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Performance Review of the Stereo Matching Algorithms

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Abstract
Stereo correspondence or disparity is a common tool in computer or robotic vision, essential for determining three-dimensional depth information of object using a pair of left and right images from a stereo camera system. Some applications of disparity are autonomous vehicle and robot navigation, virtual reality and stereo image analysis. Stereo correspondence or disparity is determined of matching windows of pixels by using Sum of Square Differences (SSD), Sum of Absolute Differences (SAD), or normalized correlation techniques. As a result to identify the problem of matching pixels between two images of a stereo pair several algorithms have been invented in the respective arena. In this paper comparative performance analysis of existing stereo matching algorithms are explored detailed up to date. The methods that are considered in the paper are classified into two categories. First one is named as local method while the second one is global method. The algorithms taken consideration in literature are analyzed by speed, accuracy and disparity range. Experimental results applied on different image sizes and different image sets (Tsukuba Stereo pair, Sawtooth stereo pair, Map Stereo pair and Venus Stereo pair) are also presented. Some neural network and automata based latest algorithms are discussed. Besides these some algorithms are not fallen into above mentioned categories are also discussed in details.

1. Introduction

The difference in the coordinates of the corresponding pixels is known as disparity, which is inversely proportional to the distance of the object from the camera. Stereo correspondence is a common tool in computer or robot vision, essential for determining three-dimensional depth information of object using a pair of left and right images from a stereo camera system. For of a pixel in the left image, its correspondence has to be searched in the right image based on the epipolar line and maximum disparity. Stereo correspondence or disparity is conventionally determined of matching windows of pixels by using Sum of Square Differences (SSD), Sum of Absolute Difference (SAD) or normalized correlation techniques (NCT).

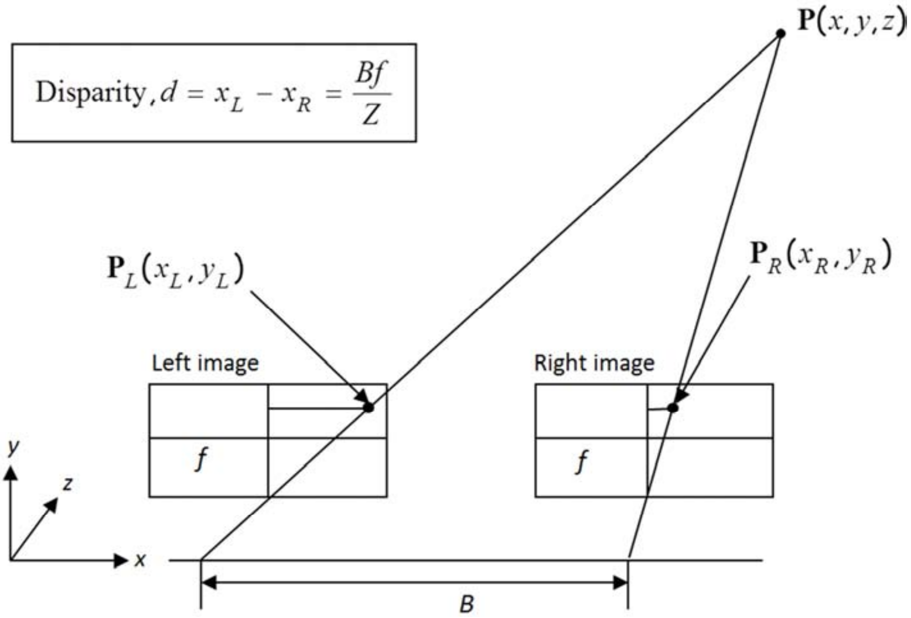

Figure 1. *Disparity in a stereo pair of images.*

The aggregation of the window cost functions, leads to the core of most of the stereo vision methods, which can be mathematically expressed as follows-

$$SSD(x,y,d)= \sum_{i=1}^{Wx}\sum_{j=1}^{Wy}\left[fL(x+i,y+j)-fR(x+i+d,y+j)\right]^2 \tag{1}$$

$$SAD(x,y,d)= \sum_{i=1}^{Wx}\sum_{j=1}^{Wy}\left|fL(x+i,y+j)-fR(x+i+d,y+j)\right| \tag{2}$$

$$\text{Correlation method NCT } (x,y,d)= \frac{\sum_{i=1}^{Wx}\sum_{j=1}^{Wy} fL(x+i,y+j)\, fR(x+i+d,j+j)}{\sqrt{\sum_{i=1}^{Wx}\sum_{j=1}^{Wy} fL^2(x+i,y+j)\sum_{i=1}^{Wx}\sum_{j=1}^{Wy} fR^2(x+i+d,y+j)}} \tag{3}$$

where *fL, fR* are the intensity values in left and right image, *(x, y)* are the pixel's coordinates, *d* is the disparity value under consideration and *W* is the window cost of masking region.

Window-based stereo correspondence estimation technique is widely used due to its efficiency and ease of implementation. However, there is a well-known problem in the selection of an appropriate size and shape of window [1, 2]. If the window is small and does not cover enough intensity variation, it gives erroneous result due to low signal to noise ratio. If, on the other hand, the window is large, it includes a region where the disparity varies or discontinuity of disparity happens, then the result becomes erroneous due to different projective distortions in the left and right images. Pixels that are close to a disparity discontinuity require windows of different shapes to avoid crossing the discontinuity. Therefore, different pixels in an image require windows of different shapes and sizes.

To overcome this problem, many researchers proposed adaptive window techniques using windows of different shapes and sizes [3-7]. In adaptive window technique, it requires comparing the window costs for different window sizes and shapes, so the computation time is relatively higher than that of fixed window based technique. For example, in the references [6] and [7] the authors used a direct search over several window shapes to find the one that gives the best window cost. Beside gray scale stereo images, the use of color stereo images brings a substantial gain in accuracy with the expense of computation time [8]. The approximation method showed in such situations for speedy determination of dense disparity [10]. But its accuracy is poor quality. At present the researcher trying to pursue real time execution speed and better accuracy. New approaches are introduced every year. But none them are still now perfect matching algorithms.

The better classifications have presented by Scharstein and Szeliski [11] and many new methods have been proposed here. Primarily matching algorithms can be classified with respect to spare output and dense output. Feature based methods that based on segments or edges between stereo images result sparse output. Such type of output has the limitations both speed and accuracy due to their disadvantages causes it dreadful for many applications. Dense matching algorithms are divided into local and global ones.

Local methods are also known as area based stereo matching that can perform better speed compare to global methods. According to this, disparity is being calculated at a point in a fixed window. Global methods are also known as intensity or energy based stereo matching that can perform better accuracy compare to local methods. According to this method, the global cost function is reduced as minimum as possible. This cost function synthesizes image data and smoothness terms. Besides these some algorithms are not fallen into above mentioned two categories. Recently, neural adaptive stereo matching [13] are done by trained neural networks based on window size and shape. One dimensional cellular automation filter [16] makes the algorithm more adaptive to each window.

2. Stereo Matching Algorithms

Most of the stereo matching experiments are tested on standard image sets. Such types of standard stereo images are shown below.

Figure 2. *(a) Left image of Tsukuba stereo pair (b) ground truth image.*

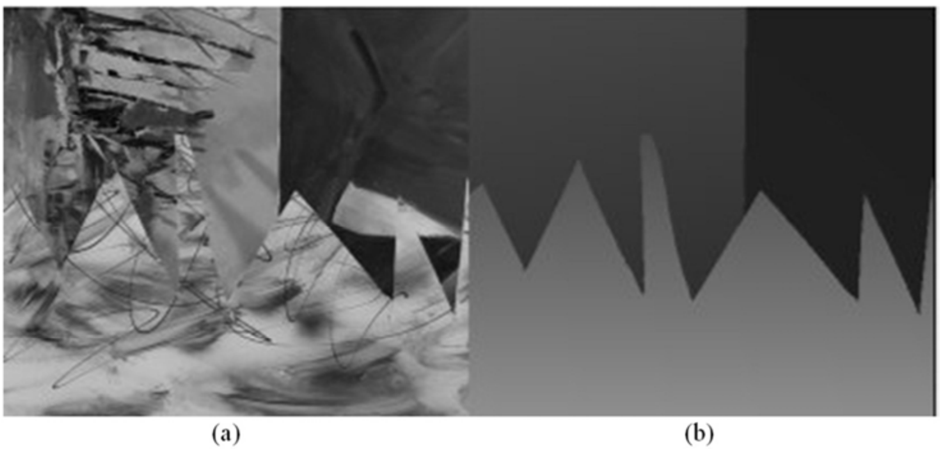

Figure 3. *(a) Left image of Sawtooth stereo pair (b) ground truth image.*

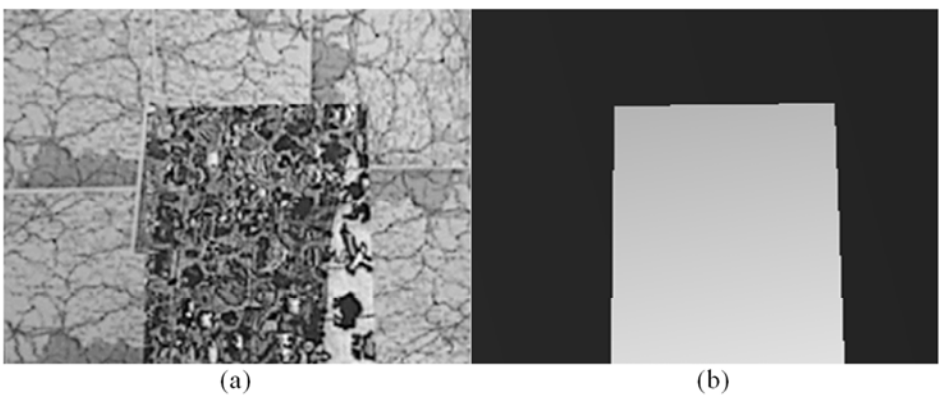

Figure 4. *(a) Left image of Map stereo pair (b) ground truth image.*

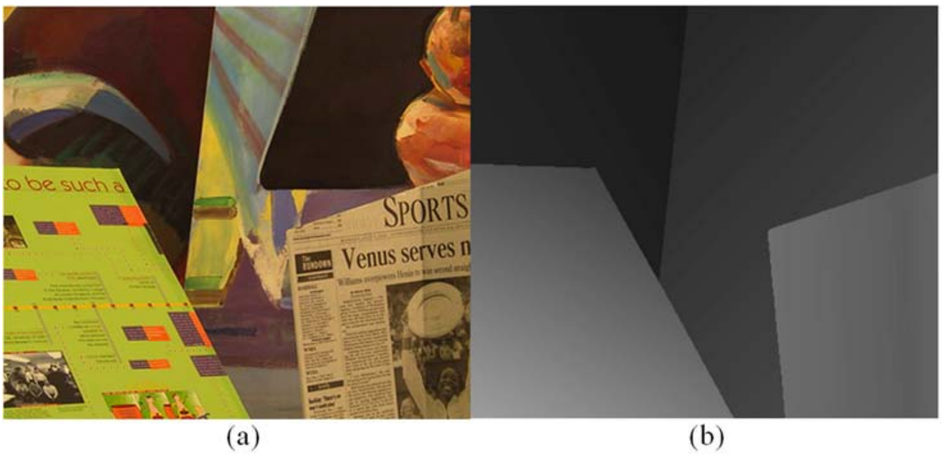

Figure 5. *(a) Left image of Venus stereo pair (b) ground truth image.*

2.1. Dense Disparity Algorithms

Because of increasing the computational power, some algorithms that results dense map became very popular in the recent decade. That is why dense disparity is more interested research area than spare results.

2.1.1. Local Methods

Local methods provide good results and show speedy performance. Disparity has been calculated from color stereo images [8]. Sum of Absolute Difference (SAD) technique is used for RGB color image and a fast median filter uses to results. Its scanning speed is 20 fps for 160×120 image size. The method is suitable for real-time application.

A fast area based stereo matching algorithm has been introduced by L. D. Stefano [12]. As searching is accomplished by unidirectional so it is also referred to as Single Matching Phase (SMP). Based on uniqueness constraint, it rejects previous matches as soon as better result is detected. It also uses SAD technique for error function, but any technique could be used. This method results a dense disparity map in real – time. It perform 39.59 fps speed for 320×240 image size and 16 disparity levels and the root mean square (rms) error for Tsukuba pair is 5.77.

A novel method has been introduced in [13]. This method uses zero mean normalized cross correlation for matching, it also uses neural model that uses least-mean-square delta rule for training. Proper window size and shapes are selected by the neural network for each considering region. The results obtained by the network are better but the computational costs are not suitable for real –time applications.

Shaped based stereo matching is reported in [14] in which shape of the target is depicted by the algorithms. It demonstrates the importance of the horizontal and vertical slanted surfaces. The authors propose the replacement of the standard uniqueness constrain referred to pixels with a uniqueness constraint referred to line segments along a scanline. In this method interval matching is performed instead of pixel matching. Matching factor is performed based on the absolute intensity difference and the stretching factor is obtained. Also the object is achieved by minimum segmentation. The experimental results show that 1.77%, 0.61%, 3.00% and 7.63% errors for the Tsukuba, Sawtooth, Venus and Map stereo pair respectively. The execution speed of the algorithm varies from 1 to 5 seconds on 2.4 Ghz processor.

Almost real-time performance method is reported in [15] presented by Yoon. It uses SAD method and a left-right consistency check. This method is able to find out the errors in the problematic regions are reduced using different sized correlation windows. Accordingly, a median filter is used in order to interpolate the results. The algorithm can process 7 fps for 320×240 pixels images and 32 disparity levels. The result has been justified by using an Intel Pentium 4 at 2.66GHz Processor.

The use of Cellular Automata (CA) is presented in [16]. This work presents architecture for real-time extraction of disparity maps. The proposed method can process 1Mpixels image pairs at more than 40 fps. The key idea behind the algorithm relies on matching pixels of each scan-line using a one-dimensional window and the SAD matching cost. According to the method a pre-processing mean filtering step and a post-processing CA based filtering ones are employed. CA's are models of physical systems, where space and time are discrete and interactions are local. They can easily handle complicated boundary and initial conditions. In CA analysis, physical processes and systems are described by a cell array and a local rule, which defines the new state of a cell depending on the states of its neighbors [27].

A window-based method is presented in [18] that use different support-weights. The support-weights of the pixels in a given support window are adjusted based on geometric proximity and color similarity to reduce the image ambiguity. The running time for the Tsukuba image pair with a 35×35 pixels support window is about 0.016 fps on an AMD 2700+ processor. The error ratio is 1.29%, 0.97%, 0.99%, and 1.13% for the Tsukuba, Sawtooth, Venus and Map image sets respectively. The experimental results can be further improved through a left-right consistency checking.

Table 1. *Comparative study of Local Algorithms.*

Author & year	Method	Speed (fps)	Image Size	Disparity Levels	Computational Platform
Muhlmann 2002	SAD	20	160×120		Processor: P3 Speed: 800MHz RAM: 512 MB
Di Stefano, Marchionni and Mattoccia 2004	SMP	39.59	320×240	16	Processor: P3 Speed: 800MHz RAM: 512 MB
Binaghi et al. 2004	ZNCC	0.024	284× 216	30	Processor: P3 Speed: 300MHz
Ogale and Aloimonos 2005	SAD	1	384 288	16	Processor: P3 Speed: 2.4 GHz
Yoon et al. 2005	SAD	7	320 240	32	Intel Pentium 4 2.66GHz
Yoon and Kweon 2006	SAD	0.016	384 288	16	AMD 2700þ
Zach, Karner and Bischof 2004	SAD	50	256 256	88	ATI Radeon 9700 Pro
Mordohai and Medioni 2006	NCC	0.002	384 288	20	Intel Pentium 2.8MHz

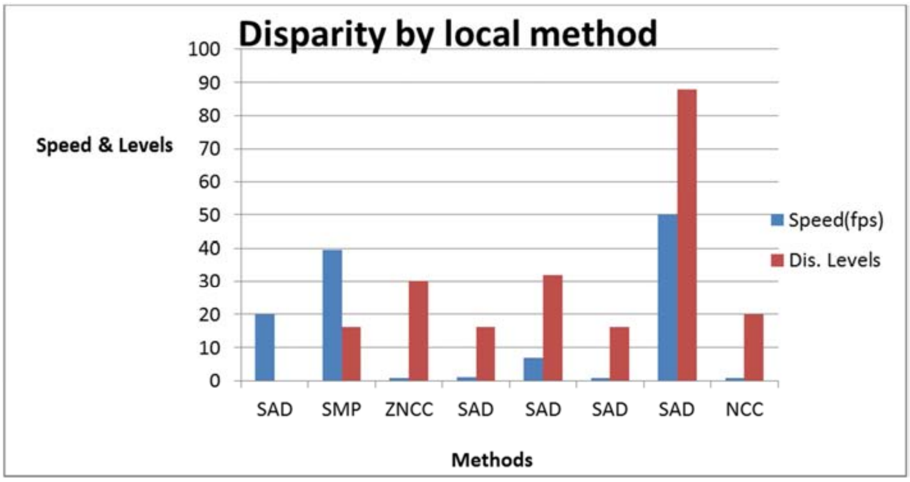

Figure 6. *Graphical performance of local method.*

2.1.2. Global Methods

In a global algorithm, the disparity of every single pixel is calculated by taking into consideration the whole image. Global optimization methodologies involves segmentation of the input images according to their colors. The accuracy of the global methods is very high but the computational costs are also high due to repetitive comparison.

The research work presented in [18] based on unified framework that supports the fusion of any partial knowledge such as matching features and surfaces about disparities. Accordingly, it combines the results of edge, corner and dense stereo matching algorithm to act as a guide points to the standard dynamic programming method. The result is a fully automatic dense stereo system with up to four times faster running speed and greater accuracy compared to results obtained by the sole use of dynamic programming.

A method based on the Bayesian estimation theory with a prior Markov Random Fields model for the assigned disparities is described in [19]. According to this method, the continuity, coherence, occlusion constraints and the adjacency principal are taken into considerations. The optimal estimator is computed using a Gauss-Markov random field model for the corresponding posterior marginal, which results in a diffusion process in the probability space. The results are accurate but the algorithm is not suitable for real-time applications, since it needs a few minutes to process a 256×255 stereo pair with up to 32 disparity levels, on an Intel Pentium III running at 450 MHz.

Image color segmentation is reported in [20]. By this method disparity map is calculated using an adapting window based technique. The segments are combined in larger layers iteratively. A global cost function is used to optimize the segments to layers. The quality of the disparity map is measured by warping the reference image to the second view and comparing it with the real image and calculating the color dissimilarity. For the 384×288 pixel Tsukuba and the 434×383 pixel Venus test set, the algorithm produces results at 0.05 fps rate and needed 20 s to produce results. For the 450×375 pixel Teddy image pair, the running speed decreased to 0.01 fps due to the increased scene complexity. Running speeds refer to an Intel Pentium 4 2.0GHz processor. The root mean square error obtained is 0.73 for the

Tsukuba, 0.31 for the Venus and 1.07 for the Teddy image pair.

The work done by Md. Abdul Mannan Mondal and Md. Al-Amin Bhuiyan [10] presents a two-stage approximation algorithm consisting of a vector quantization and backtracking. The dense disparity is estimation is accomplished by two steps. First one is quantized the window pixels and second one is retrieved the pixel's position to reconstruct the original image. The running time of this algorithm is 10 ns measured by Intel Pentium-III 2.4 GHz processor.

An algorithm which is focused on achieving contrast invariant stereo matching [22]. It depends on multiple spatial frequency channels for local matching.

The global solution is determined by a fast non-iterative left right diffusion process. Occlusions are found by imposing the uniqueness constraint. The algorithm can perform significant changes in contrast between the two images and can handle noise in one of the frequency channels. The algorithm has been justified on standard image pairs and needs 2 to 4 seconds to process.

Another algorithm that generates high quality results in real time is reported in [23]. This algorithm is based on the minimization of a global energy function comprising of a data and a smoothness term. The propagation iteratively optimizes the smoothness it achieves fast convergence by removing redundant computations. For real-time operation authors take advantage of the parallelism of graphics hardware. Experimental results indicate 16 fps processing speed for 320×240 pixel self-recorded images with 16 disparity levels.

Table 2. *Comparative study of Global Algorithms.*

Author and year	Method	Speed (fps)	Image Size	Disparity Levels	Computational Platform
Hong and Chen 2004	graph cuts	0.33	384 ×288	16	Processor: P4 Speed: 2.4 GHz
Bleyer and Gelautz 2005	Global cost function	0.05	384 ×288	16	Processor: P4 Speed: 2.0 GHz
Gutierrez and Marroquin 2004	Gauss-Markov random field	0.017	256×255	32	Processor: P3 Speed: 450MHz
Veksler 2006	graph cuts	1.04	434 ×383	20	Processor: P4 Speed: 2.6 GHz
Ogale and Aloimonos 2005	Left-right diffusion process	0.5	384×288	16	Intel Pentium 4 Speed: 2 GHz
Kim et al. 2005	DP	0.23	384×288	16	Intel Pentium 4 Speed: 2 GHz
Wang et al. 2006	DP	43.5	320×240	16	3.0GHz CPU -ATI Radeon XL1800 GPU
Lei et al. 2006	DP	0.1	384 ×288	16	1.4 GHz Intel Pentium M

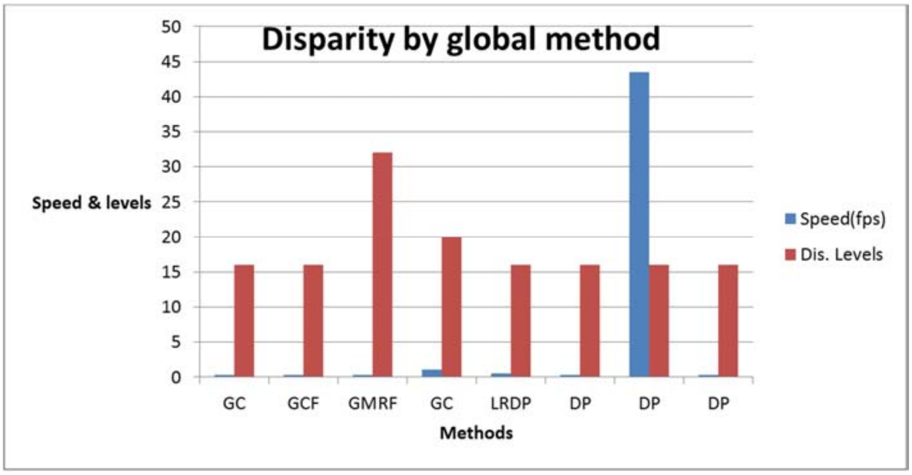

Figure 7. *Graphical performance of global method.*

2.1.3. Spiral Methods

We introduced a searching algorithm called "Spiral Searching Algorithm (SSA)" for computing stereo correspondence or disparity of the stereo images. The method was based on computation of the minimum window cost among the contributions of the windows bounded in the range from minimum depth of spiral to maximum depth of spiral [29]. This algorithm can estimate stereo correspondence of a pair of images concurrently two dimensionally and it avoids false matching causes to increase the accuracy and requires minimum executing time than the traditional one dimensional searching strategies. This method first calculates two window costs - one in positive x-direction and another in negative y-direction using the same distance from the origin. Minimum of the two window costs and coordinate distances are considered for second calculation. Secondly, following the same way another two window costs are calculated - one in negative x-direction and another in positive y-direction using the same distance from the origin. Minimum of the two window costs and coordinate distances are compared to the previous two window costs.

Figure 8. *Stereo Correspondence window size 11×11.*

Figure 9. *Stereo Correspondence window size 15×15.*

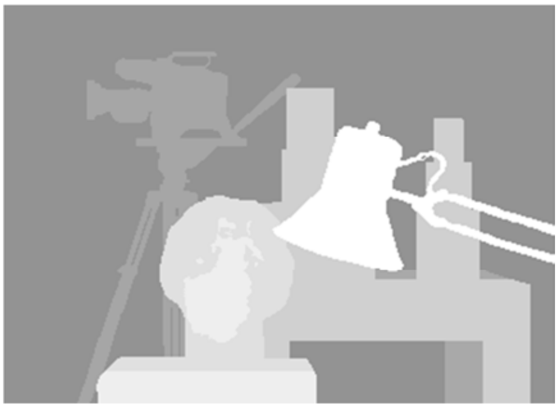

Figure 10. *Standard ground truth image.*

This process is bounded from minimum depth of spiral to maximum depth of spiral. Experimental result (Figure 8 and Figure 9) demonstrates that the visual quality of the output image is very close to ground truth image (Figure 10).

2.2. Other Methods

Besides the three above mentioned methods there are also some methods producing dense disparity maps. Continuous Wavelet Transform (CWT) reported in [24] can be placed in neither of previous categories. It makes use of the redundant information that results from the CWT. Using 1D orthogonal and bio-orthogonal wavelets as well as 2D orthogonal wavelet the maximum matching rate obtained is 88.22% for the Tsukuba pair.

An algorithm based on non-uniform rational B-splines (NURBS) curves presented in [25]. The curves replace the edges extracted with a wavelet based method. The NURBS are projective invariant and so they reduce false matches due to distortion and image noise. Stereo matching is then obtained by estimating the similarity between projections of curves of an image and curves of another image. A 96.5% matching rate for a self-recorded image pair is reported for this method.

D. Scharstein, H. Hirschmüller, Y. Kitajima, G. Krathwohl, N. Nesic, X. Wang, and P. Westling [28] reported in High-Resolution Stereo Datasets with Subpixel Accurate Ground Truth to find high resolution thirty-three stereo datasets of static indoor scenes with highly accurate ground-truth disparities [28]. The system includes novel techniques for efficient 2D subpixel correspondence search and self-calibration of cameras and projectors with modeling of lens distortion.

3. Conclusion

The stereo matching problem is a big challenging for computer and robotic vision researchers. A review performance survey has been justified over the latest stereo vision algorithms and are categorized according to the processing method, speed and disparity levels. It seems that both area and energy based method tends to reach their satisfactory experimental results and objectives.

Local algorithms that aggregate support can perform well, especially in textured regions. From Table 1 the SAP method of L. D. Stefano, Marchionni and Mattoccia consistently outperforms the good optimization compared to other methods. It scans 40 frames per second and shows the 16 disparity levels. Among the local algorithms the best performance have been done by Zach, Karner Bischof using SAD method. It scans 50 frames per second and shows the 88 disparity levels at a time. The rest of local algorithms show the average performances. This method can be applied in real time application as Md. Abdul Mannan Mondal uses vector quantization and backtracking technique by SSD method in real time application.

Global optimization methodologies involves segmentation of the input images according to their colors. The accuracy of the global methods is very high but the computational costs are also high due to repetitive comparison. GC (Graph-Cut) and DP (Dynamic Programming) are clearly superior to simulated strengthening. DP is better than GP. From Table 2 the GP method of Veskler consistently outperforms the good optimization compared to other methods. It scans 1.04 frames per second and shows the 20 disparity levels. Comparing to all global algorithms, the best performance has been done by Wang using DP method. It scans 43.5 frames per second and shows the 16 disparity levels at a time.

Besides the above mentioned methods the CWT method uses the redundant information results 88.2% matching rate for tsukuba pair images. The new method introduced here by Md. Abdul Mannan Mondal and Md. Haider Ali called spiral method. According to this method matching is done by two dimensionally at a time. This method first calculates two window costs - one in positive x-direction and another in negative y-direction using the same distance from the origin and vice versa results good quality of dense disparity.

Lastly, we hope that the prospective researchers will consider this review paper that will lead to a deeper understanding for current work on stereo correspondence algorithms.

References

[1] S. T. Barnard and M. A. Fischler, "Stereo vision," in *Encyclopedia of Artificial Intelligence,* (John Wiley, New York, 1987), pp. 1083-1090.

[2] W. Hoff and N. Ahuja, "*Surfaces from stereo: Integrating feature matching, disparity estimation and contour detection*," IEEE Trans. Pattern Anal. Machine Intell., vol. 11, no. 2, pp. 121-136, (1989).

[3] T. Kanade and M. Okutomi, "*A stereo matching algorithm with an adaptive window: Theory and experiment*," IEEE Trans. Pattern Anal. Machine Intell., vol. 16, no. 9, (1994).

[4] Olga Veksler, "*Stereo matching by compact windows via minimum ratio cycle*," in Proceedings of the IEEE International Conference on Computer Vision (ICCV 2001*)*, pp. 540-547.

[5] Mohammad Shorif Uddin, Tadayoshi Shioyama, Mozammel Hoque Chowdhury, Md. Abdul Mannan Mondal, "Fast Window Based Approach For Stereo Matching", *Journal of Science, Jahangirnagar University*, vol. 27, pp: 145-154, June 2004.

[6] S. S. Intille and A. F. Bobick, "*Disparity-space images and large occlusion stereo*," in Proceedings of the European Conference on Computer Vision (ECCV 1994), pp. 179-186.

[7] A. Fusiello and V. Roberto, "*Efficient stereo with multiple windowing*," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (ICVPR 1997*)*, pp. 858-863.

[8] K. Muhlmann, D. Maier, J. Hesser, R. Manner, "*Calculating dense disparity maps from color stereo images, an efficient implementation*," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (ICVPR 2001), pp. 30-36.

[9] Mohammad Shorif Uddin, "*Stereo correspondence estimation using window- based methods by a fast algorithm*" journal of electronics and computer science, vol. 4, June 2003, pp. 5-11.

[10] Md. Abdul Mannan Mondal, Md. Al-Amin Bhuiyan "Disparity Estimation By A Two-Stage Approximation Real Time Algorithm" T*he International Management and Technology Conference (IMT)*, pp: 12-17, 8 - 10 December 2004, Orlando, Florida 32819, USA.

[11] D. Schartein, R. Szeliski, "A taxonomy and evaluation of dense two frame stereo correspondence algorithms", IJCV 7, 1/3, 2002.

[12] Lugi Di Stefano, Massimiliano Marchionni, Stefano Mattoccia, "A fast Area Based Stereo Matching Algorithm", Image and vision Computing 22, pp. 983-1005, 2004.

[13] Elisabetta Binaghi, Ignazio Gallo, Giuseppe Marino, Mario Raspanti, "Neural adaptive stereo matching", Pattern Recognition Letters 25, pp. 1743-1758, 2004.

[14] Abijit S. Ogale and Yiannis Aloimonos, "Shape and the Stereo Correspondence Problem", IJCV 65, 3, pp. 147-167, 2005.

[15] Sukjune Yoon, Sung-Kee Park, Sungehul Kang, Yoon Keun Kwak, "Fast correlation –based stereo matching with the reduction of systematic errors", Pattern Recognition Letters 26, pp. 2221-2231, 2005.

[16] L. Kotoulas, A. Gasteratos, G. Ch. Sirakoulis, C. Georoulas, and I. Andreadis, "Enhancement of Fast Acquired Disparity Maps using a 1-D Cellular Automation Filter", proceedings of the fifth IASTED International Conference on Visualization, Imaging and Image Processing, Benidorn, Spain, September 7-9, 2005.

[17] Kuk-Jin Yoon and In So Kweon, "Adaptive Support –Weight Approach for Correspondence Search", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 4, April 2006.

[18] P. H. S. Torra, A. Criminisi, "Dense stereo using pivoted dynamic programming", Image and Vision Computing 22, pp. 795-806, 2004.

[19] Salvador Gutierrez, Jose Luis Marroquin, "Robust approach for disparity estimation in stereo vision", Image and Vision Computing 22, pp. 183-195, 2004.

[20] Michael Bleyer, Margrit Gelautz, "A layered stereo matching algorithm using image segmentation and global visibility constraints", ISPRS Journal of Photogrammetry and Remote Sensing 59, pp. 128-150, 2005.

[21] Hansung Kim, Kwanghoon Sohn, "3D reconstruction from stereo images for interactions between real and virtual objects", Signal Processing: Image Communication 20, pp. 61-75, 2005.

[22] Abijit S. Ogale and Yiannis Aloimonos, "Robust Contrast Invariant Stereo Correspondence", Proceedings of the 2005 IEEE International on Robotics and Automation, Barcelona, Spain, April 2005.

[23] Qingxiong Yang, Liang Wang, Ruigang Yang, Shengnan Wang, Miao Liao, David Nister, " Real – time Global Stereo Matching Using Hierarchical Belief Propagation", The British Machine Vision Conference (BMVC), 2006.

[24] Xiaodong Huang, Eric Dubois, “Dense Disparity Estimation based on the continuous wavelet transformation”, CCECE 2004- CCGEI 2004, Niagara Falls, May 2004.

[25] C. Liu, W. Pei, S. Niyokindi, J. C. Song and L. D Wang, “Micro stereo matching based on wavelet transform and projective invariance”. Meas Sci. Technol. 17, pp. 565 -571, 2006.

[26] Olga Veksler, “Dense Features for Semi-Dense Stereo Correspondence”, IJCV 47, pp. 247-260, 2002.

[27] Lazaros Nalpantidis, Georgios Ch. Sirakoulis and Antonios Gasteratos, “Rieview of stereo matching algorithms for 3D vision”, 16th International Symposium on Measurement and Control in Robotics ISMCR, pp. 116-124, 2007.

[28] D. Scharstein, H. Hirschmüller, Y. Kitajima, G. Krathwohl, N. Nesic, X. Wang, and P. Westling. “High-resolution stereo datasets with subpixel-accurate ground truth”. In *German Conference on Pattern Recognition (GCPR 2014),* pp: 1-12, *Münster, Germany,* September 2014.

[29] Md. Abdul Mannan Mondal, Md. Haider Ali “On Stereo Correspondence Estimation: A Spiral Search Algorithm” *Proceeding of International Conference on Signal and Information Processing (ICSIP)*, pp: 204-207, 14-15 December 2010, Changsha, China.