Performance Evaluation of Bit-plane Slicing based Stereo Matching Techniques

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Abstract: In this paper, we propose a hierarchical framework for stereo matching. Similar to the conventional image pyramids, a series of images with less and less information is constructed. The objective is to use bit-plane slicing technique to investigate the feasibility of correspondence matching with less bits of intensity information. In the experiments, stereo matching with various bit-rate image pairs are carried out using graph cut, semi-global matching, and non-local aggregation methods. The results are submitted to Middlebury stereo page for performance evaluation.

1 INTRODUCTION

Stereo matching is one of the most active research areas in computer vision. In the existing stereo algorithms, block matching techniques exploiting local constraints and energy minimization for global optimization have been extensively studied (Min and Sohn, 2008; Chen et al., 2001; Szeliski et al., 2008; Sun et al., 2003). While a large number of algorithms for stereo correspondence matching have been developed (Brown et al., 2003), relatively little work has been done on characterizing their performance (Hirschmuller and Scharstein, 2007). Since Scharstein and Szeliski published a paper regarding the taxonomy and evaluation of stereo correspondence algorithms (Scharstein and Szeliski, 2002b), many authors used various methods and algorithms to participate in an on-line evaluation platform which is known as Middlebury Stereo Evaluation (Scharstein and Szeliski, 2002a). This on-line evaluation website provides many stereo data sets to evaluate the performance of stereo matching algorithms. Furthermore, because the progress in stereo algorithm performance is quickly outpacing the ability of existing stereo data sets to discriminate among the best-performing algorithms, (Scharstein and Szeliski, 2003) present new stereo data sets to the on-line evaluation website, which act as the four stereo data sets for the new Middlebury's Stereo Evaluation - Version 2.

In this work, we address the feasibility of hierarchical stereo matching in the intensity domain (Lin and Lin, 2013). Similar to the conventional image pyramids, a series of images with less and less information is constructed hierarchically. They are created with different intensity quantization levels. In this kind of image presentation, more bits per pixel will contain more detailed texture for stereo matching. However, processing the low intensity quantization images generally requires less memory usage. Thus, obtaining good disparity results without using the full intensity depth of the images is an important advantage for stereo matching algorithms (Humenberger et al., 2010; Lu et al., 2009).

Based on the previous investigation of stereo matching on low intensity quantization images (Lin and Chou, 2012), this paper evaluate the bit-plane slicing techniques with recent well-known stereo algorithms. The objective is to integrate the hierarchical framework with the high-performance stereo matching techniques (Yang, 2012; Akhavan et al., 2013), and report the improvement over the Middlebury Stereo Vision Page for on-line evaluation. In the experiments, stereo matching on various bit-rate image pairs is implemented using graph cut (Kolmogorov and Zabin, 2004), semi-global matching (Hirschmuller, 2008), and non-local aggregation (Yang, 2012). The results demonstrate an alternative for the development of stereo matching algorithms, especially for the high intensity depth images.

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Table 1: The pixel values in bit-plane representation with binary format.

Bit-Plane	Bit Preserved	Slice Value	Binary Value
0	Bit 0 (LSB)	$(0000\ 0000)_2$	$(0)_2$
1	Bit 1	$(0000\ 0010)_2$	$(1)_2$
2	Bit 2	$(0000\ 0000)_2$	$(0)_2$
3	Bit 3	$(0000\ 1000)_2$	$(1)_2$
4	Bit 4	$(0000\ 0000)_2$	$(0)_2$
5	Bit 5	$(0010\ 0000)_2$	$(1)_2$
6	Bit 6	$(0000\ 0000)_2$	$(0)_2$
7	Bit 7 (MSB)	$(1000\ 0000)_2$	$(1)_2$

2 THEORETICAL BACKGROUND ON BIT-PLANE SLICING

We start by looking into a bit-plane sliced image, preserving one bit per bit-plane while masking out all other bits on each bit-plane. Given an 8-bit grayscale image, we can slice an image into the following bit-planes: Bit-plane 0 preserves only the least significant bit (LSB) while Bit-plane 7 preserves only the most significant bit (MSB). Adding all 8 bit-planes together will result in the 8-bit pixel value for the original image. For easier understanding, a pixel's bit-plane sliced result is illustrated in Table 1.

For demonstration purposes, if the masked remaining bit is 1, we convert it to a binary image setting that pixel to 1. On the other hand, if after masking a certain pixel results in a 0 value, we will show it as 0 in the binary image. We do this to show how much detail exists in each bit position for all 8 bits visually. The bit-layer slicing visual results are shown in Fig. 1. We can clearly see that the bit-planes closer to the MSB seem to preserve more important information about the objects in the image. From this observation, if we could use fewer bits to calculate dense stereo disparity maps, it would greatly reduce the total bit-rate required, and thus reduce the memory usage, communication bandwidth, etc.

To implement this idea, we combine the bit-planes and form a "bit-plane pyramid". The top-most plane of the pyramid is the same as the bit-layer No. 7 in Table 1. Stepping down in the pyramid each time we add an extra bit-plane to the pyramid, and thus increase the bit-rate while preserving more data from the original image. The proposed "bit-plane pyramid" is illustrated in Fig. 1. The goal is to use the least amount of bits to achieve certain image quality requirement. We implement and derive results from this bit-plane pyramid used in dense stereo disparity map calculation.

In our proposed bit-plane pyramid, the lower layers (the bottom layers in the pyramid) in the hierarchy preserves more detailed information than the top layers in the original image (Gong and Yang, 2001). Note that the information reduced is in terms of the representation using the image intensity, instead of the image resolution. With less information needed to be processed, stereo algorithms which originally require a large amount of memory space may be reduced dramatically while maintaining good quality stereo image disparity estimation output.

3 FRAMEWORK FOR EXISTING STEREO MATCHING ALGORITHMS

The proposed stereo matching framework is first carried out on a low bit-rate image pair (Bit-layer 1 of the bit-plane pyramid). If the resulting disparity meets some quality requirements, the stereo matching algorithms terminates. The process continues until the disparity estimate is satisfactory or the finest level (bit-layer 8 of the bit-plane pyramid) in the hierarchy is reached. While using the finest level may give the best disparity result, the proposed technique minimizes the amount of data required to achieve certain quality thresholds for disparity computation. Furthermore, in the experiments we sometimes find less bits give better disparity results.

The chosen stereo matching algorithms are separated to two categories for performance evaluation. The first category is for the ones which use 8-bit grayscale stereo images as the input, and the second category use 3-channel RGB color stereo image pair as the input. These two implementations only differ in the bit-slicing stage.

While the grayscale stereo image input is bit-plane sliced hierarchically as described previously, 24-bit RGB color stereo images need to be bit-plane sliced by each of the three color channels simultaneously

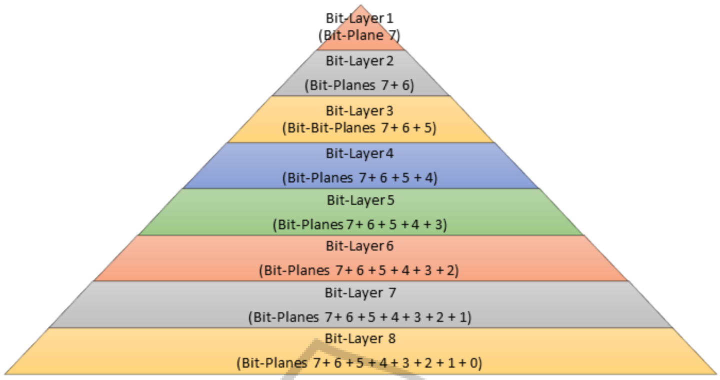


Figure 1: The image pyramid constructed with bit-plane slicing. Top layers contain less information and lower layers contain more information, in terms of image intensity depth.

in the same way as grayscale images separately. For instance, the top-most bit-plane (layer 1) of the bit-plane pyramid for the color stereo images preserves the most significant bit (MSB) from each of the 3 color channels forming a bit-plane sliced stereo image pair. Layer 2 preserves top-most 2 bits of each color channel (bit-plane 8 + bit-plane 7), and so on. Fig. 2 shows the original image and all 8 layers of the bit-plane pyramid. We can clearly see that using only a few bits we still can show most details in an image.

To implement the bit-plane pyramid stereo matching technique, we adopt the existing dense stereo algorithms and integrate with our framework. The proposed bit-plane slicing pyramid is tested with the algorithms which the authors provided source code for others to use. First we look into the OpenCV library and find that it provides 2 methods to calculate a dense disparity map. Second, we survey the top performing algorithms on the Middlebury Stereo Evaluation site. In all submissions to the Middlebury Stereo Evaluation website in the past 10 years, many authors have provided source code for their stereo algorithms. We've gathered a couple of submissions who also provided the source codes for testing.

OpenCV provides 3 implementations to compute a disparity map for input rectified stereo image pairs; all of these algorithms use single channel 8-bit grayscale stereo images as input. The first one is a faster method called "block matching" by Kurt Konolige (Konolige, 1997). It is a fast one-pass stereo matching algorithm that uses sliding sums of absolute differences between pixels in the left image and the right image. It is fast but the results are not so good unless the parameters are tuned according to the input images. The second one is called "semi-global block matching", which is a variation to (Hirschmuller, 2008). Since we match blocks rather than individual pixels, the results are often better than the first method. The third one is a "Kolmogorov's graph cuts-based" stereo correspondence algorithm (Kolmogorov and Zabin, 2004). It gives the best results of all.

Middlebury stereo evaluation site provides the evaluation of algorithms submitted to their web site using specific data sets with ground-truth disparities. There is also an on-line submission script to allow evaluation of the stereo algorithm comparing it to other existing submissions. In hundreds of submissions, we choose a high ranked method "NonLocalFilter" (Yang, 2012) for testing. This algorithm and many top performing methods takes color stereo images as input rather than grayscale to take advantage of the additional color intensity data to compute aggregation costs.

4 EXPERIMENTAL RESULTS

In the experiments, we use semi-global block matching, graph cut based, and Non-local filter stereo algorithms to test the bit-plane slicing method. The disparity map results are shown in Figure 3. We then submit the results to Middlebury stereo page for evaluation. The website provides online submission and evaluation for provided disparity maps for stereo image pairs, Tsukuba, Venus, Teddy and Cones. Submitted results will be compared with disparity map ground truth, getting average percent of bad pixels for each image pair. One thing worth noting is the website evaluates disparities for the whole image (except for a border region in the Tsukuba and Venus stereo image pairs). So if the stereo algorithm does not produce the disparity in occlusion and border areas, the stereo algorithm must extrapolate the disparities in those regions or else they will be seen as bad pixels.

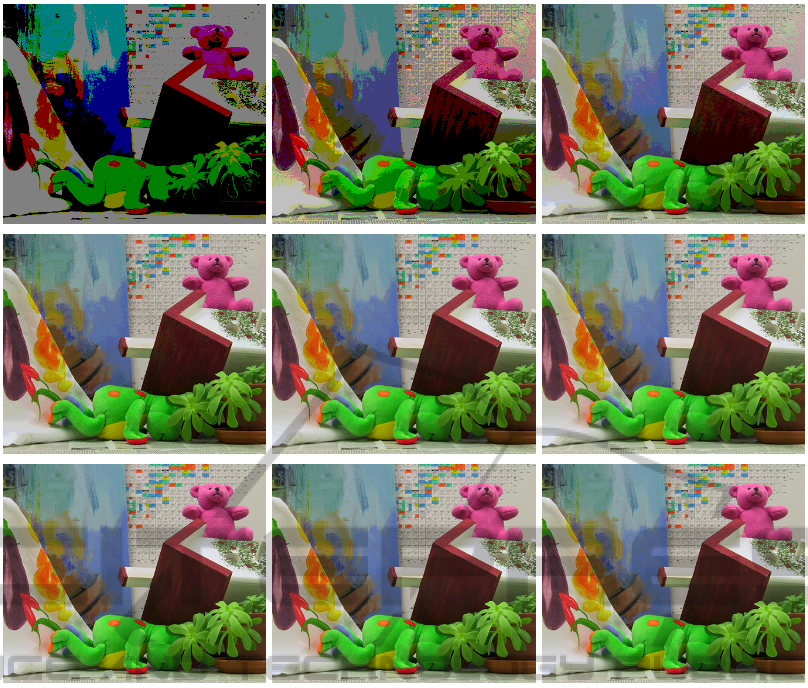


Figure 2: 24-bit RGB color image bit-plane sliced into 8 layers. From top-left to bottom-right: layer 1, layer 2, ..., layer 8, and the original image.

Table 2: The averages of bad matching pixels (in percentage) obtained using SG, GC and NL algorithms.

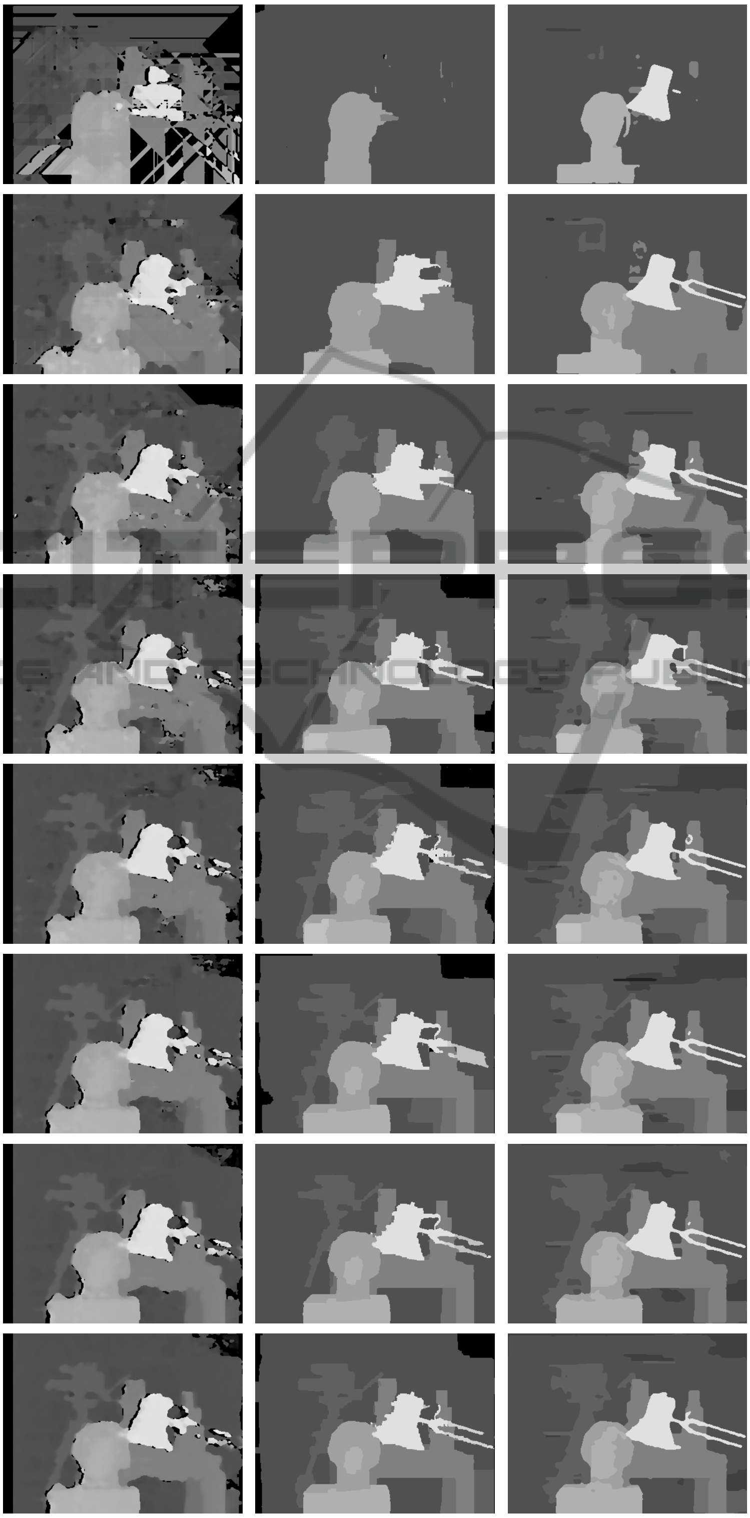
Algorithm	8-bit	7-bit	6-bit	5-bit	4-bit	3-bit	2-bit	1-bit
Semi-global matching	20.6 %	20.7 %	21.0 %	21.5 %	22.8 %	24.8 %	30.6 %	38.8 %
Graph cut	14.4 %	14.7 %	14.5 %	15.1 %	16.0 %	17.9 %	41.8 %	52.2 %
Non-local aggregation	5.48 %	5.31 %	6.00 %	7.40 %	11.9 %	15.7 %	21.2 %	40.8 %

The evaluation with average percentage of bad pixels and average rank is shown in Tables 2 and 3. For semi-global matching, although the bad-pixel rate and the average rank are not so good, it reduces only 1 percent of bad pixels with half of the image data (with a 4-bit image). Graph cut method from OpenCV also shows good results, losing only 2 - 3% of the average bad pixels compared to the one using all 8 bits. Note that these two dense stereo algorithms use 8-bit grayscale stereo images as input. On the other hand, NonLocalFilter uses 24-bit RGB color stereo image pairs as input (8 bits for each color channel). Bit-plane slicing color stereo input images is done similar to the 8-bit grayscale stereo pairs, but it is done in each of the three color channels simultaneously. It seems that taking the advantage of color stereo input images gains the ability to calculate the aggregation costs better. This results in having the best performance when using all stereo pairs input data or even when masking out lower-bits in each color channel.

It is noted that if we compare the disparity preserving only top-most 2 bits and top-most 3 bits results, NonLocalFilter's disparity map seems capable of estimating objects in the foreground such as the lamp (white shape in the disparity map) and the head sculpture's disparity still can be seen. Items with larger disparities seems to vanish from disparity map. This may have something to do with the color luminance existing in each 3 RGB color channels. On the other hand, Graph cut's disparity estimation performance for foreground and background objects degrade evenly while masking input stereo image pair bits.

5 CONCLUSIONS

In this work, a hierarchical stereo matching framework is presented. A pyramid image representation is used to combine with existing stereo matching algorithms for disparity computation. Graph-cut, semi-global matching and non-local aggregation methods are tested in our framework with various bit-rate image pairs. The disparity computation for



(a) Semi-global matching (b) Graph-cut (c) Non-local filter

Figure 3: The disparity maps computed using the stereo matching algorithms, semi-global matching, graph-cut and non-local aggregation.

Table 3: The averages rank obtained by performing stereo matching using SG, GC and NL algorithms.

Algorithm	8-bit	7-bit	6-bit	5-bit	4-bit	3-bit	2-bit	1-bit
Semi-global matching	148.2	148.3	148.8	149.6	150.8	151.2	151.8	152
Graph cut	121.7	124	131.4	130.3	135.8	140.4	151.5	152
Non-local aggregation	45.4	43.2	65.5	89	117.2	137	149.3	151.9

stereo datasets are submitted to Middlebury stereo site for performance evaluation. The results have demonstrated the feasibility of our bit-plane slicing based stereo matching framework.

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REFERENCES

Akhavan, T., Yoo, H., and Gelautz, M. (2013). A framework for hdr stereo matching using multi-exposed images. In *Proceedings of HDRi2013 - First International Conference and SME Workshop on HDR imaging (2013)*.

Brown, M. Z., Burschka, D., and Hager, G. D. (2003). Advances in computational stereo. *IEEE Trans. Pattern Anal. Mach. Intell.*, 25(8):993–1008.

Chen, Y.-S., Hung, Y.-P., and Fuh, C.-S. (2001). Fast block matching algorithm based on the winner-update strategy. *IEEE Transactions on Image Processing*, 10(8):1212 –1222.

Gong, M. and Yang, Y.-H. (2001). Multi-resolution stereo matching using genetic algorithm. In *SMBV '01: Proceedings of the IEEE Workshop on Stereo and Multi-Baseline Vision (SMBV'01)*, page 21.

Hirschmuller, H. (2008). Stereo processing by semiglobal matching and mutual information. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 30(2):328–341.

Hirschmuller, H. and Scharstein, D. (2007). Evaluation of cost functions for stereo matching. In *Computer Vision and Pattern Recognition, 2007. CVPR '07. IEEE Conference on*, pages 1–8.

Humenberger, M., Zinner, C., Weber, M., Kubinger, W., and Vincze, M. (2010). A fast stereo matching algorithm suitable for embedded real-time systems. *Computer Vision and Image Understanding*, 114(11):1180 – 1202. Special issue on Embedded Vision.

Kolmogorov, V. and Zabin, R. (2004). What energy functions can be minimized via graph cuts? *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 26(2):147–159.

Konolige, K. (1997). Small vision systems: hardware and implementation. In *Eighth International Symposium on Robotics Research*, page 111–116.

Lin, H.-Y. and Chou, X.-H. (2012). Stereo matching on low intensity quantization images. In *Pattern Recognition (ICPR), 2012 21st International Conference on*, pages 2618–2621.

Lin, H.-Y. and Lin, P.-Z. (2013). Hierarchical stereo matching with image bit-plane slicing. *Mach. Vision Appl.*, 24(5):883–898.

Lu, J., Rogmans, S., Lafruit, G., and Catthoor, F. (2009). Stream-centric stereo matching and view synthesis: A high-speed approach on gpus. *IEEE Transactions on Circuits and Systems for Video Technology*, 19(11):1598 –1611.

Min, D. and Sohn, K. (2008). Cost aggregation and occlusion handling with wls in stereo matching. *IEEE Transactions on Image Processing*, 17(8):1431 –1442.

Scharstein, D. and Szeliski, R. (2002a). Middlebury stereo vision page. *http://vision.middlebury.edu/stereo*.

Scharstein, D. and Szeliski, R. (2002b). A taxonomy and evaluation of dense two-frame stereo correspondence algorithms. *Int. J. Comput. Vision*, 47(1-3):7–42.

Scharstein, D. and Szeliski, R. (2003). High-accuracy stereo depth maps using structured light. In *Computer Vision and Pattern Recognition, 2003. Proceedings. 2003 IEEE Computer Society Conference on*, volume 1, pages I–195–I–202 vol.1.

Sun, J., Zheng, N.-N., and Shum, H.-Y. (2003). Stereo matching using belief propagation. *IEEE Trans. Pattern Anal. Mach. Intell.*, 25(7):787–800.

Szeliski, R., Zabih, R., Scharstein, D., Veksler, O., Kolmogorov, V., Agarwala, A., Tappen, M., and Rother, C. (2008). A comparative study of energy minimization methods for markov random fields with smoothness-based priors. *IEEE Trans. Pattern Anal. Mach. Intell.*, 30(6):1068–1080.

Yang, Q. (2012). A non-local cost aggregation method for stereo matching. In *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on*, pages 1402–1409.