TECHNICAL REPORT

Robust Optical Flow Algorithm Based on Spatial Domain Optical Flow

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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.

Research Field: Digital Image Processing, Digital Signal Processing.

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1. INTRODUCTION

Motion estimation is the process of determining motion vectors (MV) that describe the transformation from one 2D image to another; usually from adjacent frames in a video sequence. Motion estimation is an important technique in video compression area which impacts various video encoding standards such as MPEG-1, MPEG-2, MPEG-4, H.261, H.263, and H.264 [1, 2, 3]. It reduces data redundancy to render image in video sequences and allowed a better compression of video which the smaller size, faster transmission, and the quality of the reconstruction video sequence are the consequence outcome. Moreover, it is used in video filtering on moving object tracking and reconstruction a higher resolution still image or video sequence from a sequence of low resolution images in super-resolution. In general, the algorithms about the block-matching algorithms [4, 5, 6, 7, 8, 9, 10, 11] are presented to use in practice due to their simplicity allowing efficient hardware implementation. However, in some particular areas, the accuracy of the reconstruct image is very importance parameter. Then, optical flow for motion estimation is presented.

Optical flow or optic flow is the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer (an eye or a camera) and the scene [12, 13]. Recently the term optical flow has been co-opted by roboticists to incorporate related techniques from image processing and control of navigation, such as motion detection, object segmentation, time-to-contact information, focus of expansion calculations, luminance, motion compensated encoding, and stereo disparity measurement [14, 15]. Optical flow tries to classifying the density velocity or MV in a degree of pixel basis for motion classification of image in video sequences which are taken at times t and t+1 as shown in Fig.1.There are many techniques of optical flow such as Spatial Correlation-Based (Block-Based Optical Flow Optical [16], Horn–Schunk [17], and Lucas–Kanade [18]), Phase-Based (Fleet and Jepson [19], and Waxman Wu and Bergholm [20]), and Energy based (Heeger [21]).

2. Problem Statement

During the last two decades, one of the most powerful and effective image reconstruction algorithms is the multiframe image Super Resolution Reconstruction (SRR) because its performance is better than previous algorithms and can be implemented easily. As a rule, the main concept of the SRR algorithm [32-35] is based on combining a group of noisy blurred low resolution images for synthesizing a higher resolution and better quality image by the registration/motion estimation process. Typically, almost all motion estimation techniques [32-37] which apply to almost all SRR algorithms, are designed for noiseless environments but the registration information of SRR usually calculates from a group of noisy blurred low resolution image. Thereby, the registration information from these motion estimation techniques under the SRR framework is inaccurate and it makes the SRR performance decreasing.

In actual situation, many unpleasant situations usually generate noises over the video sequences. These unpleasant situations corrupt the performance in efficiency of optical flow.

The performance in efficiency of 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) [22] modified the intensity kernel over Horn–Schunk (H&S) [17], and Lucas–Kanade (L&K) [18] algorithm 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 H&S and L&K.

In 2008, R. Li and S. Yu presented a bidirectional confidence based optical flow (BC) [23]. In accordance with the results of performance evaluation from D. Kesrarat and V. Patanavijit in 2010 [24], BC 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 a median filter for robust motion estimation (MF) [25] where median filter (L1) was utilized over the MV of original gradient-based algorithm. In accordance with the results of a performance evaluation from D. Kesrarat and V. Patanavijit in 2011 [26], MF 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.

3. Literature Review

1. Spatial correlation based optical flow (SC) [16]

SC is classical spatial based intensity gradient optical flow that uses 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.

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 [24].

2. Global based optical flow (GB) [17]

GB was proposed by B.K.P. Horn and B.G. Schunck in 1981 by introducing a global constraint of smoothness (global based) with the technique of gradient intensity and minimization to for motion classification in mean filter (L2) as a result.

The image intensity (*Ix, Iy, It*) is determined by image velocity from spatiotemporal of image gradient is defined as:

$$I_x = \tfrac{1}{4}\{I(x,y+1,t) - I(x,y,t) + I(x+1,y+1,t) - I(x+1,y,t) + I(x,y+1,t+1) - I(x,y,t+1) + I(x+1,y+1,t+1) - I(x+1,y,t+1)\} \quad (1.1)$$

$$I_y = \tfrac{1}{4}\{I(x+1,y,t) - I(x,y,t) + I(x+1,y+1,t) - I(x,y+1,t) + I(x+1,y,t+1) - I(x,y,t+1) + I(x+1,y+1,t+1) - I(x,y+1,t+1)\} \quad (1.2)$$

$$I_t = \tfrac{1}{4}\{I(x,y,t+1) - I(x,y,t) + I(x+1,y,t+1) - I(x+1,y,t) + I(x,y+1,t+1) - I(x,y+1,t) + I(x+1,y+1,t+1) - I(x+1,y+1,t)\} \quad (1.3)$$

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 neighboring points where the relevant smoothness weight (α) should be regarded to minimize the sum of error and obtain MV (u, v) as follow:

$$u^{k+1}(x,y,t) = \bar{u}^{k}(x,y,t) - \frac{I_x(x,y,t)\left[I_x(x,y,t)\bar{u}^{k}(x,y,t) + I_y(x,y,t)\bar{v}^{k}(x,y,t) + I_t(x,y,t)\right]}{\alpha^2 + I_x^2(x,y,t) + I_y^2(x,y,t)} \quad (2.1)$$

$$v^{k+1}(x,y,t) = \bar{v}^{k}(x,y,t) - \frac{I_y(x,y,t)\left[I_x(x,y,t)\bar{u}^{k}(x,y,t) + I_y(x,y,t)\bar{v}^{k}(x,y,t) + I_t(x,y,t)\right]}{\alpha^2 + I_x^2(x,y,t) + I_y^2(x,y,t)} \quad (2.2)$$

Where $\bar{u}^k(x,y,t)$ and $\bar{v}^k(x,y,t)$ denote neighborhood 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 [24], 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

3. Local based optical flow (LB) [18]

LB 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. It assumes that the flow is essentially constant in a local neighborhood (local based) of the pixel under consideration, and solves the basic optical flow equations for all the pixels in that neighborhood. Differential technique is derived like GB 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 H&S 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.

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 mask coefficient to compute image intensity which has been applied in the primary part over H&S and L&K algorithms. The gradient estimation of BFB uses 4-point central differences for determining image intensity.

The image intensity for gradient constraint on mask coefficient 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 GB and LB algorithms.

5. Interpolation technique

Interpolation [27, 28] is very effective technique that increases the performance of optical flow by increase the resolution of an image or up sampling but computation time is increasing up on the number of up sampling size. In this paper, we focus on bilinear interpolation where the distance weighted average of the four nearest pixel values to estimate a new pixel value.

6. Bidirectional confidence based optical flow (BC) [23]

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 H&S with extra computation on confidence assessment in reliability.

Early, this algorithm was implemented over GB [17] only, but we also utilized this model in our experiment over FS [16] and LB [18] for performance evaluation. The reliability rate of MV is described as:

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

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

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 ($N(s0)$) over each pixel base on frame t of the location $s0 = (x, y, t)$ is defined as:

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

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

The final optimum MV is obtained by using the $\overline{u}(x,y,t)$ and $\overline{v}(x,y,t)$ 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 [24, 26].

7. Median filter for robust motion estimation (MF) [25]

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:

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

Where $u(x,y,t)$ and $v(x,y,t)$ are the MV from tradition optical flows in horizontal and vertical axis (such as SC, GB or LB 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 GB [17] only, but we also utilized the model in our experiment over SC [16] and LB [18] 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 [24, 26].

8. Bilateral filer (BF) [29]

Bilateral filer (BF) is a robust edge-preserving filter that was referenced in many computer vision and image processing. This model was introduced by C. Tomasi and R. Manduchi that was applied several computer vision and image processing [29-31]. The bilateral kernel is defined as:

$$\phi(x+n) = \exp\left(\frac{|n|^2}{2\delta_a^2} + \frac{|I(x+n) - I(x)^2|}{2\delta_b^2} \right) \tag{8}$$

Where δ_a is standard deviation of signal $v(x)$ multiple by 7 and δ_c is standard deviation of signal $I(x)$.

Bilateral filter is applied to adjust the computation as follows:-

$$v_b(x) = \frac{1}{W} \sum_{|n|<N} v(x)\phi(x+n) \tag{9}$$

Where $\phi()$ is bilateral Gaussian kernel, and N is number of neighborhood. In our experiment, we set N equal to ±7. W is the kernel normalization factor is defined as:-

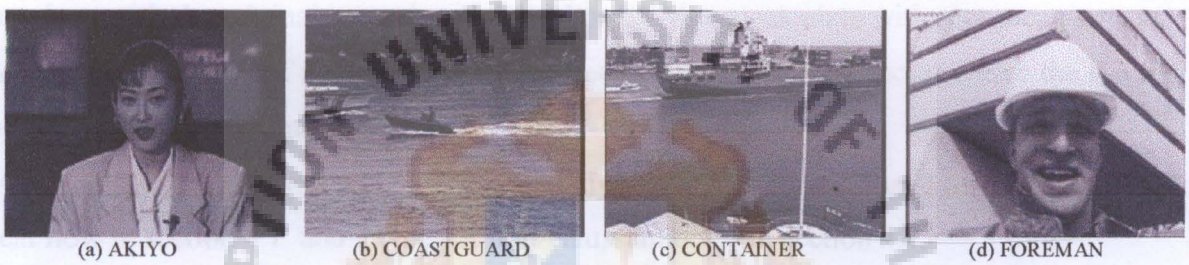
$$W = \sum_{|n|<N} \phi(x+n) \tag{10}$$

4. EXPERIMENTAL RESULTS

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.1.



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

***Fig.1:** 4 different standard sequences used in experiment.*

Then, we simulate 5 set of non-Gaussian noises over these 4 sequences as showed in Fig.2.

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

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 (α) = 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 (si) = ±1.

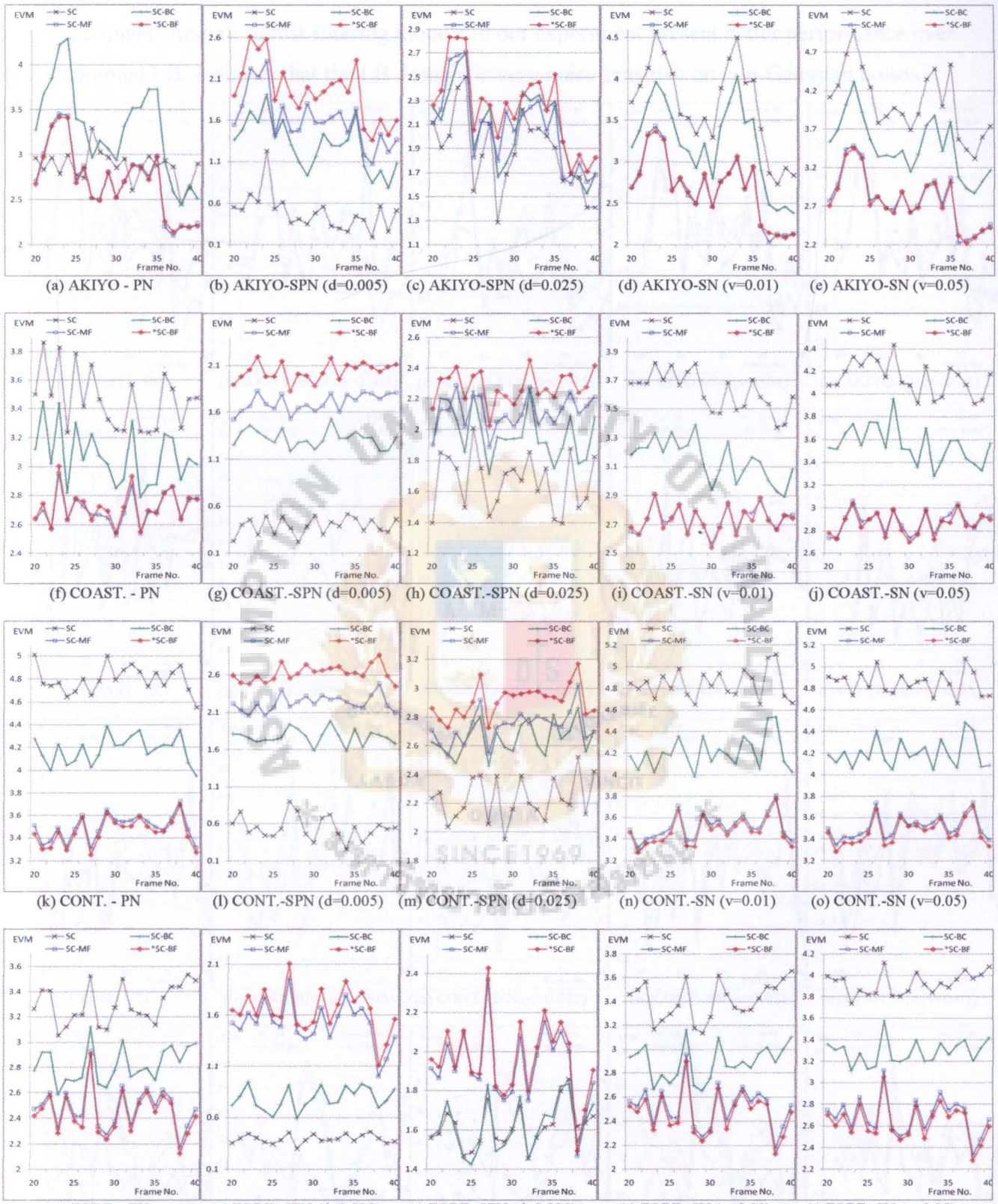
Finally, the performances analysis on robustness is evaluated by using EVM in comparison with the original ground truth MV. For EVM, we calculate with root-mean-square by average with the no. of non zero movement vector of ground truth vector where the lower value means better performance.

According to the experimental result, we analyze our experiment based on 3 domains of optical flow in section 4.1. and 3 types of non-Gaussian noise in section 4.2.

4.1 Analysis based on domain of optical flow

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

Fig.3 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.



(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)

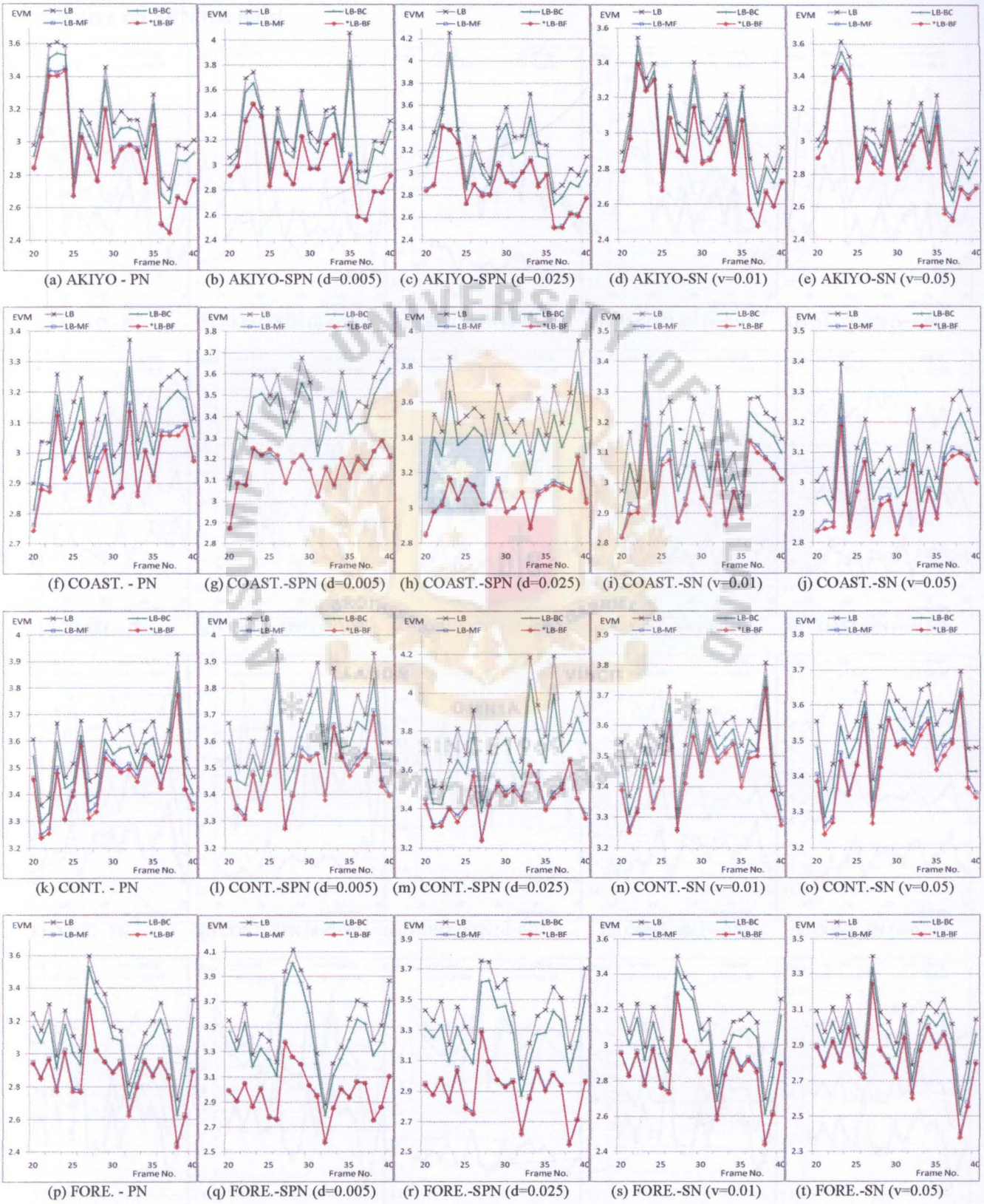
(f) COAST. - PN (g) COAST.-SPN (d=0.005) (h) COAST.-SPN (d=0.025) (i) COAST.-SN (v=0.01) (j) COAST.-SN (v=0.05)

(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.3: *EVM of SC domain.*

Fig.4 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.



(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)

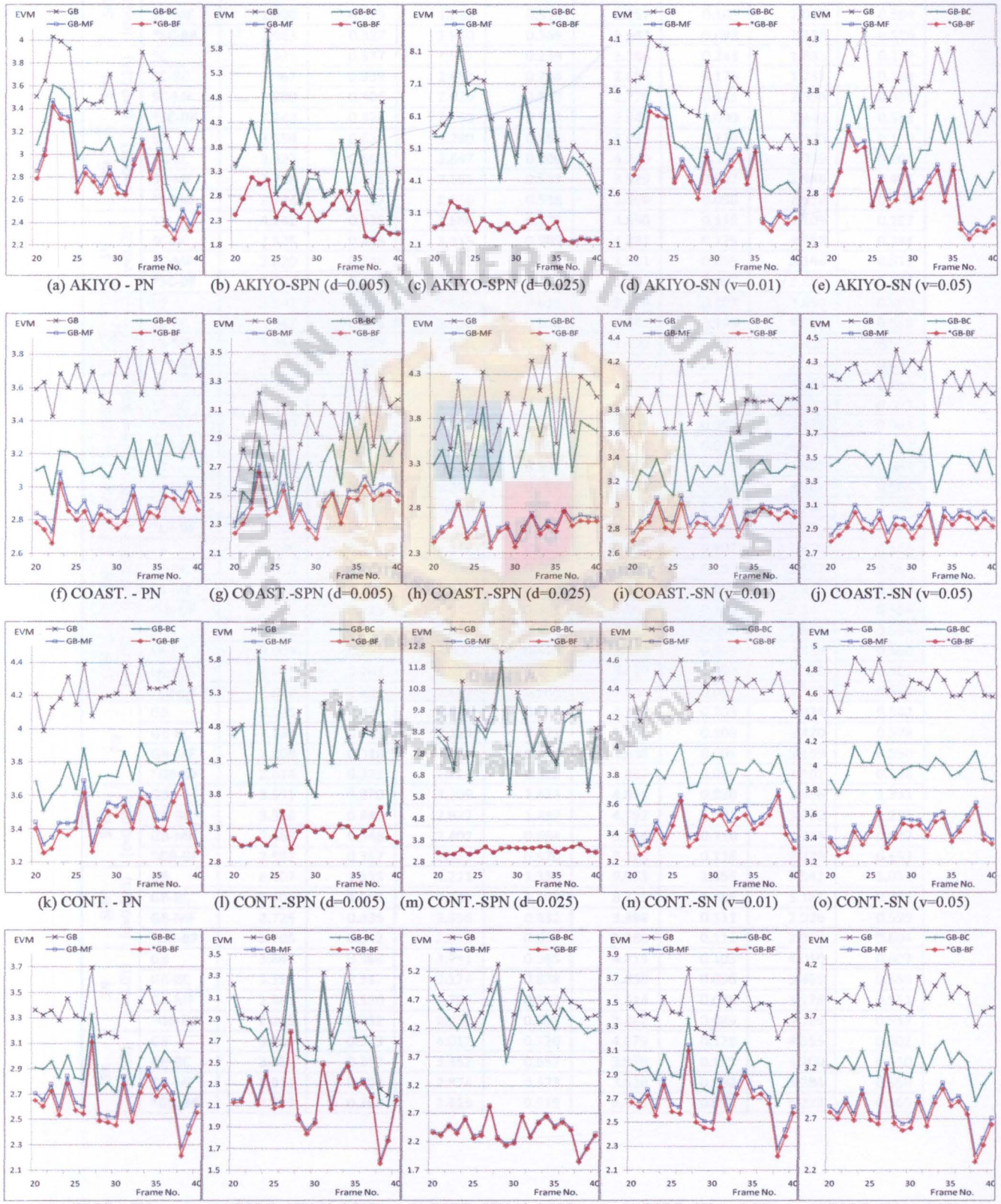
(f) COAST. - PN (g) COAST.-SPN (d=0.005) (h) COAST.-SPN (d=0.025) (i) COAST.-SN (v=0.01) (j) COAST.-SN (v=0.05)

(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.4: *EVM of LB domain.*

Fig.5 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.



(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 GB domain.*

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

4.2 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.

5. 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.

6. Lists of Publication (from this research project) (4 papers)

6.1 Research Articles (International Journal and Transactions)

1. Experimental Study in Error Vector Magnitude of Bidirectional Confidential with Median Filter on Spatial Domain Optical Flow under Non Gaussian Noise Contamination, Journal of the Electrical Engineering/Electronics, Computer, Communications and Information Technology Association (ECTI) Transactions on Electrical Engineering, Electronics, and Communications (EEC), Vol. 14 (ISSN 1685-9545) No.2, 2016 (Indexed by SCOPUS)
2. Experimental Analysis on Noise Tolerance of Bidirectional Confidential with Bilateral Filter in Local Based Optical Flow for Image Reconstruction, RANGSIT JOURNAL OF ARTS AND SCIENCES (RJAS), Vol.6 ISSN 2229-063X (Print)/ISSN 2392-554X (Online), No.2, 2016 (Indexed by TCI Group 1 and ACI)

6.2 Research Articles (International Proceeding and Conference)

1. Robust Optical Flow Using Adaptive Lorentzian Filter for Image Reconstruction under Noisy Condition, The 2016 8th International Conference on Graphic and Image Processing (ICGIP 2016), Tokyo, Japan, October 2016. (SPIE Digital Library)
2. Verification of Bidirectional Local Based Optical Flow with Bilateral Filter on Non-Gaussian Noise Contamination for Video Reconstruction, The 14th annual international conference organized by Electrical Engineering / Electronics, Computer, Telecommunications and Information Technology (ECTI) Association. Phuket, Thailand, June, 2017. (IEEE Xplore)

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0408

PROJECT BUDGET

FACULTY / DEPT. VINCENT MARY SCHOOL OF SCIENCE AND TECHNOLOGY 1 B 0 5 0 0 0 0 0 0

PROJECT Robust Optical Flow Algorithm Based on Spatial Domain Optical Flow P-58-0599

EFFECTIVE FROM 25 July 2016 **TO** 24 July 2017

	BAHT
TOTAL EXPENSES	100,000

TO : UNIVERSITY PLANNING AND BUDGETING COMMITTEE

FOR YOUR CONSIDERATION AND APPROVAL

The project was approved by

AU Research Support Committee

SIGNATURE

(DR. VINDHAI COCRACUL)

VICE RECTOR FOR ACADEMIC AFFAIRS

Aug. 4, 2016

- [x] CRITERIA FOR BUDGET ALLOCATION HAVE BEEN MET.
- [x] BUDGET IS INCLUDED IN THE ONE - YEAR PLAN.
- [ ] BUDGET IS NOT INCLUDED IN THE ONE - YEAR PLAN.
- [x] OTHER INFORMATION Project No. 4.9

SIGNATURE

(MS. NATTHAYAMON PAYONRAK)

DIRECTOR, FINANCIAL MANAGEMENT OFFICE

01 AUG 2016

TO : CHAIR, UPBC OF UNDERGRADUATE PROGRAMS

FOR YOUR CONSIDERATION AND APPROVAL

SIGNATURE

(MR.ANNOP PEUNGCHUER)

SECRETARY, UPBC OF UNDERGRADUATE PROGRAMS

2 Aug 2016

TO : THE PRESIDENT

FOR YOUR CONSIDERATION FOR :

- [x] APPROVAL FOR IMPLEMENTATION
- [ ] APPROVAL FOR CONSIDERATION OF

SIGNATURE

(DR. VINDHAI COCRACUL)

CHAIR, UPBC OF UNDERGRADUATE PROGRAMS

Aug. 4, 2016

- [x] APPROVED
- [ ] NOT APPROVED

SIGNATURE

(REV. BRO. SIRICHAI FONSEKA, F.S.G., PH.D.)

VICE RECTOR FOR STUDENT AFFAIRS

ON BEHALF OF THE PRESIDENT

- 5 AUG 2016

BG018

Project Proposal

1. Project Number and Title : Robust Optical Flow Algorithm Based on Spatial Domain Optical Flow

2. Respomsible Person(s) : Asst.Prof. Dr. Darun Kesrarat

☐ School ☑ Program Information Technology (specify)

3. Nature of Project ☐ Routine ☑ New/Development

Mission ☐ Graduate Production ☑ Research

☐ Academic Service ☐ Preservation of Art and Culture

☐ Administration

4. Alignment with School's Five-Year Strategic Plan

Strategy 1: Attain academic excellence in the national/international arena

5. Project Objectives

1. Study performance and limitation of spatial bases intensity gradient optical flow and robust technique.
2. Develop the robust technique that can be applied over spatial bases intensity gradient optical flow with more accuracy for image reconstruction under noisy condition.
3. Study the performance of the proposed technique and provide a comparative study of proposed technique with other traditional proposed by many authors in the past.

6. Participants : Asst. Prof. Dr. Darun Kesrarat (Lecturer)

7. Time – frame : 25 July 2016 - 24 July 2017 (12 months)

8. Venue : Thailand

9. Activities : Research

10. Expected Outcomes

1. Acquire a basic knowledge of optical flow motion estimation for image reconstruction.
2. Obtain an effective noise tolerance model in optical flow's MV under noisy condition when it is applied over optical flow algorithms based on intensity gradients technique as a filtering model under simple frame-to-frame correlation technique.
3. Publish in at least one international conference (in IEEE Explore)

4. Publish in at least one international journal (indexed by TCI (Group 1), ACI or Scopus).

11. Project Achievement Indicators and Targets

Achievement Indicators	Target
Publish in at least 1 international conference.	1
Publish in at least 1 international journal (indexed by TCI (Group 1), ACI or Scopus).	1

12. Budget Source ☑ University ☐ External Source

☐ University and External Source ☐ No Funding Needed

13. Budget Type ☑ Project Budget ☐ Auxiliary Enterprise Budget

14. Coordinator : .....

(Asst. Prof. Dr. Darun Kesrarat)

15. Dean/Director : .....

( )

BUDGET OF EXPENSES

FACULTY / DEPT : Vincent Mary School of Science and Technology

PROJECT / ACTIVITY TITLE : Robust Optical Flow Algorithm Based on Spatial Domain Optical Flow

VENUE : Thailand

TIME – FRAME : 25 July 2016 – 24 July 2017

EXPENSES :-	(Account code)			
1. Materials	(.....)	(INDEX 1)	20,000.00	BAHT
2. Data Backup Storage	(.....)	(INDEX 2)	30,000.00	BAHT
3. Document Printing & Buying	(.....)	(INDEX 3)	20,250.00	BAHT
4. Research assistances	(.....)	(INDEX 4)	29,750.00	BAHT
	TOTAL EXPENSES		100,000.00	BAHT

.....

(Asst. Prof. Dr. Darun Kesrarat)

CO-ORDINATOR

22 / 7 / 2016

REFERENCE

INDEX1 **Materials** (Account code)

1. Material for upgrade computer	( )	( )	16,000.00	BAHT
2. UPS	( )	(1 item @ 4,000 baht)	4,000.00	BAHT
		TOTAL	20,000.00	**BAHT**

INDEX2 **Data Back Storage**

1. DVD Disk (for 1TB)	( )	(200 disks @ 10 baht)	2,000.00	BAHT
2. External Storages (10TB)	( )	(6 items @ 4,000 baht)	24,000.00	BAHT
3. Flash Drive (256GB-512GB)	( )	(4 items @ 1,000 baht)	4,000.00	BAHT
		TOTAL	30,000.00	**BAHT**

INDEX3 Document Printing & Buying

1. The research documents	( )	( )	10,250.00	BAHT
2. The cost of book report	( )	( )	3,000.00	BAHT
3. The office equipment i.e. paper, folder, printer's ink	( )	( )	7,000.00	BAHT
		TOTAL	20,250.00	**BAHT**

INDEX4 Research Assistants

1. Research Assistants	( )	(1 person x 6 months @ 4,958.33 baht)	29,750.00	BAHT
		TOTAL	29,750.00	**BAHT**