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COMPUTATION AND PERFORMANCE ANALYSIS OF DOUBLE STAGE FILTER FOR IMAGE PROCESSING

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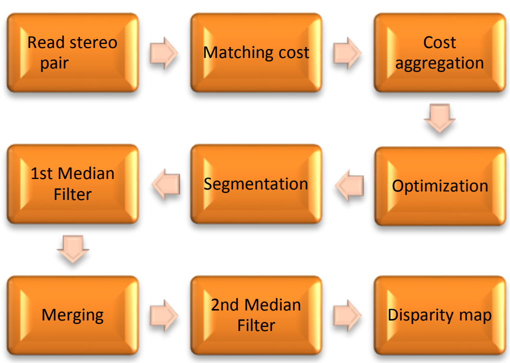
Graphical abstract



Abstract

Double Stage Filter (DSF) is a hybrid stereo matching algorithm which consists of basic block matching and dynamic programming algorithms, basic median filtering and new technique of segmentation. The algorithm acquire disparity maps which will be analyzed by using evaluation functions such as PSNR, MSE and SSIM. The computation of DSF and existing algorithms are presented in this paper. The Phase 2 in DSF is to remove the unwanted aspects such as depth discontinuities and holes from occlusion from the raw disparity map. Segmentation, merging and median filtering are the major parts for post processing of DSF algorithm. From the results of evaluation functions, the disparity maps attained by DSF is closer to the ground truth compared to other algorithms while its computation takes only few seconds longer than DP algorithm but its capable to obtain better results of disparity map.

Keywords: Hybrid stereo matching, block matching, double stage filter, dynamic programming, computation, segmentation, merging, filtering

1.0 INTRODUCTION

Stereo vision is a popular discussion in the field of computer vision among researchers in image processing. There are many type of stereo matching algorithms has been created, which can be search in the Middlebury Stereo Vision Website page by Scharstein and Szelinski [1]. There are various kind of datasets of stereo images can be found in the Middlebury website page and there is also an evaluation system for researchers to evaluate and compare the results obtained and performance of their proposed stereo matching algorithm with other kind of algorithms. Commonly, stereo matching algorithms contain four basic steps such as matching cost computation, cost aggregation, disparity computation optimization and disparity refinement says, Scharstein [1]. However, not all the basic steps are included in creating a stereo matching algorithm as it is based on how is the design managed by the researchers. The most interesting part of stereo matching algorithm is the post-processing which dig up the interest from researchers of image processing, where this part can be rebuilt to generate a better disparity depth map[2]. Post-processing is a part to refine the raw disparity map that computed from the step of optimization. The raw disparity maps consist unwanted aspects such as holes from occlusion, depth discontinuities, less textured region that require to be removed [3]. There are various existing approaches for post-processing such as surface fitting and cross-checking. The techniques which commonly applied in stereo matching are sub-pixel estimation and median filter [4]–[7]. However, there are also approaches with fast processing which bring up less accuracy and undesired results of disparity map [8]–[10].

The main concern of this research is to design a hybrid stereo matching algorithm with less complexity in computation, and enable to minimize the unwanted aspects of a raw disparity depth map. The proposed hybrid stereo matching algorithm consists Basic Block Matching (BBM) and Dynamic Programming (DP) with modified approaches of segmentation and basic median filter. BBM algorithm is applied in DSF algorithm to acquire the matching corresponding with Sum of Absolute Difference(SAD) [11], while Dynamic Programming algorithm as part of disparity computation to find the minimum cost of matching pixels between the scanlines correspondence. However, the feature of Dynamic Programming in optimizing the disparity map may cause horizontal streaks due to its reliability of inter-scanline function [4], [9], [12]–[14]. Thus, the main focus of the research is to solve the horizontal streaks on the raw disparity map achieved from dynamic programming. In order to lessen the horizontal streaks, the new expansion of proposed algorithm that occupied segmentation, merging and median filtering method. There are twice of median filtering steps involved in this algorithm, hence the planned technique is called Double Stage Filter (DSF). The entire design of DSF algorithm will be presented in the following section.

2.0 DESIGN OF DOUBLE STAGE FILTER (DSF)

The outline of algorithm design formation for Double Stage Filter (DSF) algorithm is shown in Figure 1. DSF algorithm contains two phases: Phase 1 and Phase 2. Phase 1 occupies of basic stereo matching and Phase 2 consist of new expansion of double stage filter. In the Phase 1, it involves three basic elements, which required in a stereo matching algorithm according to [1], such as matching cost computation, cost aggregation and disparity computation or optimization. Meanwhile, in Phase 2, the refinement process consists new process of segmentation and fundamental median filter.

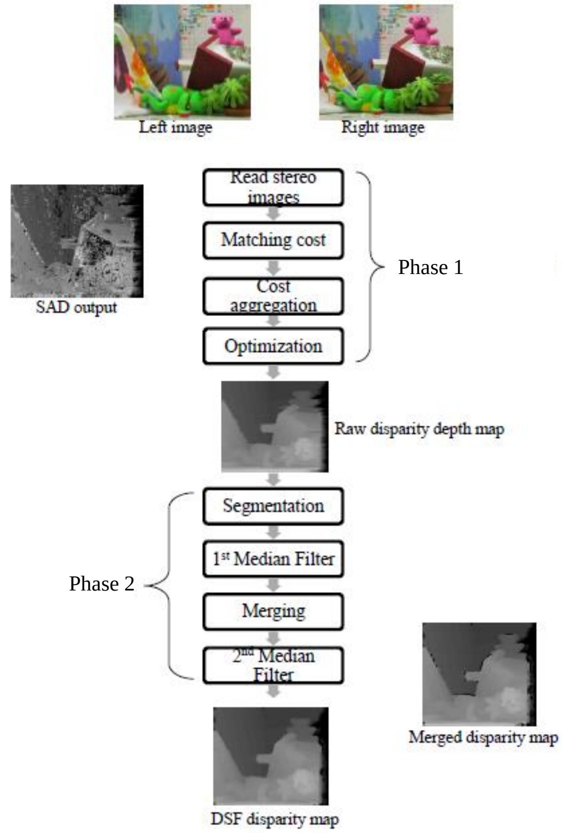


Figure 1 Block diagram design of DSF algorithm

2.1 Matching Cost

At the creation of the algorithm, Sum of Absolute Differences (SAD) is applied to get the corresponding pixels between stereo images. It also applied to find out and compare the matching cost of image regions between every block with the area of interest due to its ease in calculation [15]–[17]. SAD also reduce matching errors between the points of the block, coordinate (*x, y*) of the target image I_t, whereas (*x+u, y+v*) is coordinate of reference image as I_{t-1} where *u* and *v* specify the motion vector and these parameters can be definite as sum of absolute difference (SAD) [11].

$$(u, v) \equiv \sum_{j=0}^{S-1} \sum_{i=0}^{S-1} |I_t (x+i, y+j) - I_{t-1}(x+u+i, y+v+j)| \qquad (1)$$

where *S* as the block size whereas *i* and *j* as the pixels. The $\mathrm{SAD}_{(X,Y)}(u, v)$, (*a, b*) is determined as the motion vector estimation to balance up every point in $(x+u, y+v)$for minimization [9].

$$(a, b) \equiv \arg \min_{(u,v)\in Z} SAD_{(x,y)}(u,v) \qquad (2)$$

where Z is similarly to {(u, v)| -B ≤ u, v ≤ B and $(x+u, y+v)$ specify the exact point of pixel in the reference image, I_{t-1}} whereas B signify as an integer to get the appropriate range. BBM is usually applied in image processing due to its less complexity of computation in attaining a disparity depth map. On the other hand, the judgment on the correct point of images in order is less precise and resultant noises due to every pixel pick independently on the disparity of all other pixels [18].

2.2 Cost Aggregation

Cost aggregation is based on window-based that choose the average above the cost values from Disparity Space Image (DSI) [19]. Fixed square window of cost aggregation is applied in this algorithm as it is regularly used for stereo vision applications, which mostly on real-time execution due to its uncomplicated strategy and less calculation complexity [20]–[23]. The window size require to be chosen suitably as a small window do not generate preferred results on less-textured regions, whereas the larger size of window do not deal with tiny and thin objects [24]. Fixed square window has its own restriction such as assumes frontal-parallel surfaces indirectly, ignores depth discontinuities, unable to spot on uniform areas and repetitive patterns [25]. Nevertheless, the restraints of fixed square window can be solved in the disparity computation and refinement steps.

2.3 Optimization

The Dynamic Programming (DP)approach is a part of DSF algorithm, which perform as an optimizer and diminish the noises on disparity map obtained from SAD with fixed square window [26].This technique is to optimize energy function of non-deterministic polynomial-time hard (NP-hard) for smoothing [1], [27]. There are two categories of global optimization; one-dimension and two-dimension. One dimension optimization is a conventional method which it's smoothing approach uses horizontal direction. The progression is on the disparity along a pixel that subject on all other pixels on the same scanline, while independent disparity focuses on other scanlines. Thus, this approach is not a truly global optimization, though it is still applied by researchers due to its simple implementation in attaining a good disparity depth map.

Two-dimension optimization smoothen out the stereo images in vertical and horizontal directions by mean-field annealing, continuation approaches and using simulated annealing. Unfortunately, these approaches are less capable in optimizing the equation (1) [28]–[30].

$$E(d) = E_{data}(d) + E_{smooth} \tag{3}$$

where $E_{data}(d)$symbolizes the disparity function through the correspondence pixels of disparity map, d which is minimized from its input data when there are equivalent intensities. It will steadily increase when there is dissimilarity on the intensities of correspondence pixels. E_{smooth}signifies the assumptive of smoothness of algorithm, which resolve the disparity between the pixels on pixel grid [1]. There are two other approaches which able to optimize the equation (1), graph-cuts and belief propagation as it can get desire results by depending on data of ground truth [31], [32]. One dimension optimization of Dynamic Programming is chosen as a component of DSF algorithm to defeat the energy minimization issue. In the meantime, Disparity Space Image (DSI) is definite as a data structure to illustrate on Dynamic Programming algorithm in resolving matches and occlusions correspondingly [22]. As stated earlier, although DP is a fairly proficient approach in obtaining good disparity depth map, it has restriction in inter-scanline consistency, which resultant horizontal "streaks" in the obtained disparity map. There are accessible methods developed in improving the inter-scanline consistency and its only faintly diminishes the horizontal "streaks" [13], [14], [33]. In DSF algorithm, it is competent to contract with the restraint of DP where it capable to eliminate the horizontal "streaks" in the raw disparity depth map obtained from DP efficiently.

2.4 Segmentation

In the Phase 2 of DSF algorithm is the main part of the research. This fraction contain four steps which are segmentation, first median filter, merging, and second median filter. The planned step in the algorithm is segmentation. The segmentation approach that usually applied by researchers, is applied to extract on a particular or reference image. In this research, the segmentation step in the DSF algorithm is applied on the raw disparity map that attained from the step of disparity computation[34], [35]. The content of the image from the raw disparity map is extracted according to the pixel colors. The pixel colors have their own values which depending on the disparity range preferred for computation. Each extracted segment depends on the range of pixel colors in the disparity map as presented in Figure 2.

2.5 Median Filter

Median filtering is a low pass filter which applied in the research to remove noises of image. Median filtering operates by descending pixel by pixel through the image and swap every pixel value with a median value of neighboring pixels (mask), which perform as "window"[36], [37]. The median value is produced by sorting the pixel values from the window in the order of numerical and substituted the pixel with center pixel value [38]. The result of median filtering can be presented as,

$$g(x,y) = med\{f(x-i, y-j), i, j \in W\} \tag{4}$$

where $f(x,y), g(x,y)$ are the original image and target image, W is indicates as two-dimensional mask with size of n X n whereas n in odd number, 3 X 3, 5 X 5, 7 X 7, and etc. As median filter is a nonlinear filter signal processing, its mathematical is moderately complex for the image with random noise while for zero mean of noise image, the noise variance of median filtering is summarized as,

$$\sigma^2{}_{med} = \frac{1}{4nf^2(\bar{n})} \approx \frac{\sigma_i{}^2}{n+\frac{\pi}{2}-1} \cdot \frac{\pi}{2} \tag{5}$$

where $\sigma_i{}^2$ as the input of noise variance, n as the size of mask, $f(\bar{n})$ indicates the function of noise density while for the average filtering of noise variance is

$$\sigma_0^2 = \frac{1}{n}\,\sigma_i^2 \tag{6}$$

There are two things to be concerned in median filtering; the size of mask, the allocation of noise. The median filtering of random noise reduction is perform well than average filtering, however when comes to impulse noise or narrow pulse with the pulse width less than $n/2$, average filtering is much more effective. Thus, median filter with average filtering is chosen as part of DSF algorithm. Every extracted segment from the raw disparity depth map will be filtered up using median filtering.. Filtered parts are then combined into a new disparity map by adding up all filtered images of every segmented fraction as shown in Figure 3(a).

2.6 Merging

The merging process is done by summing all the filtered segments. The background object(which is in dark blue as shown in Figure 2 definite as zero value in the computation so that only the filtered segments summed up together as a new combined disparity map. The new disparity map may enclose cracks and holes due to merging process; thus the second phase of median filtering is applied to eliminate the outliers and the remaining noises. The final disparity depth map is attained with the horizontal "streaks" entirely removed as shown in Figure 3(b).

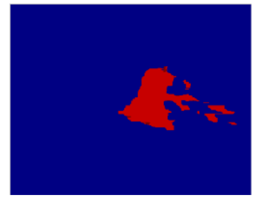
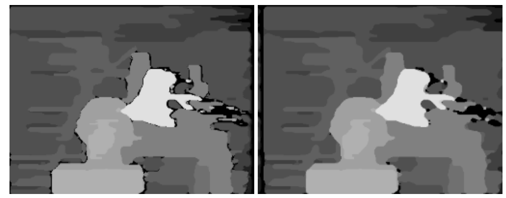


Figure 2 Sample of segmented part of raw disparity depth map for Tsukuba



(a) (b)

Figure 3 (a) Merged new disparity map; (b) Final disparity depth map

3.0 RESULTS AND DISCUSSION

3.1 Performance Analysis

There are three evaluation functions used in this paper to analyze the performance of the three stereo matching algorithms. The dataset used for the evaluation purpose is Tsukuba as this stereo pair is easy to be analyzed on the unwanted aspects that produced and the results are collected in short period due to its simple content of image [39] . One of the evaluation functions is Mean Squared Error (MSE), which is applied to obtain the average of squared errors between the generated disparity map and the ground truth.

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I_1(x,y) - I_2(x,y)]^2 \tag{7}$$

where *M* and *N* as the rows and columns of the input images of I_1 and I_2 respectively. As the value of MSE is decreasing, it indicates that the cumulative squared error is lesser [40]. Another evaluation function is Peak Signal to Noise Ratio (PSNR), it linked to MSE due to its equations include the parameters of MSE. PSNR is to establish the performance of an algorithm in obtaining a good result by comparing the quality of image using the image enhancement algorithms [40].

$$PSNR = 10\,log_{10}(\frac{R^2}{MSE}) \tag{8}$$

In PSNR, *R* is indicates the maximum fluctuation of data type in the input data which equal to 1 when the input image contains of double-precision floating-point while it is equal to 255 for 8-bit unsigned integer data type. As higher the PSNR, the better the quality of the disparity map generated, and this indicates that more noises are reduced [41]. Another technique used in this research to analyze the performance of proposed algorithm and other existing algorithms is the Structural Similarity Index Metric (SSIM). This technique is applied to calculate the similarity between the obtained disparity map and the ground truth. SSIM is designed to solve the issue on peak signal-to-noise ratio (PSNR) and mean squared error (MSE) in which less consistent to the human eye perception [42] . MSE and PSNR are evaluation methods which approximate the perceived errors, while SSIM estimate on image degradation as recognized change in structural data. Structural data is the spatially near pixels in an image which belong to strong inter-dependencies to show up crucial data regarding the structural content in the visual information [43].

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (9)$$

In SSIM equation, μ_x and μ_y as the average of x and y, σ_x^2 and σ_y^2 are indicate as the variance of x and y, σ_{xy} is the covariance of x and y. $C_1 = (k_1L)^2$ and $C_2 = (k_2L)^2$ are representing the variables to standardize the division with denominator where L represent the dynamic range of pixel values while k_1 = 0.01 and k_2 = 0.03 are as default. The results computed from SSIM index will be in decimal value between -1 to 1.

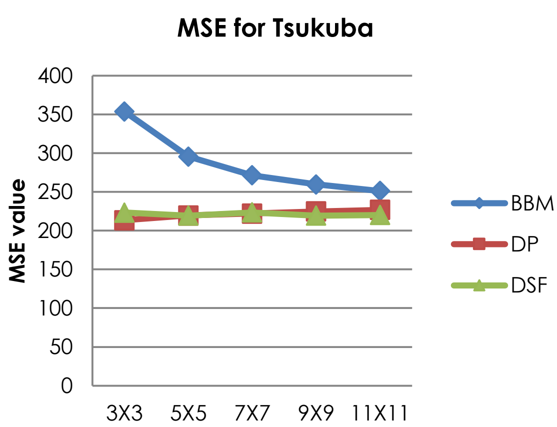


Figure 4 MSE value for Tsukuba stereo pair

In Figure 4, the graph of MSE value shows the results of MSE value for computed disparity map directly proportional to the gradually increasing window sizes of pre-processing among three stereo matching algorithms: basic block matching (BBM), dynamic programming (DP) and double stage filter (DSF). For BBM algorithm with diamond shape on line is shows that the MSE values for Tsukuba stereo pair are gradually decreasing and this indicates that as window size increasing, more errors are reduced for BBM algorithm. On the other hand, DP algorithm is vice versa to BBM algorithm as the MSE values for Tsukuba stereo pair that generated by DP algorithm are raising with the window size extending respectively. The results of DP algorithm indicates that it performs well when using smaller size of window rather than the bigger window size due to its scanline optimization on every row of pixels where bigger window size may missed scanning on tiny objects in the content of disparity map while smaller window may scan on content of image precisely and more errors can be reduced compared to larger window size. For DSF algorithm, the MSE values are specified in a standard range where there is no obvious optimum value of MSE. In the research, window size of 3 X 3 is chosen for Tsukuba stereo pair as smaller window sizes are able to capture well on tiny and thin objects of the content in an image [24]. However, the selection of window size is depending on the complexity of the content in the image.

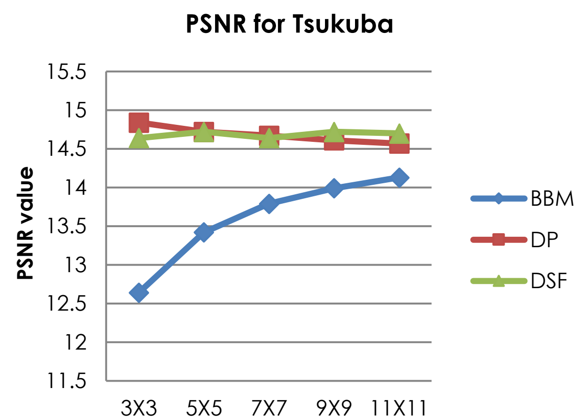


Figure 5 PSNR value for Tsukuba stereo pair

In Figure 5 shows the PSNR values obtained from three stereo matching algorithms using Tsukuba stereo pair. Based on the results from Figure 5, the graph is clearly shows that the PSNR values computed from BBM algorithm is gradually increasing with increasing of window sizes and this represent that more noises are able to be reduced with larger window size for BBM algorithm. For DP algorithm, the PSNR values generated are gradually decreasing which means less noise is removed and this shows that DP algorithm can only operate efficiently on reducing errors on image with smaller window sizes compared to BBM algorithm. Meanwhile, for DSF algorithm, the window sizes are not much affect on the performance for the whole algorithm, the graph shows that the PSNR values obtained from DSF algorithm are remain stable.

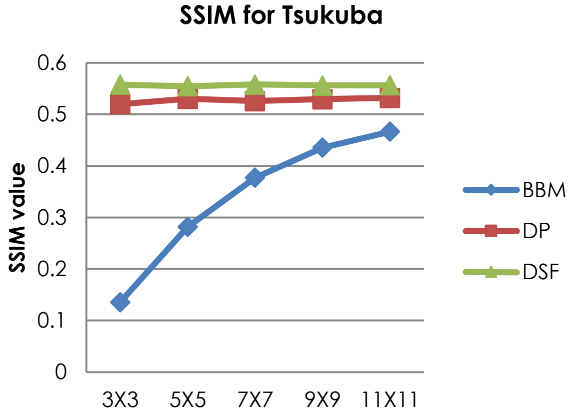


Figure 6 SSIM value for Tsukuba stereo pair

In Figure 6 shows the SSIM values generated from the three stereo matching algorithms. Based on the results of BBM algorithm, the graph indicates that the SSIM value is gradually raising and this shows that BBM algorithm require bigger window size to obtain a better quality of disparity map. However, the SSIM values of disparity map for each window size of BBM algorithm are lower than the SSIM values of disparity map for DP algorithm and DSF algorithm. For DP algorithm, the SSIM values obtained are remain steady while the SSIM values for DSF algorithm are not much different among the window sizes.

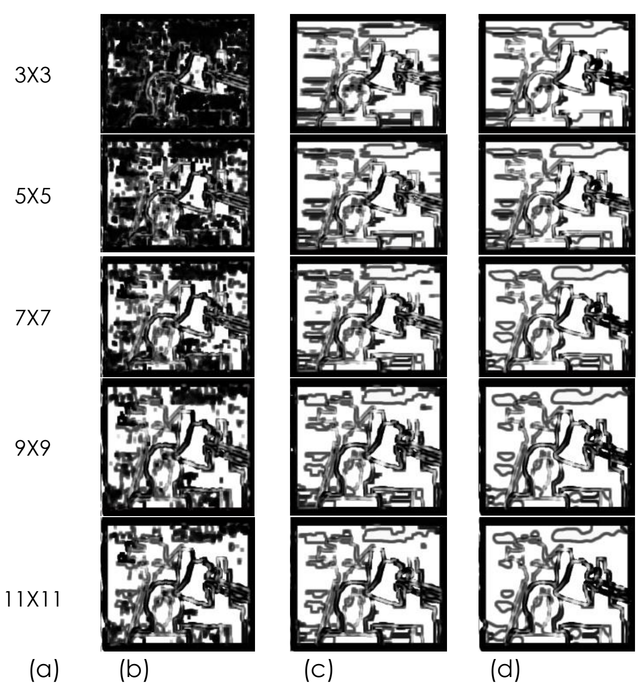


Figure 7 SSIM index map for Tsukuba (a) Window size; (b) BBM; (c) DP; (d) DSF

The SSIM index map for each window size is shown in Figure 7. From Figure 7, it obviously show that the SSIM index maps of BBM algorithm have a huge gap of improvement from smaller window size till larger window size. For the SSIM index maps of DP algorithm show there is slightly improvement on the disparity maps from smaller window size till bigger window size especially on the background of the image. The SSIM index maps of DSF algorithm show the difference between the maps are close to each other.

3.2 Computation Analysis

The method of calculating the time computation among the three stereo matching algorithms is using tic toc [44]. Tic toc method is used to measure the execution time of an algorithm. In the research, tic toc is applied to calculate only the main functions in the algorithm which not including the sub functions such as reading data and showing out figures. The computation time taken for all the algorithms are using a laptop with specifications of ATI HD6370M with 1GB video memory, on a 2.5 GHz Intel Core i5-2450M CPU with 6GB RAM. From Figure 8 shows that the computation of BBM algorithm is the fastest compared to the rest of two algorithms due to its simple algorithm, however the results obtained by the algorithm contain too much noises. Average computation time taken for DP algorithm is approximate about a minute while the average computation time of DSF algorithm is approximate a minute plus as DSF algorithm is combination of BBM and DP algorithms so for sure its computation time is slightly longer compared to the rest two algorithms. The difference of time taken for computation between DP and DSF algorithms is only few seconds while the few seconds are worth for DSF algorithm to obtain a better results of disparity map compared to BBM and DP algorithms.

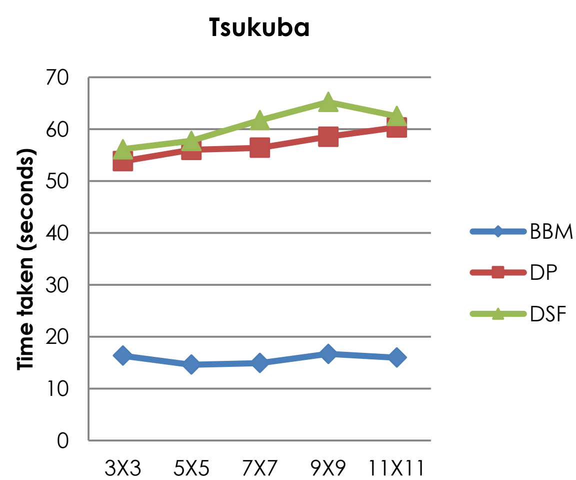


Figure 8 Computation time taken (in seconds)

4.0 CONCLUSION

The Double Stage Filter (DSF) algorithm is designed with the focus of enhancing the raw disparity maps. The proposed algorithm includes segmentation, median filtering and merging method, which is less complexity in computation. The disparity maps attained from the algorithm are assessed with MSE, PSNR and SSIM. From the inspection on the results discussed, DSF algorithm achieved well compared to DP and BBM algorithms as the graph of the evaluation functions proved that the disparity maps attained by DSF is closer to the ground truth image originality rather than the other algorithms. In the computation analysis, the time taken for DSF algorithm is only few seconds away from DP algorithm and it is capable to obtain a better results of disparity map as presented in this paper. In the future work, the DSF algorithm can be executed for a variety of 3D applications due to its simple implementation and less complexity of algorithm design. For recommendation, median filtering can be tried with other kinds of filtering to generate different outputs of the disparity depth map.

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