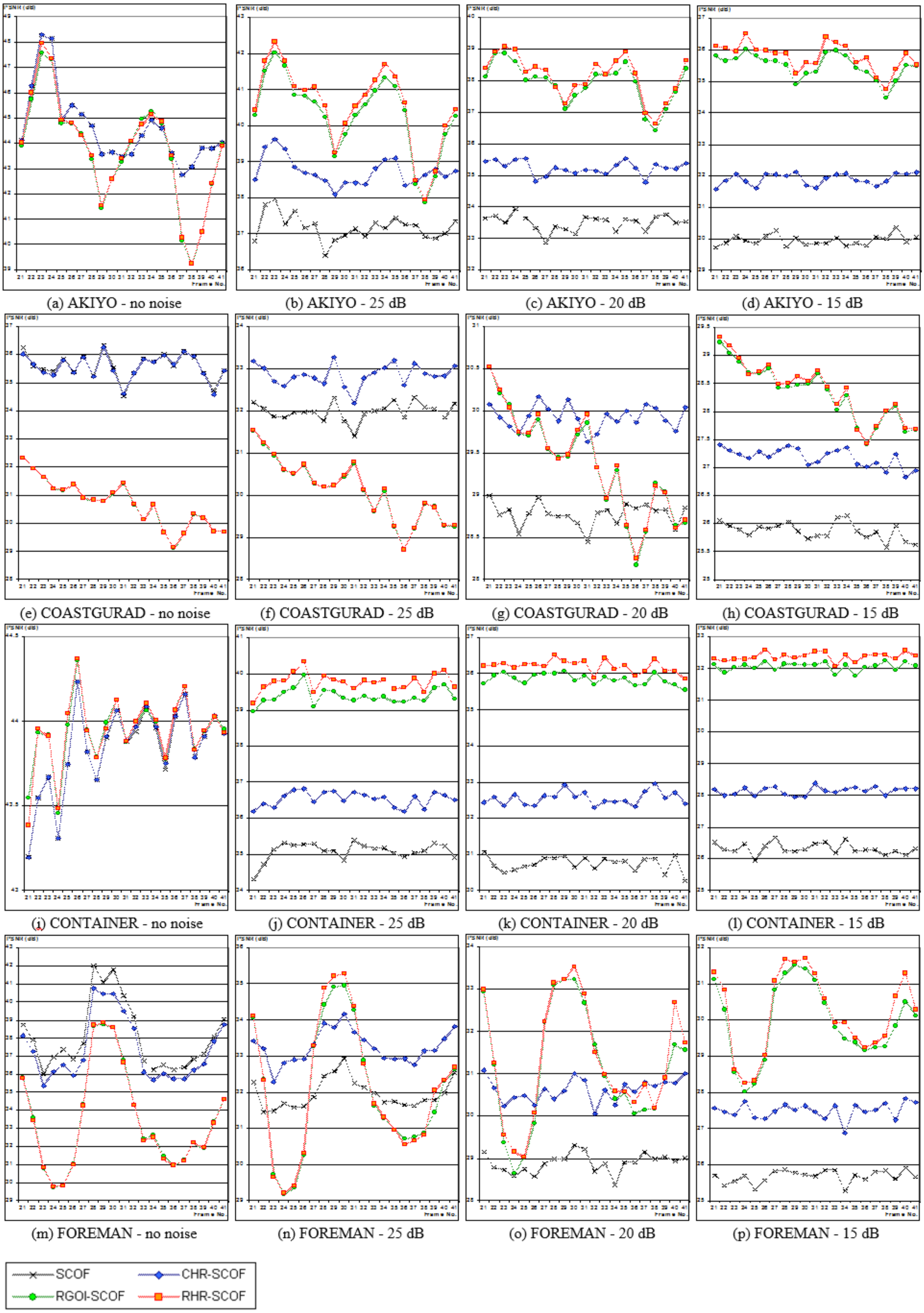

Fig.6: *PSNR of SCOF algorithm.*

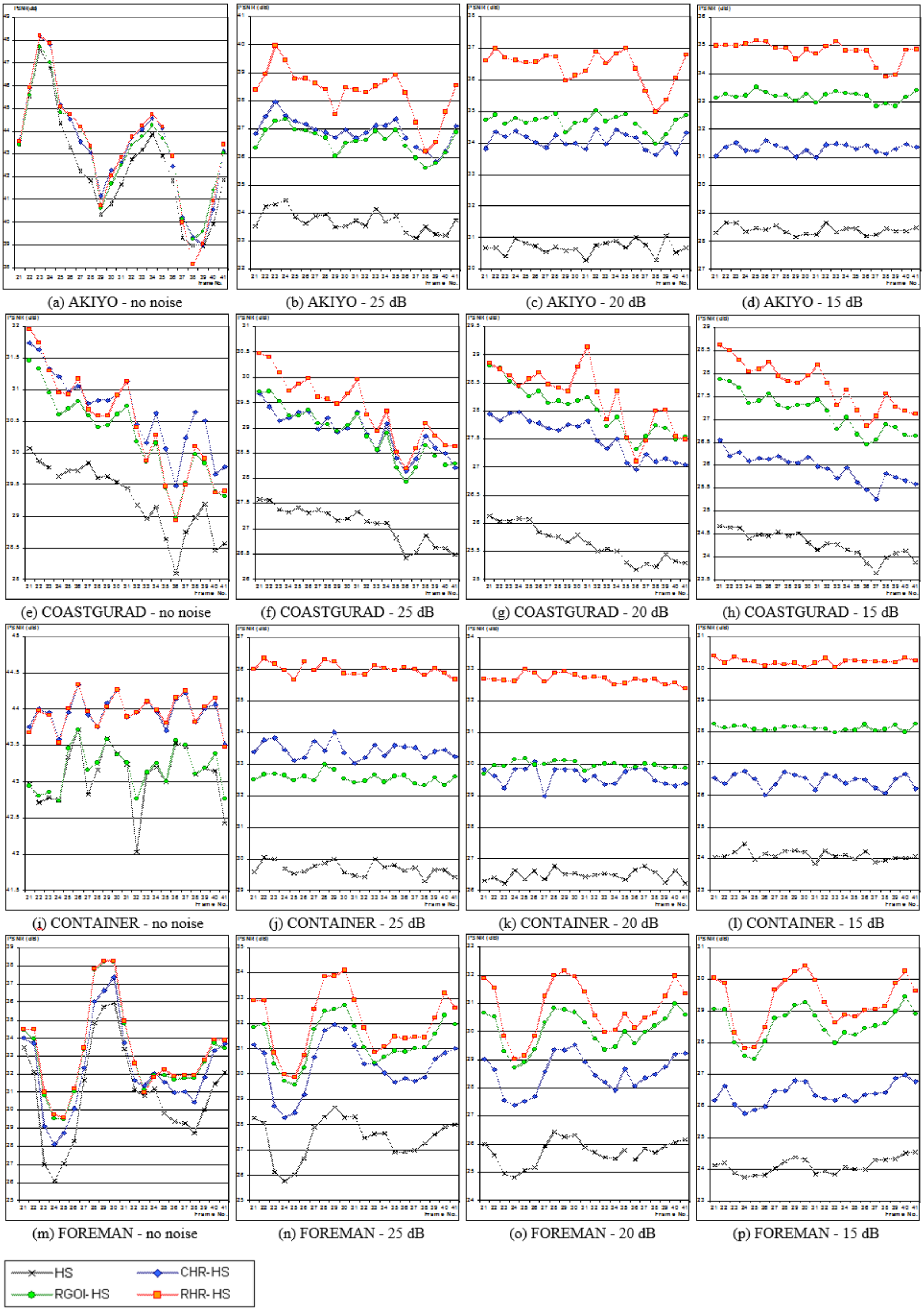

Fig. 7: *PSNR of HS algorithm.*

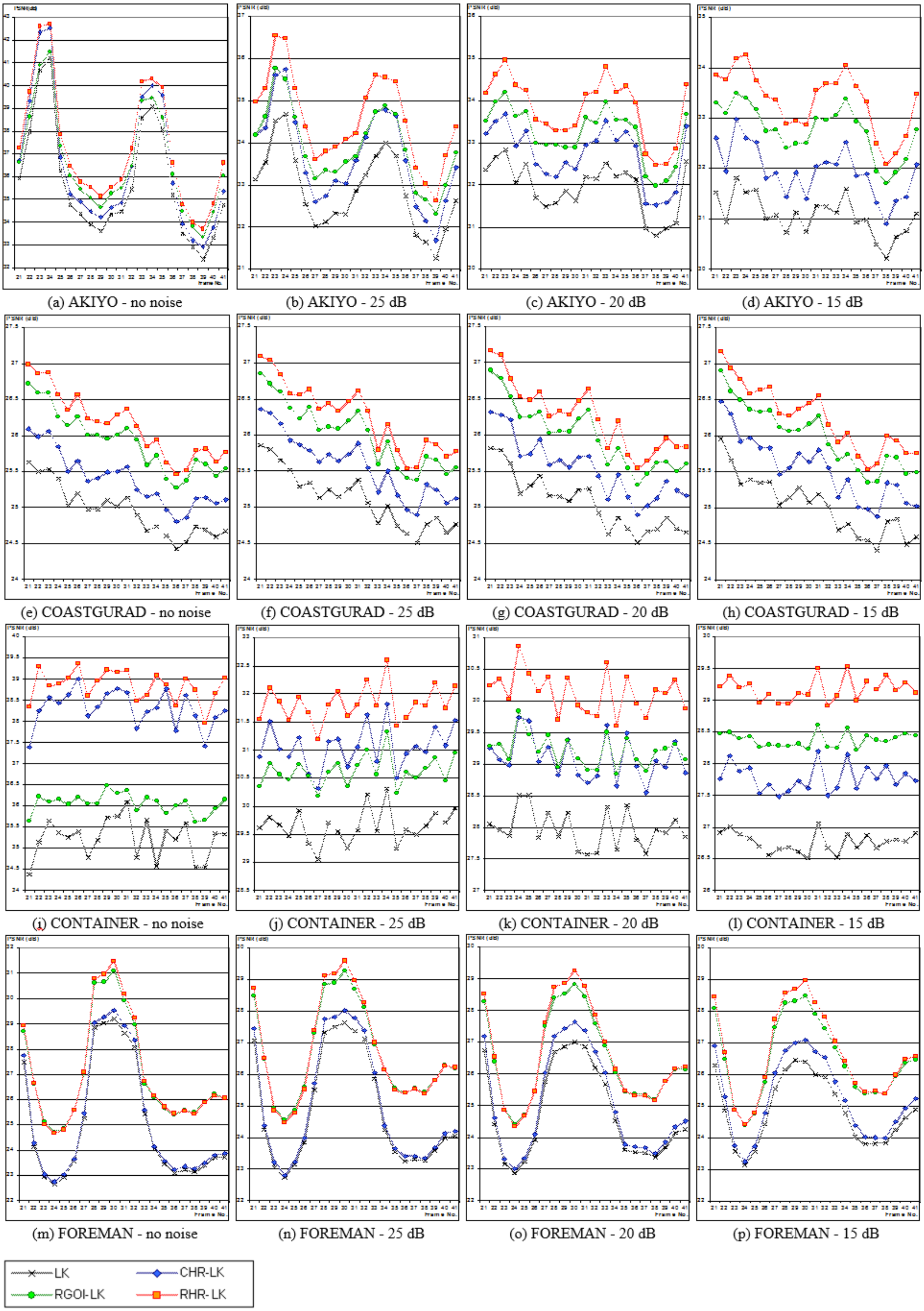

Fig.8: *PSNR of LK algorithm.*