The effect of Adaptive Weighted Bilateral Filter on Stereo Matching Algorithm

Siti Safwana Abd Razak, Mohd Azlishah Othman, Ahmad Fauzan Kadmin

Abstract: ***Stereo matching process is attracted numbers of study in recent years. The process is unique and difficult due to visual discomfort occurred which contributed to effect of accuracy of disparity maps. By using multistage technique implemented most of Stereo Matching Algorithm; taxonomy by D. Scharstein and R. Szeliski, in this paper proposed new improvement algorithm of stereo matching by using the effect of Adaptive Weighted Bilateral Filter as main filter in cost aggregation stage which able contribute edge-preserving factor and robust against plain colour region. With some improvement parameters in matching cost computation stage where windows size of sum of absolute different (SAD) and thresholds adjustment was applied and Median Filter as main filter in refinement disparity map's stage may overcome the limitation of disparity map accuracy. Evaluation on indoor datasets, latest (2014) Middlebury dataset were used to prove that Adaptive Weighted Bilateral Filter effect applied on proposed algorithm resulted smooth disparity maps and achieved good processing time.***

Index Terms**:** ***Bilateral Filter, Disparity map, SAD, Stereo matching***

I. INTRODUCTION

Disparity map or depth map from a pair of stereo (or more) image was one of popular research topics in computer vision. As we acknowledge, computer vision is one of the fields of image processing and computer vision. The important of disparity maps and depth map are it can produce many applications such as autonomous navigation [2], three-dimensional (3D) reconstruction, 3D tracking, 3D scanning and 3D mapping. Researchers mostly focusing on 3D mapping study area to get most accurate and low computational cost also low computation time in stereo visions' disparity map. The idea of stereo vision is to use two (stereo) cameras which its installed parallels to acquire the depth of the scene and capture high resolutions images that can be uses for other applications [3]. The same scene point produced by the camera planes are been used to make the matching process. This corresponding prediction of stereo cameras result process called stereo matching. Development of image matching is important to achieve good result of stereo matching [3]. The result of stereo matching process is disparity map where the mapcontains the depth data of the stereo images for reconstructed the 3D image. Coordinates from each pixel of the images (input image and reference image) contribute the disparity maps' corresponding estimation. These four steps taxonomy of stereo matching algorithm proposed by Scharstein and Szeliski [4] mostly been used are:

- Step 1: Matching cost computation (process for matching each pixel from input and reference image).
- Step 2: Cost aggregation (process of aggregate initial cost over support region).
- Step 3: Disparity optimization (optimize the function of disparity level).
- Step 4: Disparity refinement (refine the final disparity map result)

The most popular disparity map algorithm used are global, semi-global or local methods. Its depend on the algorithm and how the algorithm is calculated [4].

In global optimization disparity map algorithm, the disparity assignment problems treated as predefined minimization of global energy function. From McMillan, global method's main advantage is by using global approach of Z-buffering mechanism in disparity computation [5]. Global method usually extra computational expensive and less sensitive to local individualities. The algorithm results measurement to smooth the neighbouring pixels from global data [6]. Local method of disparity map algorithm, it is focusing on local support window. The process of this local method by using correspondence of disparity between gray value or patterns within this local support windows. This also called as windows-based or area-based methods which include fixed windows, multiple windows, adaptive window [7] and segmentation based [8][9][10] for window based method. The advantages of this methods are it require low computational and low execution runtime. The characteristic of local method is by choose every pixels of disparity map and associated with the minimum cost value at the computation of final disparities [5] also known as winner-take-all (WTA) that optimization will be perform at each pixel of disparity map. The final disparity map algorithm is semi-global (SGM) method, this method consists of Mutual Information pixel matching and combination of 1D constrains with 2D smoothness 2D constrain in global approaching [11]. In other words, the process is finding the correspondence pixels between input and reference image (stereo images). Mostly, the idea of semi-global is the combination of local and global method approach of stereo matching algorithm in the main four steps discussed earlier (i.e. use local method at matching cost and global method for cost aggregation). In that case, SGM required more space of temporary memory because it operate on both numbers of pixels and the disparity range of stereo vision [8].

Revised Manuscript Received on 24 February 2019.

Siti Safwana Abd Razak, Faculty of Electronic and Computer Engineering (FKEKK), University Teknikal Malaysia Melaka (UTeM), Durian Tunggal, Hang Tuah Jaya, 76100, Melaka, Malaysia.

Mohd Azlishah Othman, Microwave Research Group (MRG), Centre for Telecommunication Research and Innovation (CeTRI), Faculty of Electronic and Computer Engineering (FKEKK), University Teknikal Malaysia Melaka (UTeM), Durian Tunggal, Hang Tuah Jaya, 76100, Melaka, Malaysia.

Ahmad Fauzan Kadmin, Faculty of Engineering Technology (FTK), University Teknikal Malaysia Melaka (UTeM), Durian Tunggal, Hang Tuah Jaya, 76100, Melaka, Malaysia.

I. RELATED WORK

As mentioned stereo matching algorithm step in Introduction, the stereo matching block diagram for this algorithm as proposed shown in figure 1. For Matching Cost Computation process, sum of absolute (SAD) method were used together with some threshold element adjustment. The cost aggregation part, Adaptive Weighted Bilateral Filter technique used because this filter have effects of smoothing images and edge-preserving filter [12]. Then, for disparity optimization process, winner-take-all (WTA) strategy been used. The minimal aggregated corresponding value for each disparity pixel were absorbs with WTA strategy. The bad pixels or invalid pixels (i.e. occlusion or untextured areas) still occurred at this stage, these pixels can be detected by left-right (LR) consistency checking process [13]. To correct or minimize the invalid pixels, median filter was used in last step which in disparity refinement process. The advantages of median filter are extensively in smoothing and de-noising of images [12].

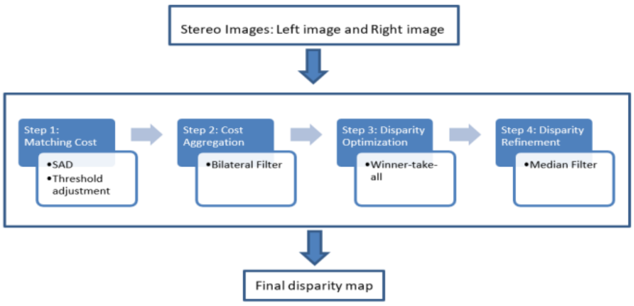

Figure 1: Stereo Matching Algorithm Framework development [14]

A. Matching cost computation

The matching cost computation is a process where a pixel from same from stereo input (left and right) images corresponded at the same point. In other words, this process defined where left and right images values parallax with each other at same point [15]. In this stereo matching algorithm, Sum of Absolute Differences (SAD) used for this stage. The SAD algorithm [16] defined at (1), the sum of absolute difference intensity between each pixel at references block (left image) and corresponding pixel at targeted block (right image). It calculated the minimum pixel value over right image (reference image) row and selected the best matching value. This process produced disparity map. Form (1), the $SAD\ (p,d)$ is sum of absolute difference and sum of differences intensity between the both left image (I_l) and right image (I_r). While (p) represented coordinate (x, y) of the pixel and d is represent disparity value and β represent the window size of SAD method.

$$SAD\ (p,d) = \sum_{p\in\omega}^{n} |I_l(p) - I_r(p-d)| \quad (1)$$

$$SAD_t\ (p,d) = \beta SAD\ (p,d) \quad (2)$$

At this stage, some threshold adjustment is introduced, this new algorithm is given in (2). The threshold is represented by $\tau_{SAD,}$, the constant value to adjust the threshold value. Equation (3) is the condition while the final sum of absolute different applied. The final matching cost function $C_{SAD}(p,d)$ is given by equation (4).

$$SAD'(p,d) = \begin{cases} \tau_{SAD,} & if\ SAD_t(p,d) > \tau_{SAD} \\ SAD\ (p,d), & otherwise. \end{cases} \quad (3)$$

$$C_{SAD}\ (p,d) = SAD'\ (p,d) \quad (4)$$

B. Cost aggregation

The important stage for stereo matching is minimizes the matching uncertainties. This related work under Cost aggregation step. In this work, Adaptive Weighted Bilateral Filter is proposed to reduce the noise and produce high accuracy of disparity map with the edge preserve by the filter. The left image selected as reference image for this whole algorithm. The equation of Adaptive Weighted Bilateral Filter is given by (5) where $B(p,q)$ represent Adaptive Weighted Bilateral Filter, p is the location of disparity which need to filter using weight of the neighbouring pixel. The σ_s indicated for spatial adjustment parameter and σ_c represent to the disparity similarity parameter. The σ represent spatial or disparity similarity. The cost aggregation equation is given by (6) where $C_{SAD}\ (p,d)$.

$$B(p,q) = \exp\left(-\frac{|p-q|^2}{\sigma_s{}^2}\right)\exp\left(-\frac{|d(p)-d(q)|^2}{\sigma_c{}^2}\right) \quad (5)$$

$$CA\ (p,d) = C_{SAD}\ (p,d)\ .\ d' \quad (6)$$

C. Disparity optimization

Winner-Take-All strategy is introduced to increase the accuracy of the disparity map. It works by selecting the minimal aggregated value for each disparity pixel value. Based on (7) d represent disparity associated with the minimum aggregated cost, p for coordinate (x, y) of the pixel and d is represent disparity value and $CA(p,d)$ means the cost aggregated volume.

$$d(p) = \arg\min CA(p,d) \quad (7)$$

D. Disparity refinement

The final step is Disparity Refinement where Median Filter as the main filter to refine the disparity map output to achieve high accuracy. The (8), $d'(p)$ is equation for disparity refinement where the input of disparity map from disparity optimization $d(p)$ will be filtered with median filter.

$$d'(p) = med\ \{d(p)\} \quad (8)$$

II. EXPERIMENTAL RESULT

On Step 1, the value $\beta = 11$ obtained the good result and produce average error on all 19.2% and 11.9% of nonocc average error. When some contras threshold was adjusted at $\tau_{SAD} = 0.8$ the error reduces to 18.8% and 11.2% for all and nonocc attribute respectively. As referred to (1) and (2) is the lower τ_{SAD} value will produce lower noise than intensity feature.On Step 2, σ_s value of 17 indicates that the 17 pixels radius emphasis within the range referred to (3) while for value of $\sigma_c = 0.3$ indicate the range of Bilateral

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Filter disparity difference which is less than 0.3. Referring to (4) enough histogram sample on size of $w_p = 19 \times 19$.On Step 4, the value of in this steps' parameter are follow the (8) and Equation 3.15 for fill in process while for Median Filter process, window size, W for 5x5 result lowest error which is 17.4%. The summary of proposed algorithm includes the usage of parameter and its values in this thesis are shows in Table 1. These final parameters value will be used for entire experiment images.

Table 1: Summary of the parameter values used in proposed algorithm.

Step	Parameter
Step 1	$\beta = 11$ and $\tau_{SAD} = 0.8$
Step 2	$\sigma_s = 17, \sigma_c = 0.3$, and $w_p = 19 \times 19$
Step 3	WTA
Step 4	$W = 5 \times 5$

E. Disparity map

The disparity map result of proposed algorithm shows in Figure 2 where Middlebury training dataset were used and the other methods of disparity map and Figure 3, the disparity map of test dataset from Middlebury.

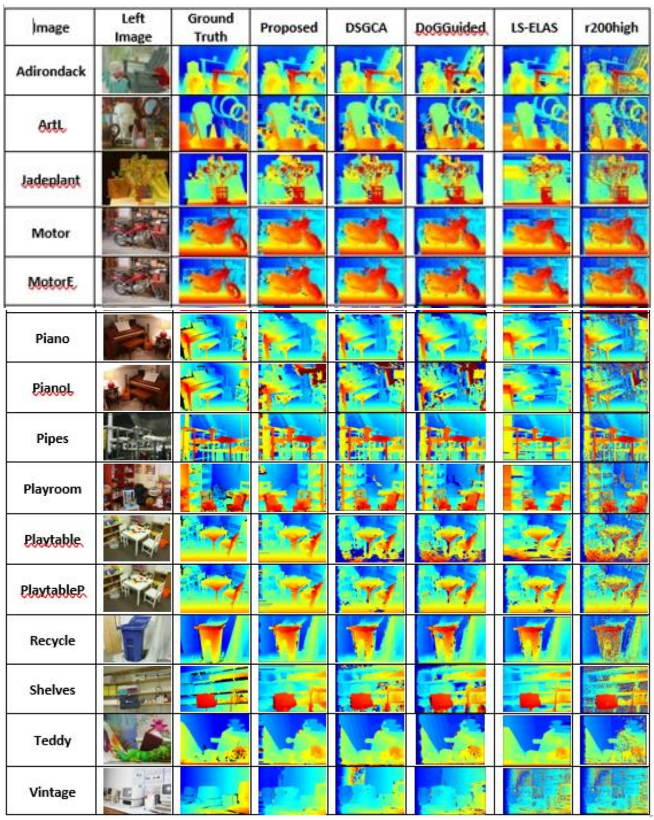

Figure 2: The disparity map of proposed algorithm with disparity map of others method from Middlebury training dataset.

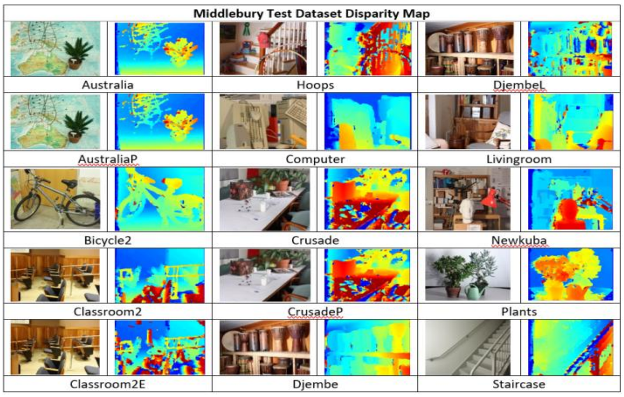

Figure 3: The disparity map of proposed algorithm from Middlebury test dataset.

F. Processing time

In Table 2, comparison proposed algorithm processed time with 1.05 second of average processed time. It followed by Glstereo, with 1.20 second and MCSC with 2.21 second. The whole process of execution time for proposed algorithm in Figure 4 and Figure 5. Figure 4 is processed time for training dataset from Middlebury and Figure 5 contained result of processed time for test Middlebury dataset.

Table 2: Performance comparison of quantitative evaluation results based on processing time from the Middlebury dataset.

Algorithm	Adiron	ArtL	Jadept	Motor	MotorE	Piano	PianoL	Pipes	Play	Playtb	PlaytbP	Recycle	Shelves	Teddy	Vintage	Ave Time
Proposed Algorithm	1.16	0.28	1.33	1.26	1.25	1.11	1.13	1.19	1.13	1.02	1.02	1.14	1.2	0.44	1.41	1.05
Glstereo	1.28	0.45	1.83	1.24	1.24	1.14	1.37	1.29	1.28	1.17	1.16	1.18	1.15	0.62	2.12	1.20
MCSC	2.38	0.65	3.29	2.54	2.42	2.11	2.34	2.36	2.37	2.16	2.2	2.17	2.38	1.03	3.62	2.21
JMR	4.64	2.41	4.6	4.78	4.76	4.53	4.2	4.77	4.6	4.38	4.08	4.87	4.76	2.87	4.36	4.28
DSGCA	10.6	16.7	13.5	6.68	6.71	5.79	5.79	6.96	7.15	5.99	5.99	5.96	5.74	27.9	16.7	10.2

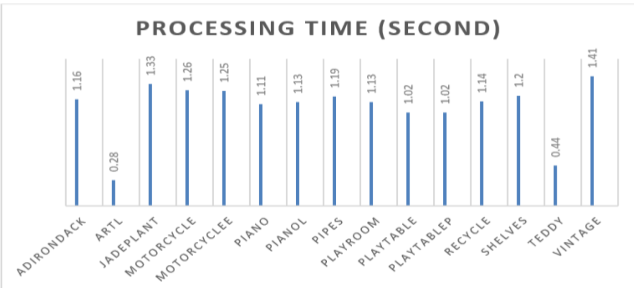

Figure 4: Processed time for proposed algorithm on training Middlebury dataset.

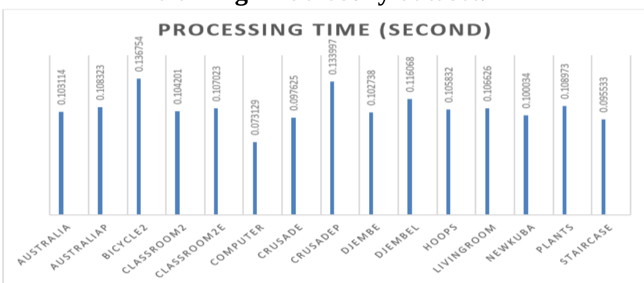

Figure 5: Processed time for proposed algorithm on test Middlebury dataset.

G. Quantitative measurement

From training set of Middlebury dataset, average error of *all* attribute of proposed algorithm is 17.4%.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

DSGCA and DoGGuided produced 18.7% and 22.3% of average error followed DF and SED which produced 22.7 and 28.7 respectively. For *nonocc* attribute, proposed algorithm produced 9.62% of average error followed by LS-ELAS 9.66%, DSGCA for 9.75 and DoGGuided and DF for 12% and 23.3%. The details of average error shows in Table 3. In Table 4, error of greater from two (BAD 2.0) for *all* and *nonocc* attribute which produce 38.6% and 31.1% respectively.

Table 3: Performance comparison of quantitative evaluation results based on *all* error from the Middlebury dataset.

Algorithm	Adiron	ArtL	Jadept	Motor	MotorE	Piano	PianoL	Pipes	Play	Playtb	PlaytbP	Recycle	Shelves	Teddy	Vintage	Ave weight
Proposed Algorithm	*10.5*	*19.9*	*62.7*	*11*	*12.5*	*9.08*	*29.7*	*21.1*	*20.7*	*9.5*	*9.75*	*7.18*	*11.4*	*9.4*	*16.8*	*17.4*
DSGCA	7.68	21.7	45	10.6	10.4	11.5	24.5	19.9	24.6	34.5	14.8	7.56	17.3	12.2	43.8	18.7
DoGGuided	*20.1*	*28*	*56.5*	*13.8*	*16.8*	*13.4*	*37.3*	*23.8*	*30.3*	*30.8*	*13*	*9.13*	*19*	*13.4*	*23.6*	*22.3*
DF	24.4	24.4	102	14.1	38.1	9.37	30.2	25.6	30.1	12.9	16.1	18.4	12.9	6.31	23.2	26.7
SED	*25.1*	*17.1*	*123*	*20.6*	*19.7*	*18.1*	*29.5*	*34.1*	*22.8*	*18.8*	*16.5*	*16.8*	*15.1*	*7.26*	*33.8*	*28.7*

Table 4: Performance comparison of quantitative evaluation results based on nonocc error.

Algorithm	Adiron	ArtL	Jadept	Motor	MotorE	Piano	PianoL	Pipes	Play	Playtb	PlaytbP	Recycle	Shelves	Teddy	Vintage	Ave weight
Proposed Algorithm	6.31	9.65	31.8	4.71	6.39	6.68	28.4	10.6	9.08	5.09	5.18	3.86	9.73	3.64	10.7	9.62
LS-ELAS	8.46	3.83	41.1	5.12	5.8	5.54	8.97	7.44	8.76	22.4	3.47	6.93	8.26	2.29	13.1	9.66
DSGCA	3.25	5.95	18.9	3.6	3.41	7.17	21.1	7.23	9.36	29.4	7.94	3.8	14.7	3.51	39.7	9.75
DoGGuided	15.2	9.57	27.1	5.64	8.31	8.09	32.4	9.67	14	24.5	5.32	5.56	16.2	4.15	15	12
DF	22.9	22.	77.8	12.1	34.9	8.96	30.4	19.4	29.4	12.5	15.1	17.7	12.5	5.2	22.1	23.2

Table 5: The results of the Middlebury dataset based on the percentage of disparity errors that are greater than two pixels (bad 2.0)

Algorithm	Adiron	ArtL	Jadept	Motor	MotorE	Piano	PianoL	Pipes	Play	Playtb	PlaytbP	Recycle	Shelves	Teddy	Vintage	Ave weight
All error proposed algorithm	35.2	44	53.2	28.5	31.2	40.4	56.3	36	46.9	36.9	35.9	30.7	51.3	25.3	52.2	38.6
nonocc proposed algorithm	30.7	30.7	40.7	21	24.1	35.4	52.9	23.5	38.6	31.5	29.6	26.2	49.1	16.5	48.4	31.1

III. CONCLUSION

In this work, new stereo matching algorithm proposed. It contained Adaptive Weighted Bilateral Filter, edge preserve function filter as main cost aggregation filter followed SAD method for matching cost, WTA as disparity optimization and Median Filter as disparity refinement. The experimental used Middlebury dataset as standard stereo matching benchmark. This proposed work is able to reduce error of disparity map and produced very short processed time with high accuracy result. For future work, GPU implementation is proposed for real time application of stereo matching.

REFERENCES

1. D. Scharstein and R. Szeliski, "A Taxonomy and Evaluation of Dense Two-Frame Stereo," Int. J. Comput. Vis. 47, vol. 47, no. 1–3, pp. 7–42, 2002.
2. J. Bagnell, D. Bradley, D. Silver, B. Sofman, and A. Stentz, "Learning for autonomous navigation," IEEE Robot. Autom. Mag., vol. 17, no. 2, pp. 74–84, 2010.
3. M. Humenberger, T. Engelke, and W. Kubinger, "A Census-based stereo vision algorithm using modified Semi-Global Matching and plane fitting to improve matching quality," in 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops, CVPRW 2010, 2010, pp. 77–84.
4. D. Scharstein, R. Szeliski, and R. Zabih, "A taxonomy and evaluation of dense two-frame stereo correspondence algorithms," in Proceedings - IEEE Workshop on Stereo and Multi-Baseline Vision, SMBV 2001, 2001, pp. 131–140.
5. H. Tao, H. S. Sawhney, and R. Kumar, "A global matching framework for stereo computation," Proc. Eighth IEEE Int. Conf. Comput. Vision. ICCV 2001, vol. 1, no. 2, pp. 532–539, 2001.
6. Y. Zhou and C. Hou, "Stereo matching based on guided filter and segmentation," Optik (Stuttg)., vol. 126, no. 9–10, pp. 1052–1056, 2015.
7. T. Kanade and M. Okutomi, "A stereo matching algorithm with an adaptive window: theory and experiment," IEEE Trans. Pattern Anal. Mach. Intell., vol. 16, no. 9, pp. 920–932, 1994.
8. R. Affendi, H. Ibrahim, and A. H. A. Hassan, "Stereo matching algorithm based on per pixel difference adjustment , iterative guided filter and graph segmentation," J. Vis. Commun. Image Represent., vol. 42, pp. 145–160, 2017.
9. A. Klaus, M. Sormann, and K. Karner, "Segment-based stereo matching using belief propagation and a self-adapting dissimilarity measure," in Proceedings - International Conference on Pattern Recognition, 2006, vol. 3, pp. 15–18.
10. H. Shi, H. Zhu, J. Wang, S. Y. Yu, and Z. F. Fu, "Segment-based adaptive window and multi-feature fusion for stereo matching," J. Algorithms Comput. Technol., vol. 10, no. 1, pp. 3–11, 2016.
11. G. Heiko Hirschmüller (Inst. of Robotics & Mechatronics Oberpfaffenhofen, German Aerosp. Center, Wessling, "Accurate and Efficient Stereo Processing by Semi-Global Matching and Mutual Information," Comput. Vis. Pattern Recognition, 2005. CVPR 2005. IEEE Comput. Soc. Conf. (Volume 2), pp. 807–814, 2005.
12. B. Weiss, "Fast median and bilateral filtering," in ACM SIGGRAPH 2006 Papers on - SIGGRAPH '06, 2006, p. 519.
13. S. Mattoccia, F. Tombari, and L. Di Stefano, "Stereo vision enabling precise border localization within a scanline optimization framework," in IEEE Asian Conference on Computer Vision, 2007, pp. 517–527.
14. X. Mei, X. Sun, W. Dong, H. Wang, and X. Zhang, "Segment-tree based cost aggregation for stereo matching," in Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2013, pp. 313–320.
15. M. Z. Brown, D. Burschka, and G. D. Hager, "Advances in computational stereo," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 25, no. 8. pp. 993–1008, 2003.
16. R. A. Hamzah and H. Ibrahim, "Literature Survey on Stereo Vision Disparity Map Algorithms," vol. 2016, 2016.

Authors Profile

Siti Safwana Abd Razak received Degree Bachelor of engineering in Computer and Communication System frim Universiti Putra Malaysia (UPM) on 2013. She also has Diploma in Electronic Engineering from Politeknik Kulim (also known as PTSB) On 2009. In September 2016, she joined Universiti Teknikal Malaysia Melaka (UTeM) as a postgraduate student at Faculty of Electronic and Computer Engineering (FKEKK). Previously she works as CRM and ERP Consultant in Techloyce Sdn Bhd on 2017. She also has experienced on IOT 4.0, Data Analytic and Computer Vision from her current job as Application Engineer from Techsource Sdn Bhd from 2018.

Mohd Azlishah Othman received Degree Bachelor of Engineering in Electrical Engineering (Telecommunication) from Universiti Teknologi Malaysia (UTM) on 2003. In September 2005 he joined Universiti Teknikal Malaysia Melaka (UTeM) as a Lecturer at Fakulti Kej. Elektronik dan Kej. Komputer (FKEKK). He received his Master's Degree in Computer and Communication Engineering from University of Nottingham, UK, continues his PhD in Electrical and Electronic Engineering in University of Nottingham, UK. Currently he is working on RF and Microwave circuits and devices.

Ahmad Fauzan Kadmin Currently attached with UTeM as a researcher, Ahmad Fauzan B. Kadmin CEng. P.Tech. has over 15 years of experience in electronic & computer engineering field with technical expert in R&D engineering, computer vision & medical electronics. He Graduated with a Bachelor Degree in Electronics Engineering from Universiti Sains Malaysia and Master Degree in Computer & Communication Engineering from Universiti Kebangsaan Malaysia. Previously, he worked with Megasteel Sdn. Bhd., Samsung SDI(M) Sdn. Bhd. and Agensi Angkasa Negara. He published several technical and engineering paperwork's in image processing and medical electronics.