# Experimental Study in Error Vector Magnitude of Bidirectional Confidential with Median Filter on Spatial Domain Optical Flow under Non Gaussian Noise Contamination

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## ABSTRACT

In this paper, we focus on the robustness in noise tolerance of spatial domain optical flow. We present a performance study of bidirectional confidential with median filter on spatial domain optical flow (spatial correlation, local based optical flow, and global based optical flow) under non-Gaussian noise. Several noise tolerance models on spatial domain optical flow are used in comparison. The experimental results are investigated on robustness under noisy condition by using non-Gaussian noise (Poisson Noise, Salt & Pepper noise, and Speckle Noise) over several standard sequences. The experiment concentrates on error vector magnitude (EVM) as performance indicators for accuracy in the direction and distance of motion vector (MV). In EVM, the result in MV of each method is used to compare with the ground truth vector in the experimental performance analysis.

**Keywords**: Spatial domain optical flow, Non-Gaussian noise, Motion estimation, and EVM.

## 1. INTRODUCTION

The spatial domain optical flow method is widely used in various areas due to its simple calculation based on image intensity from two different time frames in sequence. It is used to classify MV in a level of pixel and it is applied in advance over several areas such as super image resolution, video encoding, target tracking & segmentation, and etc. 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.

Basically, spatial correlation (SC) [1], local based optical flow (LB) [2], and global based optical flow (GB) [3] optical flow are three main methods in spatial domain optical flow where the result in MV is calculated from image intensity.

SC is classical spatial domain optical flow where the motion classification is determined by using basic block matching.

LB and GB was proposed in 1981 by B.D. Lucas and T. Kanade, and B.K.P. Horn and B.G. Schunck respectively. Both LB and GB applied the same gradient intensity in the beginning but LB applied weight least-square over the result of gradient intensity while GB applied minimization over the result of gradient intensity to determine motion classification.

However, the accuracy in efficiency of these classical spatial domain optical flows is interfered under unpleasant situations such as noise. Various algorithms have been introduced to improve the robustness in noise tolerance over the unpleasant situations or noisy domains. For example, J.L Barron, D.J. Fleet and S.S. Beauchemin [4] introduced the 4-point mask coefficient to calculate gradient intensity for LG and GB in 1994.

Bidirectional confidence based optical flow (BC) of R. Li and S. Yu [5] introduced the concept of bidirectional symmetry where the reliability rate in forward and backward direction was used to determine the final MV in 2008.

Median filter for robust motion estimation (MF) [6] of T. Kondo and W. Kongprawechnon introduced the used of median filter to increase robustness for noise tolerance in 2010.

Both BC and MF return good performance in noise tolerance according to the results of performance evaluation for image reconstruction from D. Kesrarat and V. Patanavijit [7-8].

After that, bidirectional confidential with median filter (BF) [9-12] was introduced by D. Kesrarat and V. Patanavijit by consolidate bidirectional concept from BC with L1 median from MF to present more robustness for optical flow motion classification.

The concepts of BF [9-12] were presented and showed very effective result in robustness under Gaussian noises. Then, we carry on inspecting the performance of these robust optical flow methods under non-Gaussian noise such as Poisson noise, Salt & Pepper noise, and Speckle noise where EVM is an indicator in our experiment. Poisson noise is a type of electronic noise. It occurs in photon counting in optical devices and associates with the particle nature of light. Salt & Pepper noise presents itself as

Manuscript received on May 2, 2016 ; revised on May 23, 2016.
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sparsely occurring black and white pixels. It is caused by sharp and sudden disturbance in the image signal. Speckle noise is caused by processing of backscattered signals from multiple distributed targets such as elementary scatters, and the gravity-capillary ripples. In this paper, we focus on the accuracy in the direction and distance of MV that it is very importance in advance area such as motion tracking and forecasting.

In our experiment, we study the performance in robustness of BF on spatial domain optical flows (SC, LB and GB) by using EVM as an indicator in comparison with the other robust models when they are applied in a level of sub-pixel translation on various video sequences that are contaminated with non-Gaussian noise (Poisson Noise, Salt & Pepper noise, and Speckle Noise).

This research work is organized as follow. Section 2 explains the models of spatial domain optical flow and reference robustness models. Section 3 explains the experimental analysis in robustness and performance comparison in EVM. Section 4 explains the conclusion in the experimental result.

## 2. SPATIAL DOMAIN OPTICAL FLOW

This section explains spatial domain optical flow and reference robustness models that we simulate on our experiment.

### 2.1 Spatial correlation based optical flow (SC) [1]

SC is the classical spatial domain optical flow for motion classification that applied block matching concept in a level of pixel. The determine areas is matched with the specific block size to identify the minimum sum of absolute difference as the best candidate MV.

SC presents high accuracy over non noise sequence but very sensitive under noisy condition and require high computation time according to the results of performance evaluation for image reconstruction [7-8].

$$
\begin{aligned}
I_x &= {}^1/4\{I_{x,y+1,k} - I_{x,y,k} + I_{x+1,y+1,k} - I_{x+1,y,k} + I_{x,y+1,k+1} \\
&\quad - I_{x,y,k+1} + I_{x+1,y+1,k+1} - I_{x+1,y,k+1}\} \\
I_y &= {}^1/4\{I_{x+1,y,k} - I_{x,y,k} + I_{x+1,y+1,k} - I_{x,y+1,k} + I_{x+1,y,k+1} \\
&\quad - I_{x,y,k+1} + I_{x+1,y+1,k+1} - I_{x,y+1,k+1}\} \\
I_k &= {}^1/4\{I_{x,y,k+1} - I_{x,y,k} + I_{x+1,y,k+1} - I_{x+1,y,k} + I_{x,y+1,k+1} \\
&\quad - I_{x,y+1,k} + I_{x+1,y+1,k+1} - I_{x+1,y+1,k}\}
\end{aligned} \tag{1}
$$

### 2.2 Local based optical flow (LB) [2]

LB was proposed in 1981 by B.D. Lucas and T. Kanade. LB apply spatial temporal gradient based technique where the image intensity $(I_x, I_y, I_k)$ is determined by image velocity of point $(x, y)$ from spatiotemporal of image gradient from different time frame $(k)$ is defined as:

,where $x$ and $y$ are coordinate in 2D image and $k$ is image frame no. Under LB, the flow is constant in a local neighbourhood of the pixel. The equation for all the pixels in that neighbourhood is solved by the least squares. A weight least-square is utilized as a regular model to obtain MV in each small spatial neighbourhood. A weight least-square in LB is defined as:

$$
\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} \sum I_x^2 & \sum I_x \times I_y \\ \sum I_x \times I_y & \sum I_y^2 \end{bmatrix}^{-1} \times \begin{bmatrix} -\sum I_x \times I_k \\ -\sum I_y \times I_k \end{bmatrix} \tag{2}
$$

,where $u$ and $v$ are final result in MV. The initial MV is computed by a linear system based on matrix in Eq.(2). Then, the process runs in iterative for final MV.

LB presents fast computation with good noise tolerances but low accuracy in MV.

### 2.3 Global based optical flow (GB) [3]

GB was proposed in 1981 by B.K.P. Horn and B.G. Schunck. GB apply spatial temporal gradient based technique like LB at the beginning to obtain image intensity (Ix, Iy, Ik) but GB uses minimization process by weighted average [1/12 1/6 1/12 ; 1/6 -1 1/6 ; 1/12 1/6 1/12] of the value at neighboring points to compute MV in iterative where the suitable smoothness weight (Îś) should be selected to minimize the sum of error and obtain MV.

$$
\begin{aligned}
u^{h+1} &= \bar{u}^h - \frac{I_x\left[I_x\bar{u}^h + I_y\bar{v}^h + I_k\right]}{\alpha^2 + I_x^2 + I_y^2} \\
v^{h+1} &= \bar{v}^h - \frac{I_y\left[I_x\bar{u}^h + I_y\bar{v}^h + I_k\right]}{\alpha^2 + I_x^2 + I_y^2}
\end{aligned} \tag{3}
$$

,where and are neighbourhood average of horizontal and vertical which initial are set to zero.

GB presented fast computation but the quality was varying under different smoothness weight (Îś). The suitable value of Îś should be selected in appropriated for the best performance.

### 2.4 4-point central mask coefficient [4]

4-point central differences mask coefficient was proposed by J.L Barron, D.J. Fleet and S.S. Beauchemin in 1994 to compute image intensity which has been applied in the early state over LB and GB algorithms. The image intensity is determined by using 4-point central differences. The role of the 4-point central mask is for balanced smoothed image.

$$
\begin{aligned}
I_x &= 1/12\left\{-I_{x,y-2} + 8 \times I_{x,y-1} + -8 \times I_{x,y+1} + I_{x,y+2}\right\} \\
I_y &= 1/12\left\{-I_{x-2,y} + 8 \times I_{x-1,y} + -8 \times I_{x+1,y} + I_{x+2,y}\right\} \\
I_t &= 1/12\left\{-I_{x,y,k-2} + 8 \times I_{x,y,k-1} + -8 \times I_{x,y,k+1} + I_{x,y,k+2}\right\}
\end{aligned} \tag{4}
$$

| | | | | | |
|---|---|---|---|---|---|
| 1/12 | -1 | 8 | 0 | -8 | 1 |

***Fig.1:*** *4-point central mask coefficient.*

The better performance in accuracy is presented when 4-point central differences mask coefficient is applied over GB and LB in accordance with the performance evaluation from J.L Barron, D.J. Fleet and S.S. Beauchemin [4].

### 2.5 Bidirectional confidence based optical flow (BC)[5]

This method was proposed in 2008 by R. Li and F. Yu. The concept of bidirectional in forward motion vector (frame $k \rightarrow k+1$) and reverse motion vector (frame $k+1 \rightarrow k$) was presented with confident measurement for an improvement in accuracy of motion vector.

The origin motion vectors of the forward and reverse sequences are obtained by using GB algorithm. Then, the reliability rate (R) is computed from correlation of forward and reverse motion vector by:

$$R_l^n\,(s,k) = \exp\left(-\frac{\left|\begin{array}{l} v_l^n\,(s,k)+ \\ v_{l-}^n\,(s+v_l^n(s,k),k+1) \end{array}\right|}{\frac{\left(\begin{array}{l} |v_l^n(s,k)|+ \\ |v_{l-}^n\,(s+v_l^n(s,k),k+1)| \end{array}\right)}{2+\beta}}\right) \tag{5}$$

,where $v_l^n$ (s,k) and $v_l^n - (s,k)$ are forward and backward MV of neighbour $(n)$. $s$ is coordinate (x,y) in 2D image and $\beta$ avoids the division by zero in the equation. $l$ and $l-$ are forward and reverse motion vector. The value of reliability is set to 1 when the values of the motion vector of forward and reverse are the same

After that, the average motion vector $(\bar{v}_l^n(s_0))$ is computed from the reliability of neighborhood $(N(s0))$ of the location $s0 = (x,y,t)$ by:

$$\bar{v}_l^n(s_0) = \frac{\left(\sum\limits_{s_i \in N(s_0)} R_l^n(s_i) v_l^n(s_i)\right)}{\left(\sum\limits_{s_i \in N(s_0)} R_l^n(s_i)\right)} \tag{6}$$

BC presented an improvement in accuracy under clear and noisy domains but it consumes double computation time due to the concept of bidirectional.

### 2.6 Median filter for robust motion estimation (MF)[6]

This method was proposed in 2009 by T. Kondo and W. Kongprawechnon 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:

$$(G_u, G_v) = (u/|u|, v/|v|) \tag{7}$$

,where $(G_u, G_v)$ is 2 scalars (1 and -1) and if the magnitude is 0, zeros value is assigned to represent as the final motion vector.

MF presented an improvement of noise tolerance in MV under noisy environments especially on slow movement sequence and presented high deviation in noise tolerance according to the outcomes of performance evaluation from D. Kesrarat and V. Patanavijit [9-11].

### 2.7 Bidirectional confidential with median filter (BF) [9-12]

This method was proposed in 2012 by D. Kesrarat and V. Patanavijit. This method identifies the model in consolidation of bidirectional from BC with L1 median from MF. The objective is to improve the performance in accuracy of motion vector under noisy condition.

Firstly, the motion vectors of the forward and reverse frame are obtained from spatial domain optical flow (SC, LB, or GB). Then, L1 median is applied on both result of origin the forward and reverse motion vector. At last, the reliability rate (eq. 5) and final motion vector (eq. 6) are used to measure the final result of motion vector as the process of BC.

## 3. EXPERIMENTAL ANALYSIS OF PERFORMANCE COMPARISON

In this research work, 3 main spatial domain optical flow methods (SC, LB, and GB) are concentrated with reference robust models (BC, MF, and BF) as shown in Fig.2. So, totally 12 models are used in our experimental analysis. There are:•

- SC, SC-BC, SC-MF, and SC-BF (SC domain)
- LB, LB-BC, LB-MF, and LB-BF (LB domain)
- GB, GB-BC, GB-MF, and GB-BF (GB domain)

We run the experiment by using 4 different standard sequences up to 100 frames on each. There are AKIYO, CONTAINER, COASTGUARD and FOREMAN in QCIF (176×144) as showed in Fig.3. Then, we simulate 5 set of non-Gaussian noises over these 4 sequences as showed in Fig.4. There are:•

- Poisson Noise (PN)
- Salt&Pepper Noise (SPN) at density 0.005 and 0.025
- Speckle Noise (SN) at variance 0.01 and 0.05

So, 20 sequences totally in non-Gaussian noise contamination are used in our experiment (4 sequences × 5 non-Gaussian noises).

For SC domain, we set ±3 for neighbors for block matching over ±7 window search area.

For LB and GB domain, we set global smoothness and use 4-point central differences mask coefficient for gradient estimation. In LB, we set spatial neighborhoods window (5×5) without pyramid at 5 iteration loops. And we set smoothness weight $(\propto) = 0.5$ as same as the domain in the performance evaluation of Barron, Fleet, and Beauchemin [4] at 100 iterations in minimization process for GB.

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

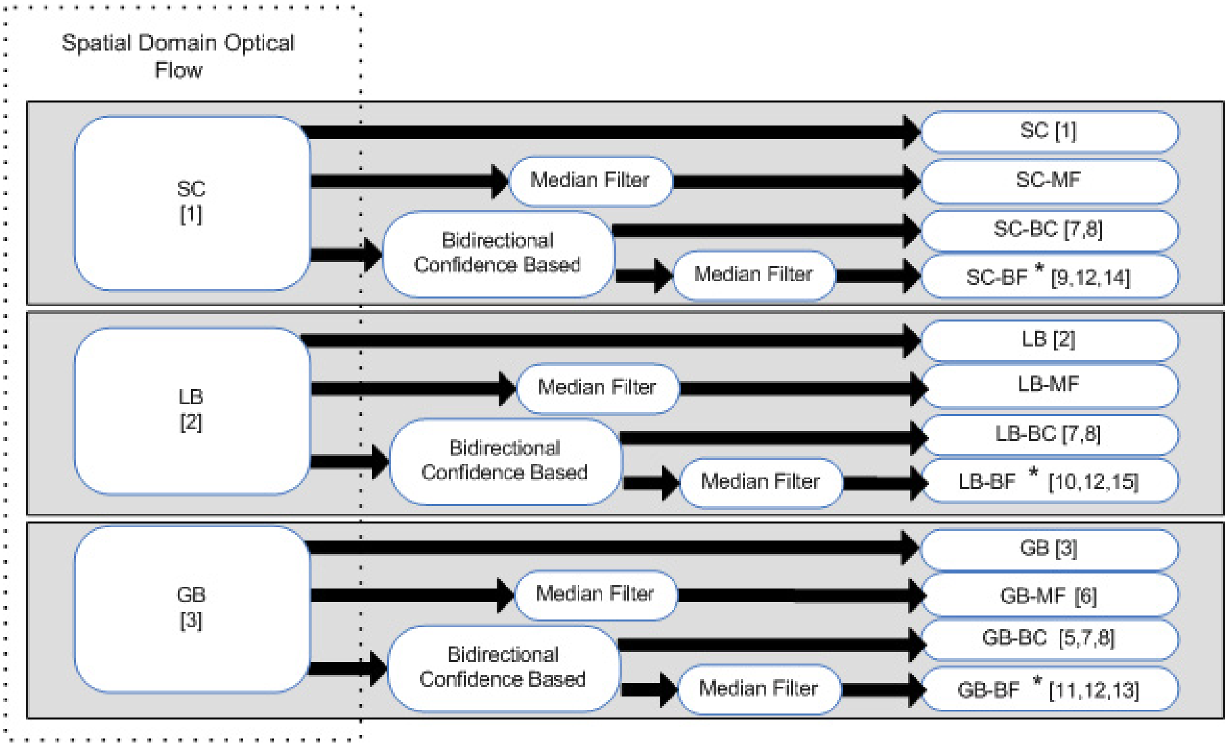
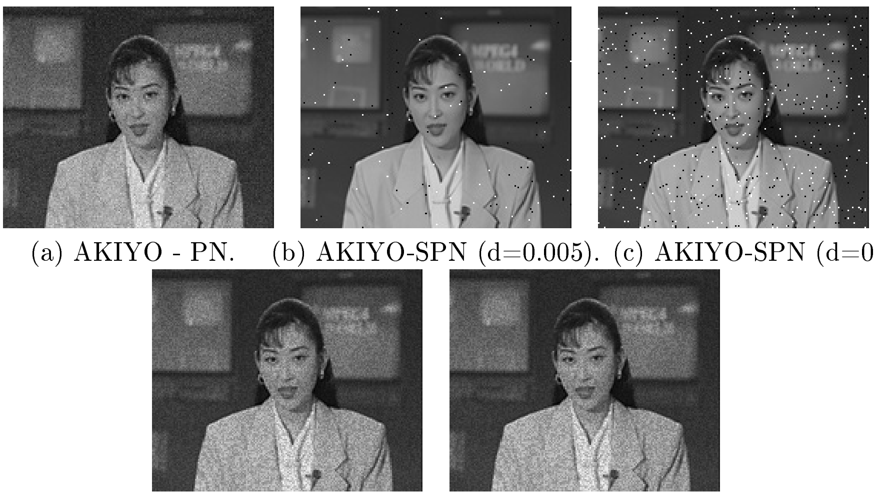



***Fig.2:*** *Optical flow research framework. (where "∗" is our research framework)*

(a) AKIYO. (b) COASTGUARD. (c) CONTAINER. (d) FOREMAN.

***Fig.3:*** *4 different standard sequences used in experiment.*



(a) AKIYO - PN. (b) AKIYO-SPN (d=0.005). (c) AKIYO-SPN (d=0.025).

(d) AKIYO-SN (V=0.01). (e) AKIYO-SN (V=0.05).

***Fig.4:*** *Example of image frame that contaminated by 5 set of non-Gaussian noise used in experiment.*

Finally, the performances analysis on robustness is evaluated by using EVM in comparison with the original ground truth MV. For EVM, we calculate with root-mean-square by average with the no. of non zero movement vector of ground truth vector where the lower value means better performance.

According to the experimental result, we analyze our experiment based on 3 domains of optical flow in section 3.1. and 3 types of non-Gaussian noise in section 3.2.

### 3.1 Analysis based on domain of optical flow

3 domains of optical flow are SC, LB, and GB. Fig. 5-7 show the graph of EVM frame by frame (frame no.1 to frame no.20) under different non-Gaussian noise.

Fig.5 concentrates on the performance under SC domain. Under SC domain, we find out that the BF model very effective over PN and SN. But very low performance for SPN. For SPN, the traditional SC provided the best result. It means that filtering models for noise tolerance do not impact the performance in SC domain under SPN.

Fig.6 concentrates on the performance under LB domain. Under LB domain, we find out that the BF model presents the best result under all 5 types of non-Gaussian noise in our experiment. And all robust filtering models in our experiment present better performance over traditional LB. It shows that the LB domain is very noise sensitive on non-Gaussian noises.

Fig.7 concentrates on the performance under GB domain. Under GB domain, we find out that the BF model presents the best result under all 5 types of non-Gaussian noise in our experiment. And all robust filtering models in our experiment present better performance over traditional GB as same as in LB domain. But It shows that the GB domain very noise sensitive on SPN the most.

### 3.2 Analysis based on non-Gaussian noise

Average EVM over 100 frames of each sequence are summarized in Table1. From Table1, we analyze our experiment based on 3 types of non-Gaussian noise. There are PN, SPN, and SN.

For PN, it shows that:•

- The robust models affect the performance when it is applied over 3 domains of optical flow. Especially BF, it shows the best result over all 3 domains optical flow under PN.
- Under slow movement sequences (AKIYO and CONTAINER), BF and MF present the best and second best with higher deviation from BC and original method while presents a little deviation under fast movement sequences (COASTGUARD and FOREMAN).

For SPN, it shows that:•

- The robust models affect the performance when it is applied over GB and LB methods.
- Upon different levels of noise in SPN, BF and MF present the best and second best with higher deviation from BC and original method upon increasing of noise level.
- SPN has a little impact over SC method. Upon increasing of noise level, it impact the overall performance but the original SC methods still present the best result and better than the other robust models.
- For SPN over SC method, the robust models do not help to increase the performance but they make it worst. Original SC method presents the best performance in overall experiment cases.

For SN, it shows that:•

- The result is similarly with PN that the robust models affect the performance when it is applied over 3 domains of optical flow.

## 4. CONCLUSIONS

This paper presents the concept of bidirectional confidential with median filter flow to increase non-Gaussian noises tolerance for spatial optical. Because of the interfered non-Gaussian noise over the sequence impacts the accuracy to determine MV. From the experimental result over 3 domains of optical flow, we conclude that the concept of bidirectional confidential with median filter is very effective in increasing the tolerance over all types of non-Gaussian noise in GB and LB domains. But, it is effective only on PN and SN over SC domains.

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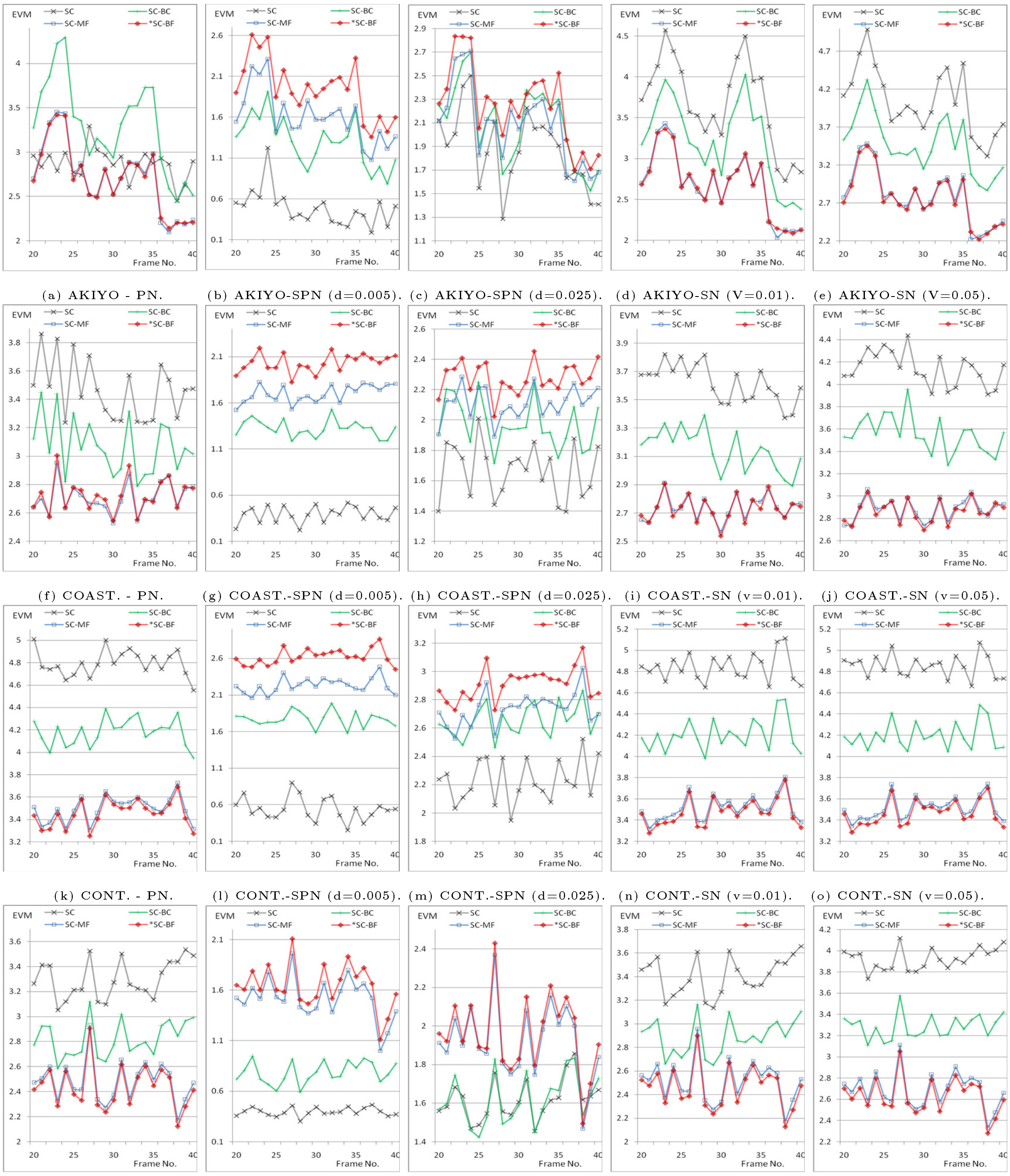
***Table 1:*** *Average EVM and standard deviation of experiment sequences in contamination with non-Gaussian noise.*

| | | AKIYO | | COASTGUARD | | CONTAINER | | FOREMAN | |
|---|---|---|---|---|---|---|---|---|---|
| | | AVG EVM | SD of EVM | AVG EVM | SD of EVM | AVG EVM | SD of EVM | AVG EVM | SD of EVM |
| PN | SC | 3.355 | 0.557 | 3.163 | 0.426 | 4.803 | 0.130 | 3.353 | 0.177 |
| | SC-BC | 3.364 | 0.556 | 2.766 | 0.400 | 4.193 | 0.132 | 2.931 | 0.191 |
| | SC-MF | 2.760 | 0.400 | 2.532 | 0.535 | 3.523 | 0.094 | 2.904 | 0.485 |
| | ***SC-BF** | **2.737** | 0.394 | **2.528** | 0.541 | **3.482** | 0.096 | **2.873** | 0.490 |
| SPN (d=0.005) | SC | **0.441** | 0.187 | **0.406** | 0.108 | **0.556** | 0.171 | **0.406** | 0.055 |
| | SC-BC | 1.308 | 0.276 | 1.192 | 0.221 | 1.778 | 0.130 | 0.853 | 0.123 |
| | SC-MF | 1.608 | 0.279 | 1.626 | 0.591 | 2.257 | 0.102 | 2.012 | 0.584 |
| | ***SC-BF** | 1.963 | 0.327 | 1.920 | 0.568 | 2.643 | 0.093 | 2.138 | 0.586 |
| SPN (d=0.025) | SC | **1.829** | 0.337 | **1.667** | 0.238 | **2.286** | 0.243 | **1.683** | 0.117 |
| | SC-BC | 2.067 | 0.339 | 1.883 | 0.266 | 2.682 | 0.175 | 1.731 | 0.158 |
| | SC-MF | 2.080 | 0.306 | 2.029 | 0.563 | 2.778 | 0.111 | 2.395 | 0.553 |
| | ***SC-BF** | 2.243 | 0.325 | 2.168 | 0.553 | 2.947 | 0.099 | 2.440 | 0.558 |
| SN (v=0.01) | SC | 3.859 | 0.632 | 3.280 | 0.456 | 4.831 | 0.128 | 3.490 | 0.170 |
| | SC-BC | 3.327 | 0.560 | 2.847 | 0.409 | 4.210 | 0.133 | 3.039 | 0.204 |
| | SC-MF | 2.748 | 0.405 | 2.565 | 0.533 | 3.529 | 0.097 | 2.946 | 0.491 |
| | ***SC-BF** | **2.724** | 0.397 | **2.560** | 0.538 | **3.490** | 0.098 | **2.912** | 0.500 |
| SN (v=0.05) | SC | 4.142 | 0.438 | 3.886 | 0.376 | 4.850 | 0.119 | 4.109 | 0.197 |
| | SC-BC | 3.525 | 0.408 | 3.315 | 0.389 | 4.221 | 0.125 | 3.552 | 0.284 |
| | SC-MF | 2.820 | 0.348 | 2.747 | 0.529 | 3.531 | 0.095 | 3.144 | 0.517 |
| | ***SC-BF** | **2.785** | 0.346 | **2.724** | 0.538 | **3.490** | 0.097 | **3.102** | 0.524 |
| PN | LB | 3.141 | 0.206 | 3.111 | 0.611 | 3.606 | 0.103 | 3.654 | 0.590 |
| | LB-BC | 3.067 | 0.206 | 3.036 | 0.600 | 3.544 | 0.103 | 3.566 | 0.588 |
| | LB-MF | 2.954 | 0.230 | 2.926 | 0.564 | 3.490 | 0.099 | 3.358 | 0.556 |
| | ***LB-BF** | **2.939** | 0.227 | **2.910** | 0.565 | **3.475** | 0.100 | **3.344** | 0.557 |
| SPN (d=0.005) | LB | 3.291 | 0.225 | 3.360 | 0.631 | 3.713 | 0.134 | 4.004 | 0.696 |
| | LB-BC | 3.215 | 0.217 | 3.274 | 0.612 | 3.640 | 0.121 | 3.877 | 0.677 |
| | LB-MF | 3.020 | 0.209 | 3.031 | 0.557 | 3.511 | 0.099 | 3.425 | 0.563 |
| | ***LB-BF** | **3.010** | 0.206 | **3.025** | 0.558 | **3.496** | 0.099 | **3.417** | 0.563 |
| SPN (d=0.025) | LB | 3.341 | 0.319 | 3.423 | 0.594 | 3.849 | 0.189 | 3.901 | 0.567 |
| | LB-BC | 3.217 | 0.282 | 3.287 | 0.584 | 3.735 | 0.167 | 3.762 | 0.565 |
| | LB-MF | 2.946 | 0.219 | 2.976 | 0.562 | 3.493 | 0.092 | 3.388 | 0.560 |
| | ***LB-BF** | **2.931** | 0.219 | **2.961** | 0.563 | **3.477** | 0.092 | **3.375** | 0.561 |
| SN (v=0.01) | LB | 3.106 | 0.206 | 3.112 | 0.601 | 3.580 | 0.102 | 3.619 | 0.588 |
| | LB-BC | 3.038 | 0.208 | 3.038 | 0.592 | 3.523 | 0.102 | 3.537 | 0.587 |
| | LB-MF | 2.945 | 0.228 | 2.930 | 0.560 | 3.482 | 0.099 | 3.355 | 0.557 |
| | ***LB-BF** | **2.929** | 0.225 | **2.915** | 0.561 | **3.466** | 0.100 | **3.341** | 0.558 |
| SN (v=0.05) | LB | 3.081 | 0.219 | 3.074 | 0.573 | 3.577 | 0.092 | 3.511 | 0.554 |
| | LB-BC | 3.009 | 0.221 | 3.000 | 0.573 | 3.519 | 0.093 | 3.438 | 0.560 |
| | LB-MF | 2.935 | 0.241 | 2.915 | 0.563 | 3.479 | 0.092 | 3.335 | 0.561 |
| | ***LB-BF** | **2.917** | 0.239 | **2.897** | 0.565 | **3.464** | 0.091 | **3.318** | 0.563 |
| PN | GB | 3.585 | 0.334 | 3.636 | 0.959 | 4.257 | 0.103 | 3.924 | 0.642 |
| | GB-BC | 3.133 | 0.323 | 3.114 | 0.825 | 3.766 | 0.108 | 3.420 | 0.578 |
| | GB-MF | 2.868 | 0.316 | 2.777 | 0.590 | 3.518 | 0.096 | 3.159 | 0.550 |
| | ***GB-BF** | **2.814** | 0.321 | **2.721** | 0.596 | **3.467** | 0.096 | **3.107** | 0.556 |
| SPN (d=0.005) | GB | 3.591 | 0.870 | 3.269 | 1.624 | 4.861 | 0.820 | 3.986 | 1.331 |
| | GB-BC | 3.506 | 0.847 | 2.927 | 1.432 | 4.792 | 0.791 | 3.778 | 1.251 |
| | GB-MF | 2.563 | 0.348 | 2.402 | 0.664 | 3.266 | 0.116 | 2.744 | 0.647 |
| | ***GB-BF** | **2.557** | 0.357 | **2.355** | 0.670 | **3.265** | 0.116 | **2.720** | 0.653 |
| SPN (d=0.025) | GB | 6.407 | 1.635 | 4.211 | 1.356 | 9.063 | 1.556 | 5.542 | 1.052 |
| | GB-BC | 6.107 | 1.567 | 3.746 | 1.192 | 8.725 | 1.488 | 5.185 | 0.982 |
| | GB-MF | 2.725 | 0.335 | 2.556 | 0.632 | 3.398 | 0.111 | 2.926 | 0.599 |
| | ***GB-BF** | **2.705** | 0.342 | **2.510** | 0.637 | **3.386** | 0.111 | **2.895** | 0.604 |
| SN (v=0.01) | GB | 3.647 | 0.364 | 3.731 | 0.965 | 4.415 | 0.103 | 4.010 | 0.607 |
| | GB-BC | 3.152 | 0.337 | 3.174 | 0.838 | 3.830 | 0.096 | 3.465 | 0.559 |
| | GB-MF | 2.861 | 0.330 | 2.797 | 0.592 | 3.514 | 0.088 | 3.178 | 0.551 |
| | ***GB-BF** | **2.805** | 0.332 | **2.738** | 0.598 | **3.462** | 0.089 | **3.125** | 0.557 |
| SN (v=0.05) | GB | 3.980 | 0.333 | 4.012 | 0.720 | 4.679 | 0.128 | 4.355 | 0.502 |
| | GB-BC | 3.358 | 0.317 | 3.352 | 0.657 | 3.989 | 0.111 | 3.700 | 0.510 |
| | GB-MF | 2.911 | 0.294 | 2.874 | 0.573 | 3.516 | 0.092 | 3.284 | 0.558 |
| | ***GB-BF** | **2.853** | 0.298 | **2.813** | 0.579 | **3.465** | 0.092 | **3.229** | 0.565 |




(a) AKIYO - PN. (b) AKIYO-SPN (d=0.005). (c) AKIYO-SPN (d=0.025). (d) AKIYO-SN (V=0.01). (e) AKIYO-SN (V=0.05).

(f) COAST. - PN. (g) COAST.-SPN (d=0.005). (h) COAST.-SPN (d=0.025). (i) COAST.-SN (v=0.01). (j) COAST.-SN (v=0.05).

(k) CONT. - PN. (l) CONT.-SPN (d=0.005). (m) CONT.-SPN (d=0.025). (n) CONT.-SN (v=0.01). (o) CONT.-SN (v=0.05).

(p) FORE. - PN. (q) FORE.-SPN (d=0.005). (r) FORE.-SPN (d=0.025). (s) FORE.-SN (v=0.01). (t) FORE.-SN (v=0.05).

***Fig.5:*** *EVM of SC domain.*

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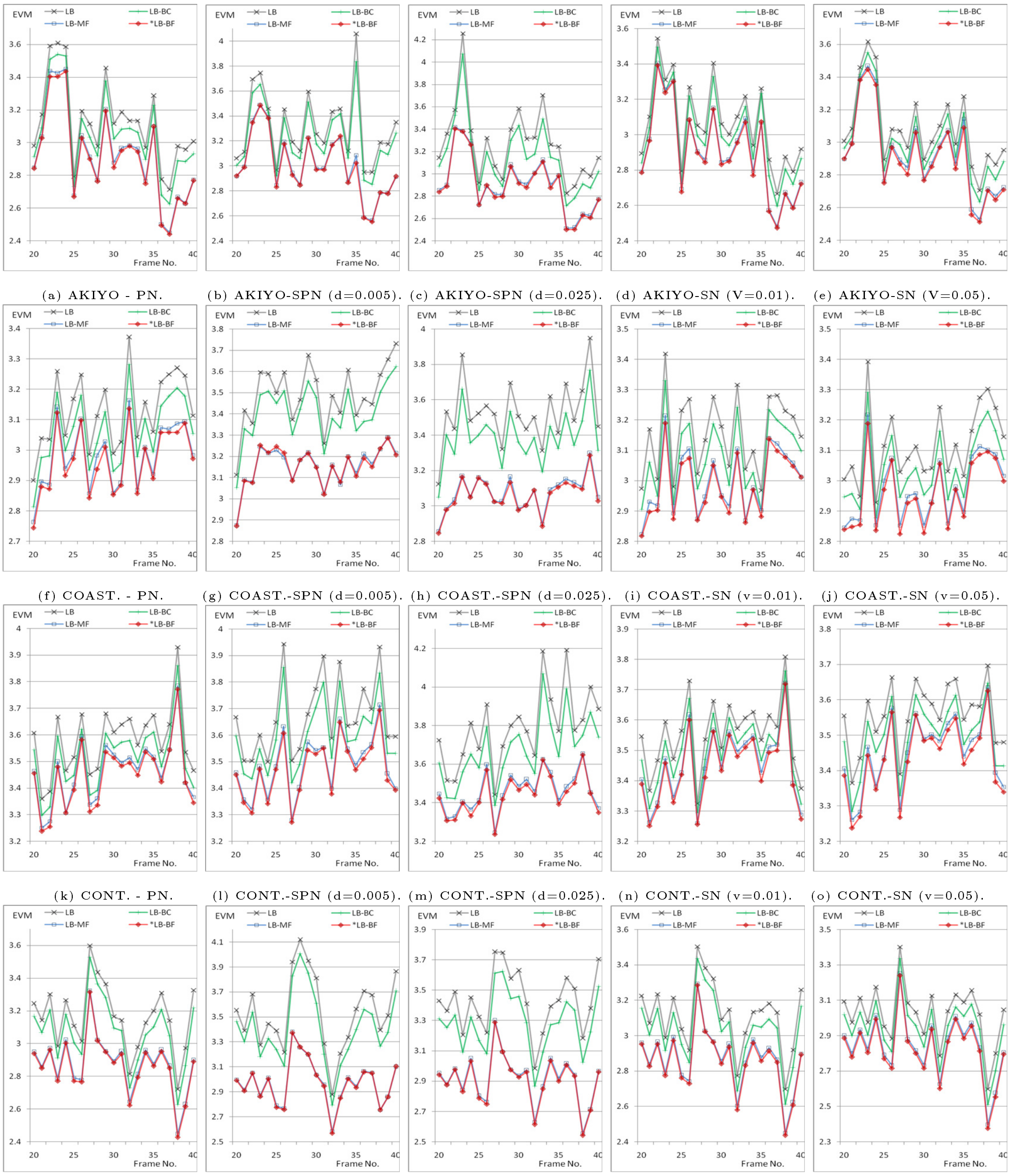


(a) AKIYO - PN. (b) AKIYO-SPN (d=0.005). (c) AKIYO-SPN (d=0.025). (d) AKIYO-SN (V=0.01). (e) AKIYO-SN (V=0.05).

(f) COAST. - PN. (g) COAST.-SPN (d=0.005). (h) COAST.-SPN (d=0.025). (i) COAST.-SN (v=0.01). (j) COAST.-SN (v=0.05).

(k) CONT. - PN. (l) CONT.-SPN (d=0.005). (m) CONT.-SPN (d=0.025). (n) CONT.-SN (v=0.01). (o) CONT.-SN (v=0.05).

(p) FORE. - PN. (q) FORE.-SPN (d=0.005). (r) FORE.-SPN (d=0.025). (s) FORE.-SN (v=0.01). (t) FORE.-SN (v=0.05).

***Fig.6:*** *EVM of LB domain.*

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(a) AKIYO - PN. (b) AKIYO-SPN (d=0.005). (c) AKIYO-SPN (d=0.025). (d) AKIYO-SN (V=0.01). (e) AKIYO-SN (V=0.05).

(f) COAST. - PN. (g) COAST.-SPN (d=0.005). (h) COAST.-SPN (d=0.025). (i) COAST.-SN (v=0.01). (j) COAST.-SN (v=0.05).

(k) CONT. - PN. (l) CONT.-SPN (d=0.005). (m) CONT.-SPN (d=0.025). (n) CONT.-SN (v=0.01). (o) CONT.-SN (v=0.05).

(p) FORE. - PN. (q) FORE.-SPN (d=0.005). (r) FORE.-SPN (d=0.025). (s) FORE.-SN (v=0.01). (t) FORE.-SN (v=0.05).

***Fig.7:*** *EVM of GB domain.*

*proceeding of Electrical Engineering / Electronics, Computer, Telecommunications and Information Technology (ECTI)*, pp. 1-5, 2015.

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