Experimental Analysis on Non-Gaussian Noise Robust Optical Flow Using Adaptive-Lorentzian

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***Abstract* - In optical flow research mobility estimation and Mobility Direction (MD) are important issues. Several noisy measurements are needed to construct a reliable optical flow models. We apply the Adaptive-Lorentzian, A-L, norm influence function to the Geographical Interaction (GI) optical flow model to achieve accurate models of optical flow with outlier tolerances. We used simulation experiments to verify higher outlier tolerance with GI optical flow's MD in Non-Gaussian Noise (NGN) when they are applied over simple GI optical flow model as a filtering process in a stage by stage interaction technique. We proved the overall performance of our model with tests on numerous standard tested dataset with variations in mobility velocity and simulation using datasets infused with several types of NGN. The objective measurement Peak Signal-to-Noise Ratio (PSNR) is used to demonstrate the very high effectiveness of outlier tolerance models.**

Keywords - Non-Gaussian noise; Optical flow; Lorentzian; Mobility estimation; PSNR

I. INTRODUCTION

Optical flow is a technique in imitation of deciding mobility direction (MD) where the MD is inherited to the manner in additional because of more than a few superior areas such movement estimation, picture reconstruction, image segmentation, tremendous photo resolution, movement tracking, image recognition, and photograph encoding. Then, the outlier in the induction of MD associated with the fine and overall performance among additional areas where they suggest the result of MD for processing. One regarding an essential have an effect on MD induction over optical flow is outlier opposition where a number of researches tackle the affect regarding outlier between optical flow. Even though, a number of outlier tolerance models have been proposed to extend the outlier tolerance stage, however, there are nonetheless wondered on "What is the best suitable model of optical flow for outlier tolerance?". Because like are dense kinds over noise where some outlier tolerance models work fantastic beneath some sorts of the outlier but it receives worse on different kinds. Also, the fashion of sequence is also important. The various fashion of sequence return various effects in performance on action dedication with the aid of optical flow such as the quickly and gradual mobility sequence additionally return distinct end result underneath exceptional models in optical flow [1-2].

In this paper, we focal point on the first-class of photo reconstruction out of MD concerning geographical interaction (GI) [3] optical flow yet its outlier tolerance fashions such the utilized mixture model concerning adaptive-Lorentzian [4], overturn confidential [5], typical bilateral model [6-7], and overturn confidential with filter [8-9] the place non-Gaussian noises (NGN) alongside along Poisson Noise, Salt & Pepper Noise, yet Speckle Noise are simulated as regards the typical overall performance of NGN tolerance. For performance studying, the sequence is reconstructed beyond result MD regarding every reference model over NGN contaminated sequence and it is tested by means of PSNR in opposition to the ground truth sequence the place the greater rate in PSNR means higher quality.

This paper is noted as follows. Part 2 states writing about GI optical flow and its referenced outlier tolerance models. Part 3 states the simulation outcome, which categorical the overall performance in PSNR. And the conclusion of the simulation outcome is cited in Part 4.

II. THEORY OF OPTICAL FLOW

In this part, the GI optical flow yet its outlier tolerance models are concentrated.

A. Geographical Interaction Optical Flow

Geographical interaction (GI) [3] is a representative optical flow technique. GI is the classical geographical area optical flow for mobility classification that utilized block matching thought in a stage of the pixel. The determine areas is matched with the specific block size to become aware of the minimal sum of absolute difference as the quality candidate MD.

GI presents excessive accuracy over non-noise sequence however very sensitive beneath noisy circumstance and requires high computation time according to the outcomes of overall performance evaluation for image reconstruction [10].

B. Overturn-Confidential

The concept of overturn confidential (OC) [5] utilized the leading MD (frame k -> $k+1$) yet the overturn vector (frame $k+1$ -> k) used to admit the confidence level for an accuracy enhancement in MD.

The origin MD of the usual and overturn sequences are got with the aid of the usage of GI algorithm. Then, the confidence level (C) is calculated from the correlation of usual and overturn MD by:

$$C_l^n(s,k) = exp\left(\frac{|v_l^n(s,k)+v_{l-}^n(s+v_l^n(s,k),k+1)|}{\frac{(|v_l^n(s,k)|+|v_{l-}^n(s+v_l^n(s,k),k+1)|)}{2+\beta}}\right) \tag{1}$$

where $v^n_l(s,k)$ and $v^n_{l-}(s,k)$ are usual and overturn MD of the neighbor (n). s is coordinate (x,y) in 2D image yet avoids the divide through the usage of nil in the equation. l and l-are ahead and overturn movement vector. The charge concerning confident is employed according to 1 when the values on the action vector of usual and overturn are the same.

After that, the average MD is calculated from the confident level of regional ($N(s0)$) of the region $s0 = (x, y, k)$ by:

$$\bar{v}_l^n(s_0) = \frac{\sum_{s_i \in N(s_0)} C_l^n(s_i) v_l^n(s_i)}{\sum_{s_i \in N(s_0)} C_l^n(s_i)} \tag{2}$$

OC introduced an enhancement in accuracy underneath clear and noisy domains however it consumes double computation time due to the idea of bi-directional.

C. Median Filter

Median filter [11] in optical flow is used to enhance the overall performance in efficiency in altering of mild prerequisites via utilized gradient orientation data of L1 median over MD of usual optical flow algorithm described as:

$$L_u, L_v = \left(\frac{u}{|u|}, \frac{v}{|v|}\right) \tag{3}$$

where (L_u, L_v) is 2 scalars (1 then -1) and proviso the magnitude is 0, zeros charge is appointed to signify as the closing action vector.

Median filter introduced an enhancement of outlier tolerance in MD below noisy environments especially on gradual motion sequence and presented excessive deviation in outlier tolerance according to the results of performance assessment.

D. Bilateral Filter

In optical flow, bilateral Filter [6-7] is a frequent smoothing filter for noise-reduction. Bilateral Filter is used to be added in optical flow where the depth in a photograph is modified through the usage of common weighted beyond neighbors (bilateral-kernel) defined as:-

$$\phi(x+n) = \exp\left(\frac{|n|^2}{2\delta_a^2} + \frac{|I(x+n)-I(x)|^2}{2\delta_b^2}\right) \tag{4}$$

where δ_a is trendy deviation of 7 × sign $v(x)$ and δ_b is widespread deviation of intensity $I(x)$. Bilateral filter is occupied in accordance with prepare the calculation as like follows:-

$$v_b(x) = \frac{1}{K} \sum_{|m|<M} v(x)\phi(x+m) \tag{5}$$

where M is volume concerning neighborhood, and $\phi()$ is Gaussian-kernel in bilateral. In our simulation, we prepare ±7 because of M according to the native work [6]. K is the kernel normalization.

$$K = \sum_{|m|<M} \phi(x+m) \tag{6}$$

E. Overturn Confidential among Filter

Overturn confidential among filter is an applied method that mix the overturn exclusive collectively with the filter in move processing such overturn confidential with the median filter (OCM) [8] and overturn confidential with bilateral filter (OCB) [9]. For OCM, it identifies the model in concentration regarding bidirectional beside OC along L1 median filter while OCB identifies the model in concentration of bidirectional from OC along the bilateral filter. The purpose is according to enhance the performance in accuracy regarding movement vector under noisy condition. Figure 1 shows the cross processing of overturn confidential among filter.

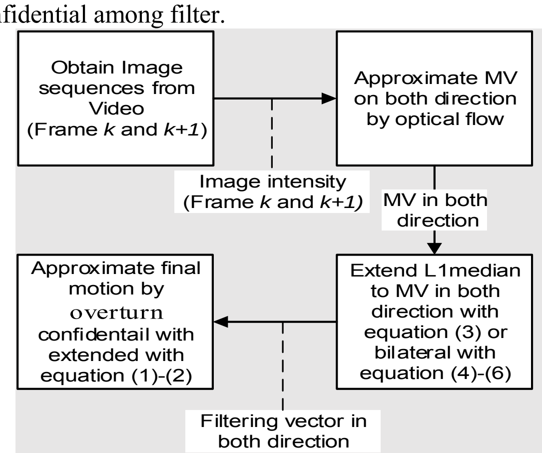


Figure 1. Process flow of overturn confidential among filter.

F. Adaptive-Lorentzian

The robust statistic [12] is the discipline of allocation troubles when the information accommodates repulsive errors. In order to improve the robustness, the adaptive Lorentzian norm, so-called the robust norm [13], has been invented for the sturdy allocation application that is normally utilized under the noisy environments because this adaptive-

DOI 10.5013/IJSSST.a.19.06.47

ISSN: 1473-804x online, 1473-8031 print

Lorentzian norm is extra robust than both L1 norm. Moreover, this function of the adaptive-Lorentzian norm is clean for that reason mathematical formulation of the minimization hassle is tractably solved into the closed form. The Adaptive-Lorentzian (A-L) norm and its function are defined mathematically as following equations:

$$P_{Lor}(x,y,s) = \log\left[1+\frac{1}{2}\left(\frac{u(x,y,s)}{T}\right)^2\right] \quad (7)$$

Then, the robust optical flow using adaptive-Lorentzian (A-L) [4] formulate adaptive-Lorentzian norm as adaptive-Lorentzian norm affect feature for remaining MD.

$$u_{Lor}(x,y,s) = \left(\frac{2\times u(x,y,s)}{(2\times T^2)+u(x,y,s)^2}\right) \quad (8)$$

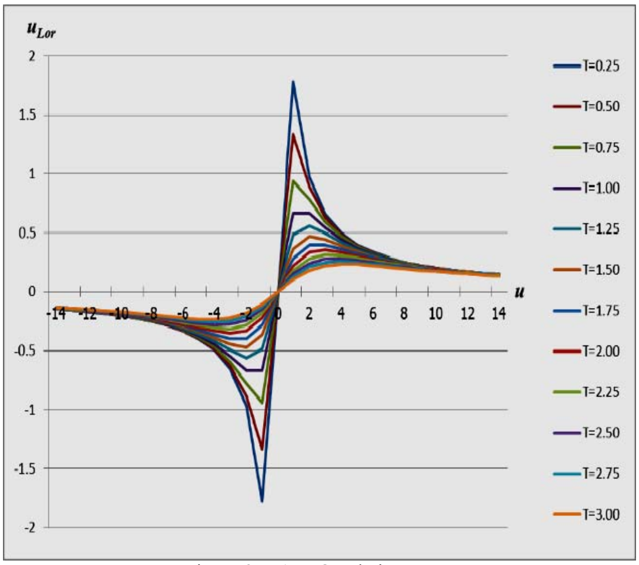


Figure 2. A-L Quadatic ranges

We suggest the value regarding *T* as 1.25 in our proposed A-L.

III. SIMULATION

We adopt four extraordinary patterns of the tested dataset (FOREMAN, COASTGUARD, AKIYO, and CONTAINER) in well-known QCIF layout (176 × 144). FOREMAN is rapid forepart movement fashion and COASTGUARD is speedy heritage whilst AKIYO and CONTAINER are gradual motion fashion. Then, we degrade each tested dataset with 5 sorts of NGN. There are Speckle Noise (0.01 and 0.05 in variance), Salt&Pepper Noise (0.005 and 0.025 in density), and Poisson Noise. The Degraded photograph with different types of NGN are illustrated in Figure 3.

So, totally 20 tested datasets (100 frames over every tested dataset) is adopt into our simulation. Figure3 illustrates the example of the captured photograph from each tested dataset where it is degraded with NGN.

For GI, we prepare ±3 for block region and prepare ±7 for looking vicinity along 0.5 sub-pixel displacements of bilinear interpolation to in the simulation.

The most important index for overall performance contrast is PSNR among decibel (dB) the place the reconstructed sequence from MD on every tested dataset is used to study with the ground truth dataset. The equation because of PSNR is described as:

$$E = \frac{1}{xy}\sum_{q=0}^{x-1}\sum_{r=0}^{y-1}[P1(q,r)-P2(q,r)]^2 \quad (9)$$

$$PSNR = \log_{10}\left(\frac{BI^2}{E}\right)\times 10 \quad (10)$$

where *P1* is a reconstructed photograph beside MD then *P2* is regional ground truth photograph at resolution ($x\times y$). E is suggest the squared error. *BI* is 255 (8 bits image). The worth regarding PSNR is mounted among dB the place the greater dB is mean higher great in the end result about the reconstructed photograph.

Average PSNR of one hundred frames over every tested dataset are summarized in Table 1. Figure 4 to Figure 7 exhibit the rate of PSNR frame by frame at exclusive NGN.

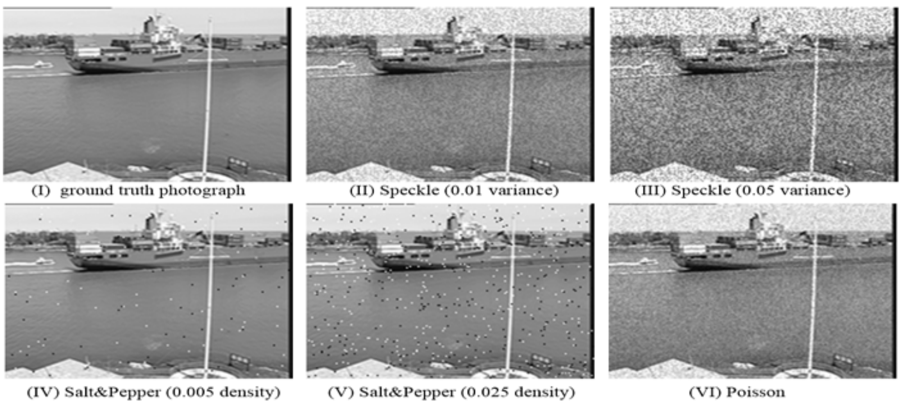
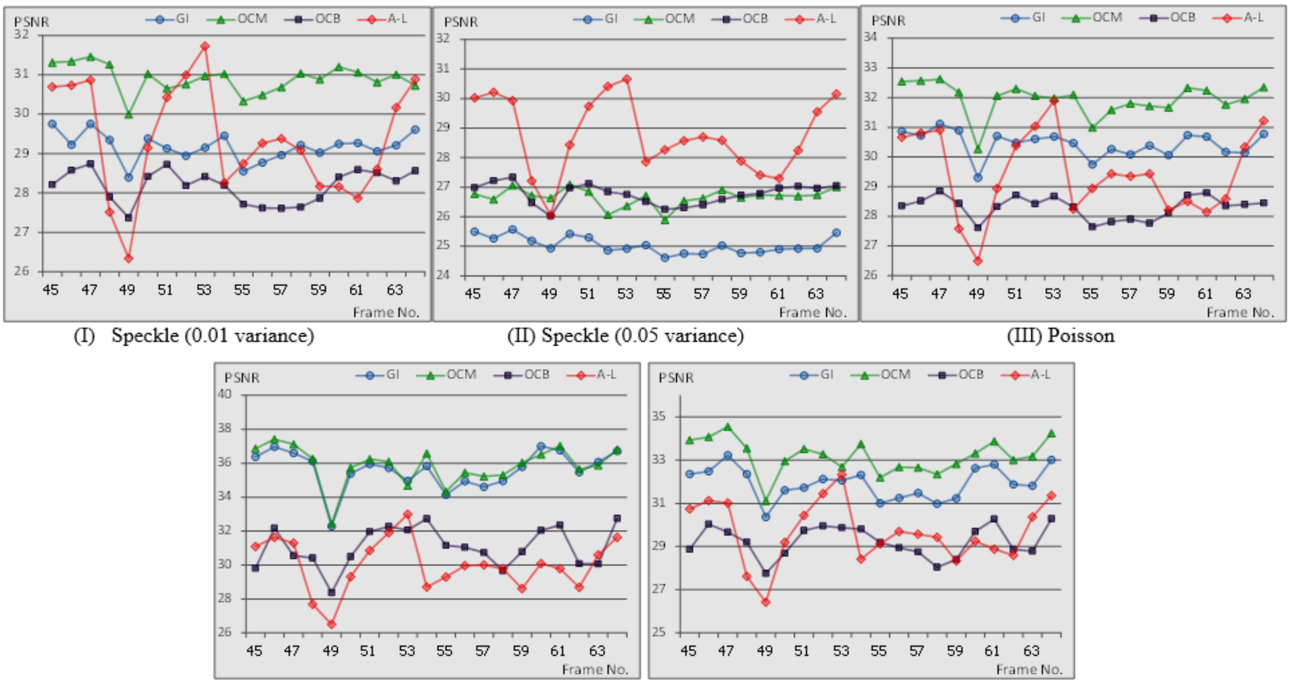


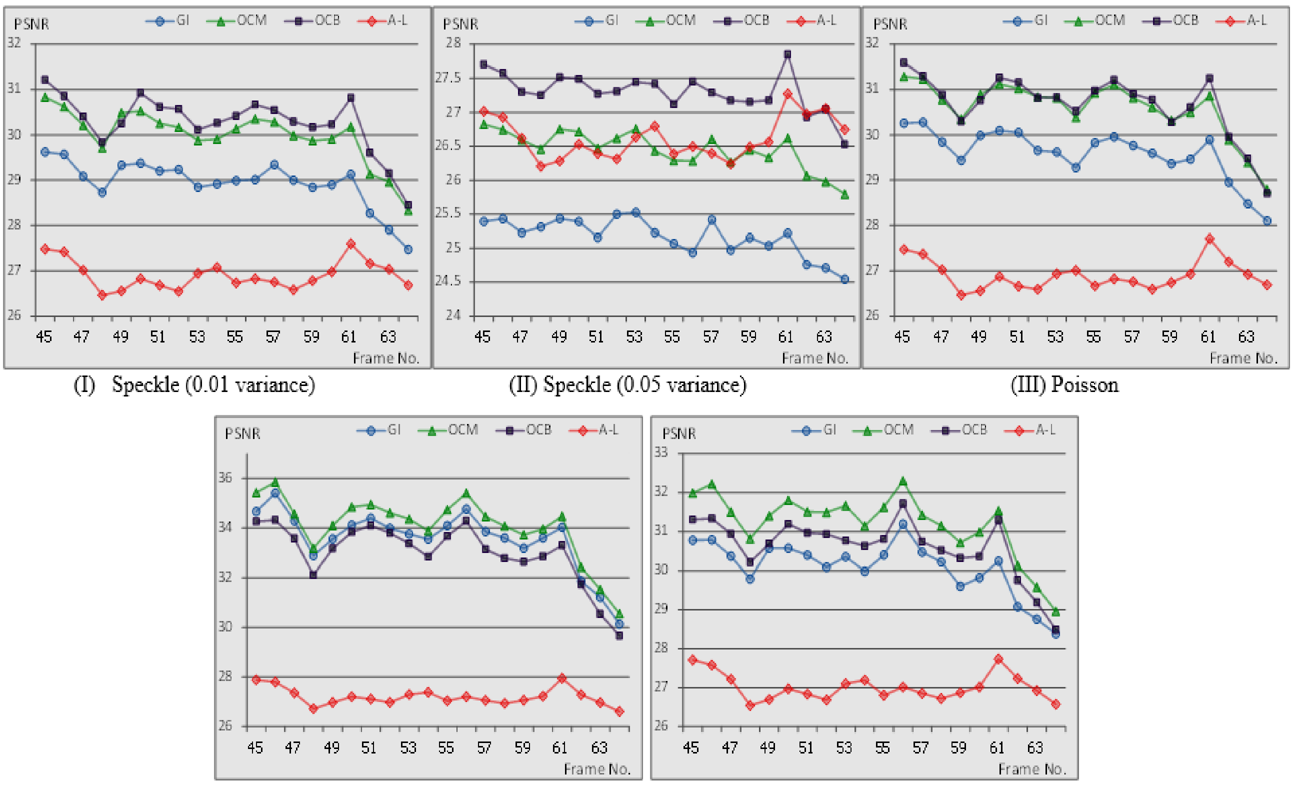
Figure 3. Degraded photograph with different types of NGN



(I) Speckle (0.01 variance) (II) Speckle (0.05 variance) (III) Poisson

(IV) Salt & Pepper (0.005 density) (V) Salt & Pepper (0.025 density)

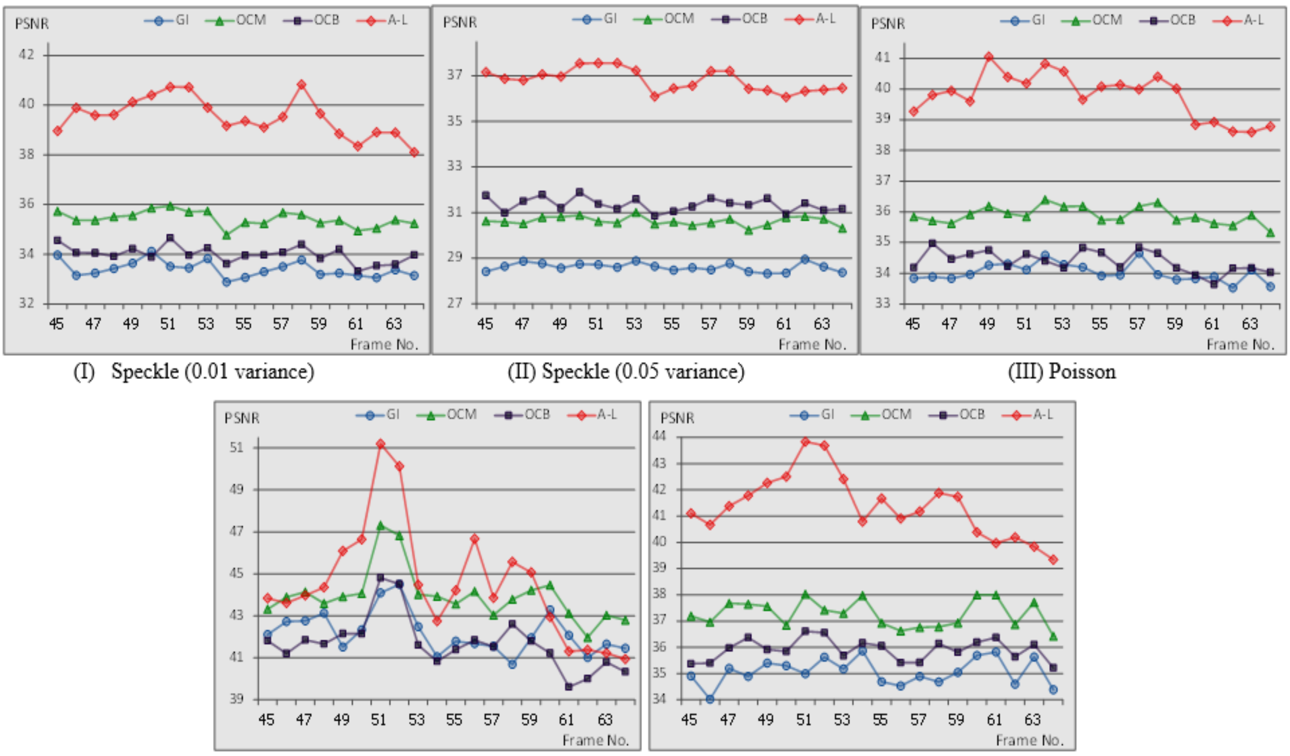
Figure 4. PSNR in continues frame no. 45-65 of FOREMAN tested dataset



(I) Speckle (0.01 variance) (II) Speckle (0.05 variance) (III) Poisson

(IV) Salt & Pepper (0.005 density) (V) Salt & Pepper (0.025 density)

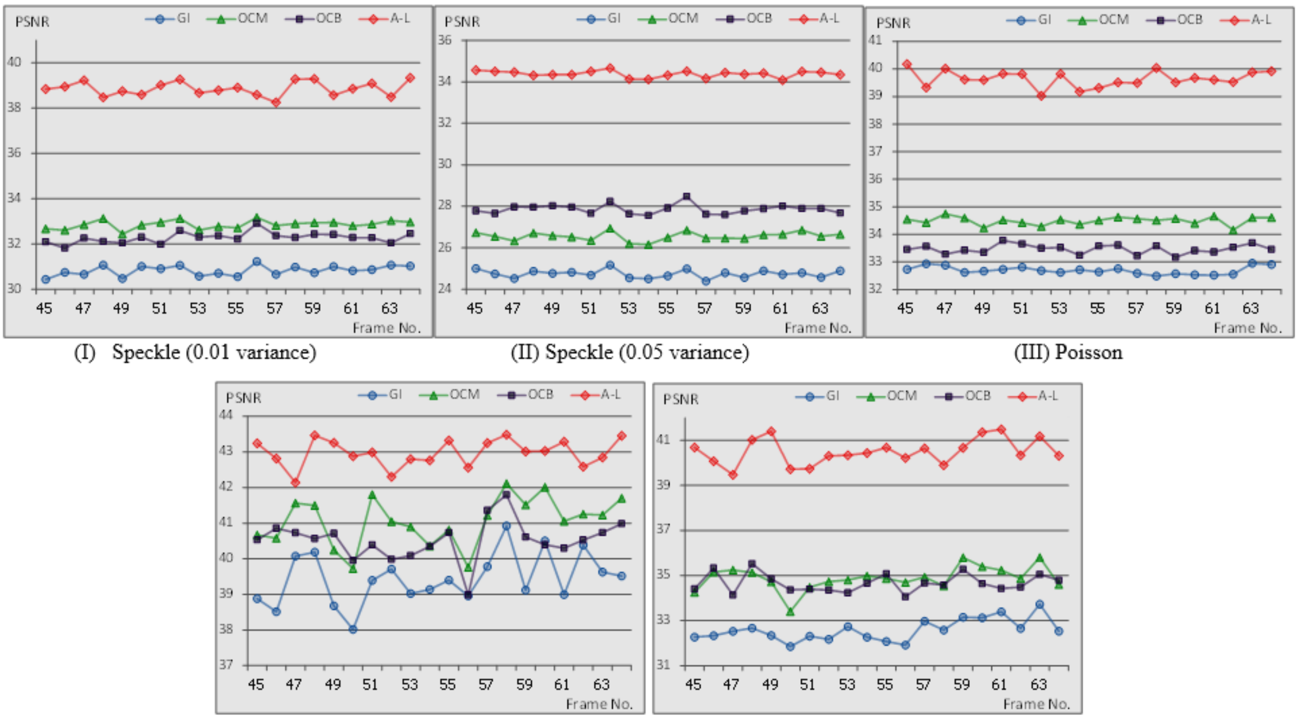
Figure 5. PSNR in continues frame no. 45-65 of COASTGUARD tested dataset



(I) Speckle (0.01 variance) (II) Speckle (0.05 variance) (III) Poisson

(IV) Salt & Pepper (0.005 density) (V) Salt & Pepper (0.025 density)

Figure 6. PSNR in continues frame no. 45-65 of AKIYO tested dataset



(I) Speckle (0.01 variance) (II) Speckle (0.05 variance) (III) Poisson

(IV) Salt & Pepper (0.005 density) (V) Salt & Pepper (0.025 density)

Figure 7. PSNR in continues frame no. 45-65 of CONTAINER tested dataset

TABLE I. SUMMARY ON AVERAGE PSNR AND SD

		POISSON				SALT&PEPPER (0.005 (density)				SALT&PEPPER (0.025 density)				SPECKLE (0.01 variance)				SPECKLE (0.05 variance)			
		GI	OCM	OCB	A-L	GI	OCM	OCB	A-L	GI	OCM	OCB	A-L	GI	OCM	OCB	A-L	GI	OCM	OCB	A-L
FOREMAN	PSNR (dB)	30.07	**31.49**	28.19	28.86	34.80	**35.08**	30.85	29.37	31.38	**32.60**	29.02	29.05	28.85	**30.48**	27.91	28.77	24.92	26.51	26.50	**28.24**
	SD	1.09	1.37	0.85	2.22	2.61	2.60	1.84	2.52	1.50	1.76	1.16	2.35	0.90	1.16	0.80	2.18	0.48	0.62	0.69	1.92
COASTGUARD	PSNR (dB)	29.08	30.04	**30.14**	27.78	32.81	**33.31**	32.32	28.15	29.52	**30.59**	30.15	27.89	28.49	29.52	**29.76**	27.77	24.87	26.19	27.06	**27.26**
	SD	2.13	2.39	2.67	3.46	3.36	3.51	3.46	3.73	2.40	2.69	2.76	3.56	1.97	2.25	2.55	3.45	1.25	1.54	1.93	3.15
AKIYO	PSNR (dB)	33.91	35.75	34.21	**39.07**	41.48	**43.12**	41.07	42.79	34.93	37.07	35.63	**40.34**	33.29	35.24	33.87	**38.82**	28.58	30.60	31.22	**36.38**
	SD	0.32	0.30	0.38	1.47	1.12	1.33	1.32	3.12	0.53	0.59	0.55	2.01	0.30	0.32	0.37	1.43	0.23	0.25	0.25	0.92
CONTAINER	PSNR (dB)	32.69	34.44	33.45	**39.74**	39.46	41.02	40.66	**42.99**	32.67	34.92	34.64	**40.58**	30.88	32.84	32.31	**38.76**	24.82	26.67	27.95	**34.39**
	SD	0.24	0.19	0.24	0.38	0.83	0.72	0.64	0.43	0.53	0.56	0.54	0.51	0.24	0.22	0.27	0.32	0.21	0.24	0.24	0.26

IV. CONCLUSION

From the simulation, we discovered a broad up to expectation of our proposed method that the outcome reflected upon the fashion of the tested dataset. Then, we separated the conclusion into 2 groups:

- The A-L returned very high outlier tolerance over gradual motion such as AKIYO and CONTAINER. A-L gave the best outcome over most types of GNG with more impact upon increasing the noise level such as SALT&PEPPER and SPECKLE.
- A-L gave excellent outcome over speedy motion dataset such FOREMAN and COASTGUARD only in the high level of noise such as SALT&PEPPER and SPECKLE but gave poor outcome over POISSON and low level of noise in SALT&PEPPER and SPECKLE.

ACKNOWLEDGMENT

This research project was funded by Assumption University.

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