

Experimental analysis of non-Gaussian noise resistance on global method optical flow using bilateral in reverse confidential

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Article Info

Article history:

Received Aug 14, 2020

Revised Dec 12, 2020

Accepted Feb 5, 2021

Keywords:

Optical flow

Non-Gaussian noise

Error vector magnitude

Bilateral filter

Reverse confidential

ABSTRACT

This paper presents the analytical of non-Gaussian noise resistance with the aid of the use of bilateral in reverse confidential with the optical flow. In particular, optical flow is the sample of the image's motion from the consecutive images caused by the object's movement. It is a 2-D vector where every vector is a displacement vector displaying the motion from the first image to the second. When the noise interferes with the image flow, the approximated performance on the vector in optical flow is poor. We ensure greater appropriate noise resistance by applying bilateral in reverse confidential in optical flow in the experiment by concerning the error vector magnitude (EVM). Many noise resistance models of the global method optical flow are using for comparison in our experiment. And many sequenced image data sets where they are interfered with by several types of non-Gaussian noise are used for experimental analysis.

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1. INTRODUCTION

During the last three-decades, optical flow [1, 2] is an approach that was applied in several fields such as motion estimation to point the moving object motion vector and motion compression. In traditional image compression [3], motion compensation [4], video encoding [5, 6], movement tracking [7, 8], and the distinction among the movement frame is coded. Then, the higher resolution is constructed in super-resolution [9, 10]. Consequently, optical flow is the computation approach for identifying the motion vector (MV) on each pixel. Several approaches of optical flow were presented such local method [11], phase correlation method [12], block-based method [13] but this paper concentrates on the proposed global method optical flow (G-OF) [14]. Because the G-OF is certain concerning the differential gradient-based algorithms where it has been applied for several area in advance because of its acceptable in performance for motion estimation. Many research works focus on the computationally efficient [15, 16] but this paper focus on the noise resistance approaches.

In the actual world, most regarding the sequences are interfered with by way of many prerequisites so purpose noises upon the sequences. The main problem is noise interference. The performance of the optical flow is sensitive to the noise that degrades the result in motion estimation. Many approaches focus on pre-processing such a noise remover model [17, 18] to remove the noise on the image earlier. And many

approaches focus post-processing on a specific area such as many approaches in advance of optical flow have been proposed during the last decade to improve the performance over the interfered noises such as the bilateral function [19] and reverse confidential [20]. The concept of the reverse confidential in optical flow and the bilateral function in optical flow was proved and presented an effective result in noise resistance.

This paper focuses on the use of the fusion approach among the bilateral filter and the reverse confidential called the application of bilateral in reverse confidential with G-OF [21]. The objective of this paper is to analyze the performance in the non-Gaussian noise resistance on global method optical flow using bilateral in reverse confidential. The non-Gaussian noises are used in the experimental analysis such as salt & pepper, speckle, and poisson. In the experimental, we analyze the performance in noise resistance with the error vector magnitude (EVM) where the EVM concerns the degree of missed direction in the MV from the optical flow's outcome. And we also compare the performance in noise resistance against the other noise resistance approaches to ensure greater appropriate noise resistance. The paper organization is arranged as follows. Section 2 explains the research method in optical flow. Section 3 explains the experimental result. Section 4 explains the conclusion.

2. RESEARCH METHODS IN GLOBAL METHOD OPTICAL FLOW AND NOISE RESISTANCE APPROACHES

In this section, it is explained the global method optical flow and the noise resistance approaches on the optical flow.

2.1. Global method optical flow

Global method optical flow (G-OF) [14] is an ordinary approach for pointing the 2-D vector motion estimation via the use of "intensity of brightness level" with four-point mean differences [22, 23] and "smoothness variation". The iterative equations are calculated to obtain image velocity as in (1):

$$\begin{aligned} u^{i+1} &= \bar{u}^i - \frac{I_x [I_x \bar{u}^i + I_y \bar{v}^i + I_k]}{\alpha^2 + I_x^2 + I_y^2} \\ v^{i+1} &= \bar{v}^i - \frac{I_y [I_x \bar{u}^i + I_y \bar{v}^i + I_k]}{\alpha^2 + I_x^2 + I_y^2} \end{aligned} \quad (1)$$

where \bar{u}^i and \bar{v}^i denote neighborhood average of horizontal and vertical. i is the number of iterative calculations. The gradient intensity is:

$$\begin{aligned} I_x &= \frac{1}{4} \{I_{x,y+1,k} - I_{x,y,k} + I_{x+1,y+1,k} - I_{x+1,y,k} + I_{x,y+1,k+1} - \\ &\quad I_{x,y,k+1} + I_{x+1,y+1,k+1} - I_{x+1,y,k+1}\} \\ I_y &= \frac{1}{4} \{I_{x+1,y,k} - I_{x,y,k} + I_{x+1,y+1,k} - I_{x,y+1,k} + I_{x+1,y,k+1} - \\ &\quad I_{x,y,k+1} + I_{x+1,y+1,k+1} - I_{x,y+1,k+1}\} \\ I_t &= \frac{1}{4} \{I_{x,y,k+1} - I_{x,y,k} + I_{x+1,y,k+1} - I_{x+1,y,k} + I_{x,y+1,k+1} - \\ &\quad I_{x,y+1,k} + I_{x+1,y+1,k+1} - I_{x+1,y+1,k}\} \end{aligned} \quad (2)$$

where $I(x,y,k)$ is the gradient intensity of an element (x,y) in the images at frame no. k .

2.2. Bilateral function in optical flow

Based on the effectiveness of noise removal from bilateral function, the use of a bilateral function (BF) in correspondent with optical flow [19] found effectiveness in the noise tolerance on the result of MV. The main process in corresponding the bilateral function in optical flow is to set the bilateral function [24-27] over the result of the G-OF. In BF, the bilateral kernel is defined as:

$$\phi(x+n) = \exp\left(\frac{|n|^2}{2\delta_a^2} + \frac{|I(x+n)-I(x)|^2}{2\delta_b^2}\right) \quad (3)$$

In our work, we assigned $7\times$ of $v(x)$ for deviation in δ_a and deviation of intensity $I(x)$ in δ_b based on the traditional work [24]. Then, the kernel (ϕ) is occupied with the prepared function as:

$$v_b(x) = \frac{1}{K} \sum_{|m|<M} v(x)\phi(x+m) \quad (4)$$

In our work, we assigned ± 7 concerning neighborhood for M , and K is the kernel normalization based on the traditional work [24].

$$K = \sum_{|m| < M} \mathcal{O}(x + m) \quad (5)$$

where m is a local range of neighborhood.

2.3. Reverse confidential optical flow

In the reverse confidential (RC) [20], the outcome of the MV from 2-ways was concerned in order to ensure the stability of the optical flow approach. Then, the confidence function used the result of MV from both directions to determine the confidence level and it was used to adjust the final result of MV.

In RC, the confidence function is defined as:

$$C_l^n(s, k) = \exp \left(\frac{|v_l^n(s, k) + v_l^n(s + v_l^n(s, k), k + 1)|}{(|v_l^n(s, k)| + |v_l^n(s + v_l^n(s, k), k + 1)|)} \right) \quad (6)$$

where v_l and v_r are normal and reverse MV, and n is the number of neighbors MV. s is coordinate (x,y) in 2D image and β avoids the division by zero in the equation. The confidence levels are used to define the final result MV in average of regional ($N(s_0)$) by:-

$$\bar{v}_l^n(s_0) = \frac{\sum_{s_i \in N(s_0)} C_l^n(s_i) v_l^n(s_i)}{\sum_{s_i \in N(s_0)} C_l^n(s_i)} \quad (7)$$

where $(\bar{v}_l^n(s_0))$ is computed from the reliability of neighborhood $N(s_0)$ of the location $s_0 = (x, y, k)$.

2.4. Bilateral in reverse confidential optical flow

The bilateral in reverse confidential (B-RC) [21] is the fusion approach that combines the traditional bilateral function in correspondence with the reverse confidential approach. The process of B-RC is shown in Figure 1. By using the 2-ways concept of RC, the bilateral function is applied to the MV of both direct and the confidence is applied later. Then, the final outcome of MV is pointed from the confidence level.

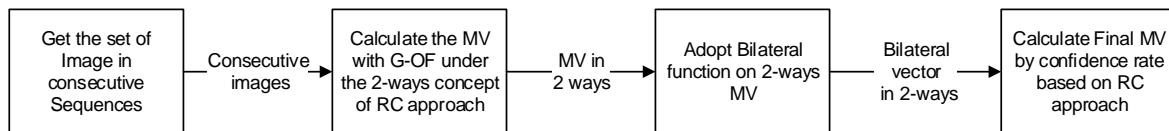


Figure 1. The process of B-RC

3. EXPERIMENTAL AND ACHIEVEMENT

In this work, we used the global smoothness weight (α)=0.5 and use 4-point central differences mask coefficient [22] for gradient estimation on G-OF. Four different well-known QCIF-176×144 sequences (Akiyo, container, coastguard, and foreman) up to 50 frames on each were used on the test. Figure 2 presents the sample of each sequence. Then, 5 kinds of non-Gaussian noise (poisson noise, salt & pepper noise at density 0.005 and 0.025, and speckle noise at variance 0.01 and 0.05) were put in the sequence for testing. Indefinitely, 20 types of the sequence were tested. And we evaluated the ordinary G-OF, BF, and RC in comparison with B-RC.

Definitely, the achievement of noise tolerance was determined by the EVM. EVM is a measure of how accurately in motion vector to quantify the performance where the lower in value of EVM means the better in performance. In this work, we compare with the original ground truth MV and count only the no. of non-zero movement vector with the root-mean-square by the average in the experimental. The Table 1 summarized the average EVM of each approach over 100 frames on the different types of non-Gaussian noise. Figures 3-6 present the achievement of EVM in a frame by frame of the experiment sequences on the different types of non-Gaussian noise by the graph.

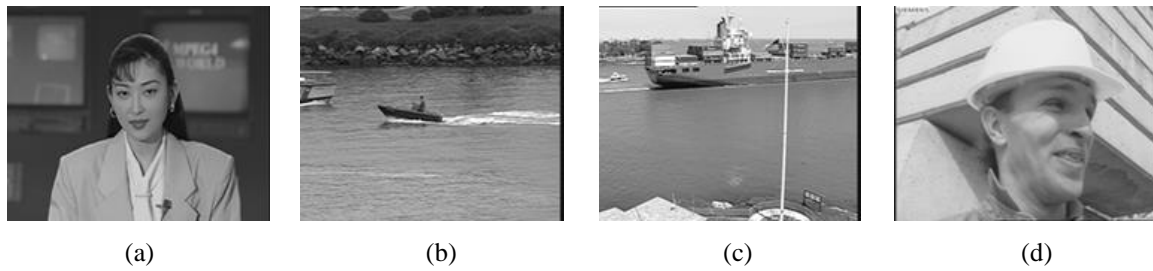


Figure 2. Experiment sequences, (a) Akiyo, (b) Coastguard, (c) Container, (d) Foreman

Table 1. Summarized the average EVM

		Akiyo		Coastguard		Container		Foreman	
		AVG EVM	SD of EVM	AVG EVM	SD of EVM	AVG EVM	SD of EVM	AVG EVM	SD of EVM
Poisson	G-OF [14]	3.653	0.305	3.608	0.148	4.252	0.113	3.776	0.543
	RC [19]	3.199	0.282	3.097	0.145	3.761	0.118	3.304	0.496
	BF [20]	3.218	0.272	3.064	0.146	3.746	0.106	3.702	0.424
	*B-RC [21]	3.057	0.253	2.903	0.152	3.558	0.112	3.488	0.441
Salt (d=0.005)	G-OF [14]	3.658	0.889	2.975	0.291	4.846	0.770	3.675	1.103
	RC [19]	3.583	0.846	2.667	0.246	4.780	0.744	3.494	1.041
	BF [20]	3.385	0.392	2.761	0.164	4.181	0.340	5.215	0.670
	*B-RC [21]	3.314	0.362	2.681	0.155	4.113	0.326	5.072	0.663
Salt (d=0.025)	G-OF [14]	6.424	1.533	4.005	0.361	9.107	1.572	5.321	0.861
	RC [19]	6.162	1.464	3.566	0.315	8.761	1.500	4.989	0.803
	BF [20]	5.109	1.090	3.458	0.287	8.262	1.322	6.063	0.555
	*B-RC [21]	4.773	0.974	3.224	0.243	7.825	1.236	5.721	0.522
Speckle (v=0.01)	G-OF [14]	3.727	0.349	3.758	0.189	4.416	0.097	3.868	0.524
	RC [19]	3.233	0.315	3.189	0.178	3.830	0.099	3.355	0.490
	BF [20]	3.192	0.267	3.092	0.139	3.783	0.103	3.707	0.423
	*B-RC [21]	3.024	0.260	2.916	0.148	3.573	0.103	3.484	0.441
Speckle (v=0.05)	G-OF [14]	4.034	0.314	4.080	0.175	4.683	0.132	4.258	0.439
	RC [19]	3.417	0.296	3.403	0.159	3.993	0.119	3.618	0.453
	BF [20]	3.449	0.298	3.323	0.154	3.982	0.124	3.716	0.420
	*B-RC [21]	3.165	0.270	3.073	0.157	3.714	0.123	3.442	0.444

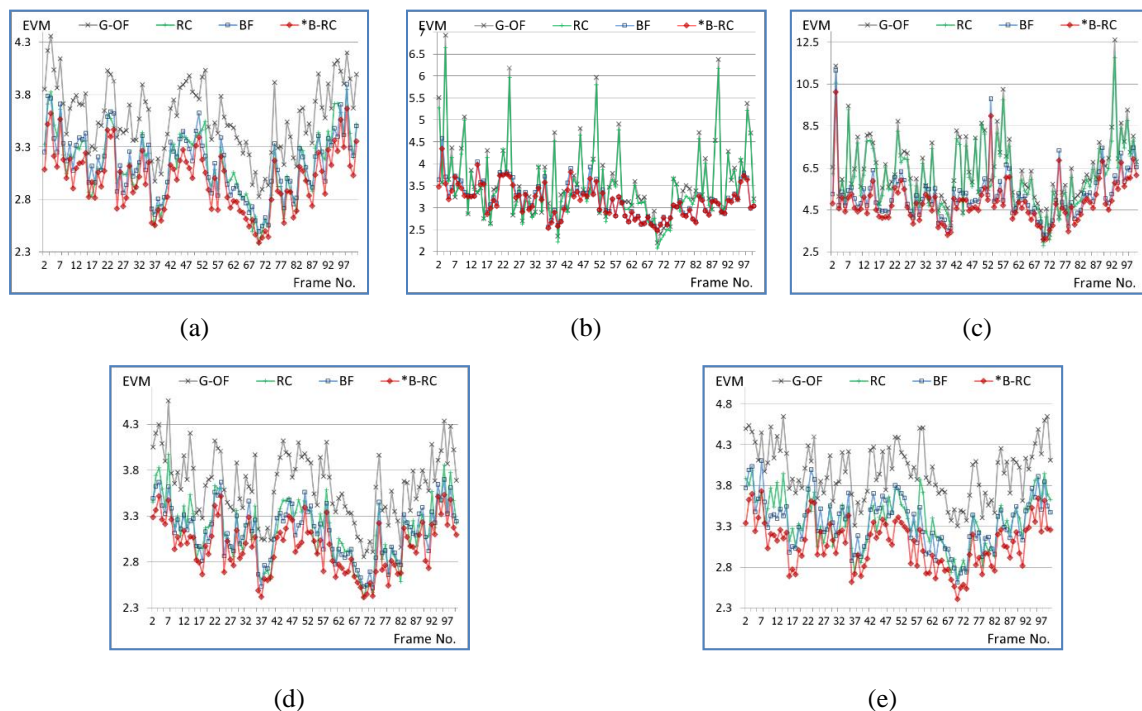


Figure 3. The achievement of EVM in a frame by frame of Akiyo, (a) Poisson, (b) Salt & pepper (d=0.005), (c) Salt & pepper (d=0.025), (d) Speckle (v=0.01), (e) Speckle (v=0.05)

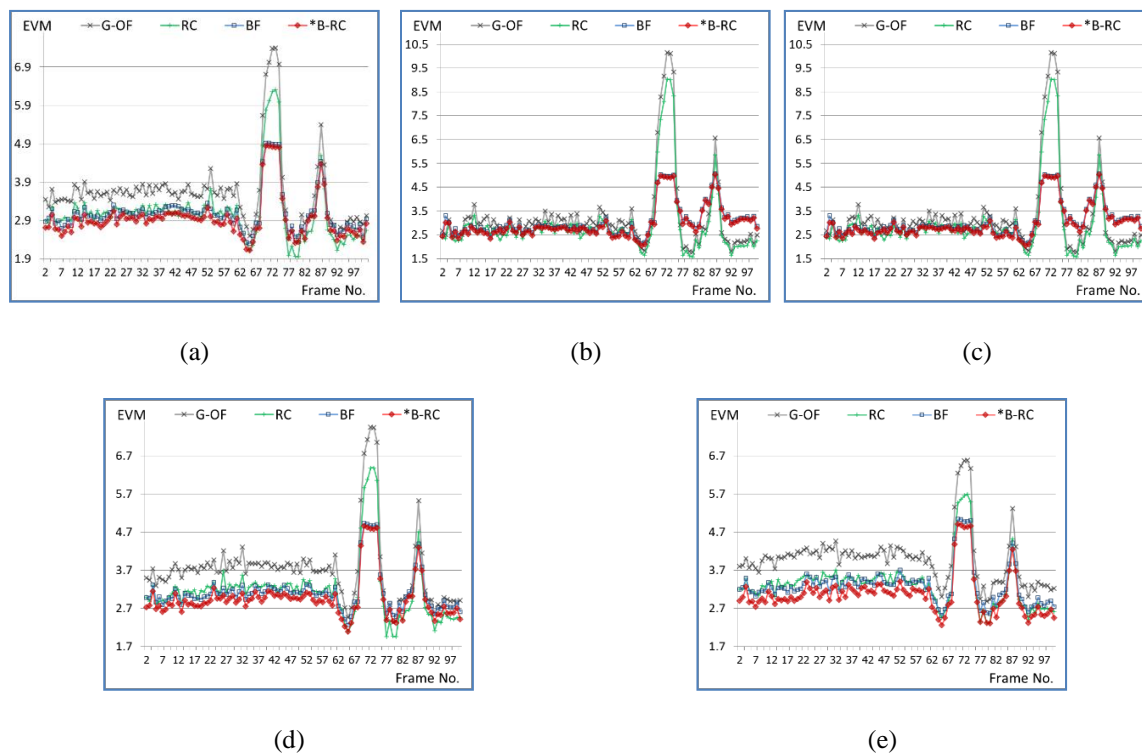


Figure 4. The achievement of EVM in a frame by frame of coastguard, (a) Poisson, (b) Salt & pepper ($d=0.005$), (c) Salt & pepper ($d=0.025$), (d) Speckle ($v=0.01$), (e) Speckle ($v=0.05$)

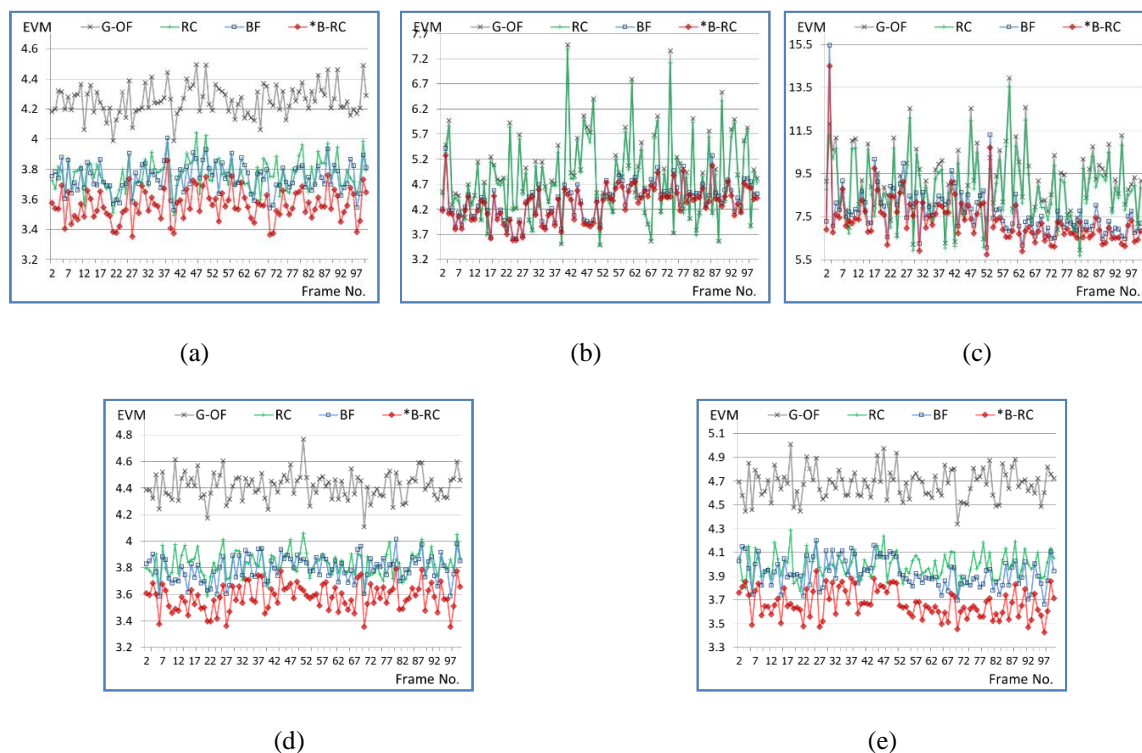


Figure 5. The achievement of EVM in a frame by frame of CONTAINER, (a) Poisson, (b) Salt & pepper ($d=0.005$), (c) Salt & pepper ($d=0.025$), (d) Speckle ($v=0.01$), (e) Speckle ($v=0.05$)

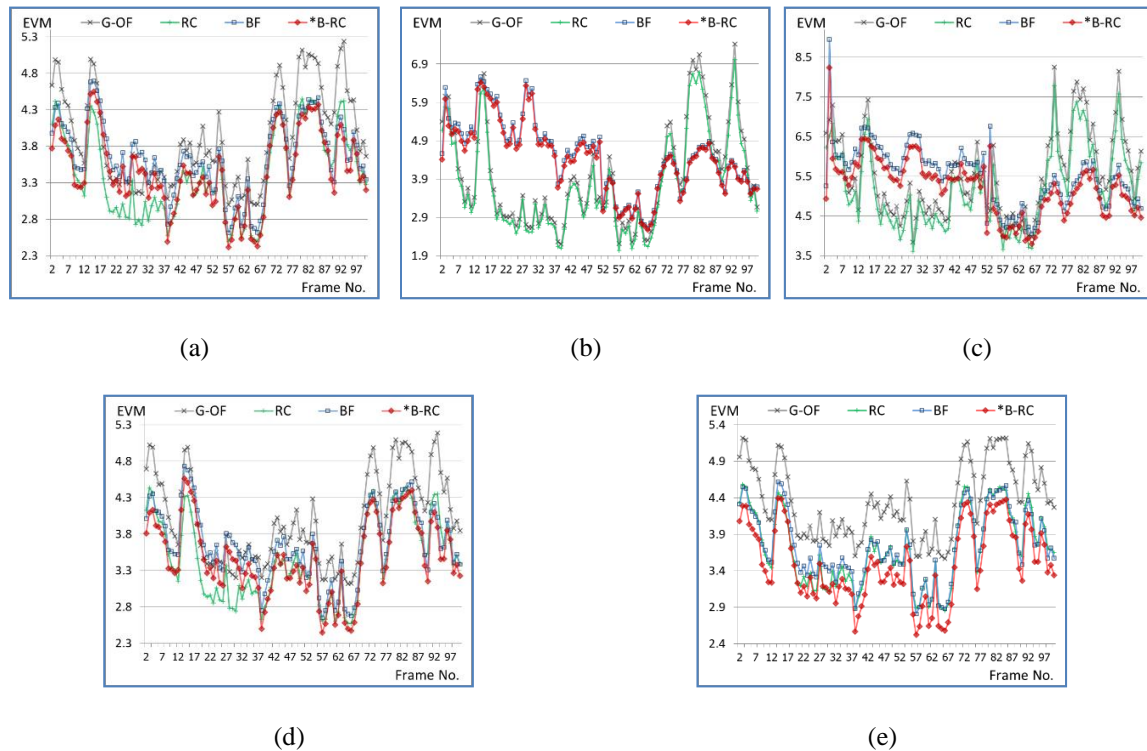


Figure 6. The achievement of EVM in a frame by frame of FOREMAN, (a) Poisson, (b) Salt & pepper ($d=0.005$), (c) Salt & pepper ($d=0.025$), (d) Speckle ($v=0.01$), (e) Speckle ($v=0.05$)

4. CONCLUSION

In our inspection, we concluded the experiment into 2 groups. The first group was concluded by the type of non-Gaussian noise and the second group was concluded by the characteristic of the experiment sequences. Because we found that the performance in noise resistance varies base on the types. Regarding the type of non-Gaussian noise, we found that different types of noise return different results from each approach. From the experimental, we found that: (i) The salt & pepper noise was the most impacted noise that degraded the performance of the optical due to the highest value of EVM, (ii) The performance of the B-RC achieved the best noise resistance over poisson and speckle noise and presented the second-best in salt & pepper noise in coastguard and foreman sequence.

Regarding the characteristics of the experimental sequences, we found that it impacted the performance of the optical flow. In this experiment, we separate the sequences into 2 subgroups for analysis. There is a group of fast movement sequences such as coastguard and foreman sequence and the group of slow movement sequences such as Akiyo and container. From the experimental, we found that: (i) The fast movement sequence impacted to degrade the performance of the optical than slow movement sequence due to the higher value in average EVM of the fast movement sequences, (ii) The performance of the B-RC achieved the best over the slow movement sequence, (iii) The performance of the RC achieved the best over the fast movement sequence only in the low level of salt & pepper and speckle noise. With the increase of noise level in salt & pepper and speckle noise, the B-RC became the best in overall.

From the overall result in the experiment, the B-RC presented the greatest result in noise resistance over the non-Gaussian noise. Then, the application areas such as motion tracking in the noisy environment are suitable to adopt this method to gain accuracy in optical flow. There is no silver bullet method for achieving the best result. Then, the study on several kinds of noises in correspond with several noise resistance approaches is an issue for future research to explore.

ACKNOWLEDGEMENTS

This research project was funded by Assumption University.

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