Efficient Disparity Computation without Maximum Disparity for Real-Time Stereo Vision

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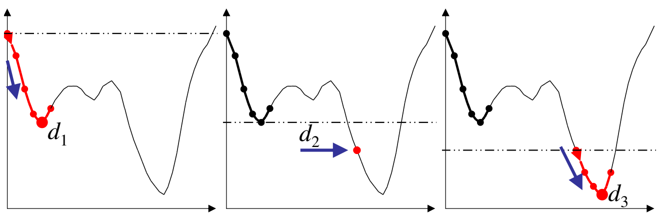
In order to improve the performance of correlation-based disparity computation of stereo vision algorithms, standard methods need to choose in advance the value of the maximum disparity (MD). This value corresponds to the maximum displacement of the projection of a physical point expected between the two images. It generally depends on the motion model, the camera intrinsic parameters and on the depths of the observed scene.

In this paper, we show that there is no optimal MD value that minimizes the matching errors in all image regions simultaneously and we propose a novel approach of the disparity computation that does not rely on any a priori MD. A local energy minimization is also proposed for fast refinement of the results.

We successfully reduce the matching errors compared to traditional local correlation since our approach uses locally a minimal MD. Furthermore, our approach is simple to implement and the iterative search technique might be integrated into other stereo matching algorithms as well. Finally, our proposal is even faster than the fastest possible implementation of local correlation with integral images [1, 4]. That is because we significantly reduce the number of required correlations which ultimately saves processing time.

Disparity Computation without MD Instead of determining disparities by a brute-force search within the whole disparity domain, we focus on an iterative algorithm that stops at the right value. We perform two operations at each pixel: a minimization followed by a propagation-step. The minimization basically follows a line search strategy and allows us to find the "next" local minimum of the matching cost function. The propagation collects neighbouring disparity values and selects the best disparity of those for the current pixel (in terms of the dissimilarity value).

The process of performing the minimization- and propagation-steps alternately is exemplified in Fig. 1(a).



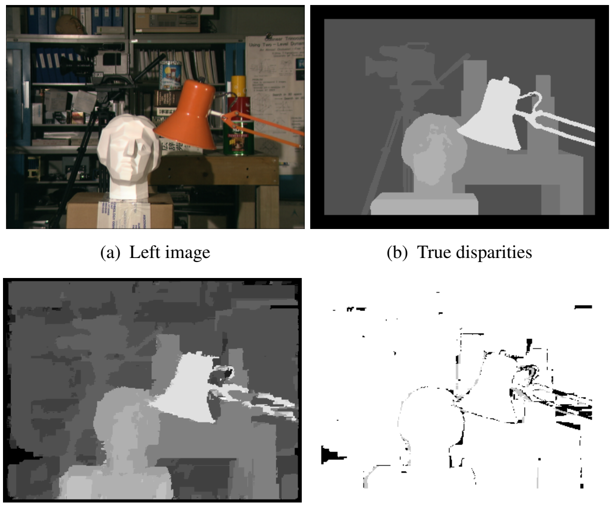
(a) Minimization (Iteration 1) (b) Propagation (Iteration 1) (c) Minimization (Iteration 2)

Figure 1: An example for a dissimilarity function (vertical axis) over disparity (horizontal axis). (a) Only the first minimum d_1 of the function is found by minimization. (b) Then, an adjacent disparity d_2 is propagated since d_2 has a lower dissimilarity. (c) Another minimization finds the optimal minimum d_3.

Local Energy Minimization Based on the assumption that the depth-map of a local method is a rough estimate of the ideal solution, we focus on enhancing a previously computed depth-map. To maximize the efficiency, we perform a winner-take-all optimization at every pixel (which is different to scanline optimization [3]). The general idea is to propagate disparities through their neighbourhood, which comes down to a minimization of

$$\mathscr{D}(\mathbf{p}) \mapsto \arg \min_{d \in N(\mathbf{p})} C(\mathbf{p}, d) \tag{1}$$

with the neighbouring disparities $N(\mathbf{p})$ and the pixelwise matching cost $C(\mathbf{p}, d)$.



(a) Left image (b) True disparities (c) Our Algorithm + Refinements (d) Bad Pixels of (c)

Figure 2: Qualitative results for the Tsukuba dataset.

Method	Tsukuba	Venus	Teddy	Cones
Traditional correlation-based	11.17	14.16	25.96	22.50
Traditional + Refinements	3.71	4.02	18.84	17.50
Our Algorithm	9.11	11.65	22.60	22.39
Our Algorithm + Refinements	3.93	4.54	17.00	17.15
Hirschmüller [2]	4.25	1.53	–	–
Graph-Cuts (gray scale)	4.43	4.53	25.93	17.76
Graph-Cuts (color)	4.13	2.66	17.65	15.97

Table 1: The errors of the methods (percentage of disparities that differ by more than 1; we ignore a border of 18 pixels) Correlation with our efficient disparity computation algorithm in conjunction with our refinements (local energy minimization with occlusion detection) comes close to the graph-cuts method.

Method	Tsukuba	Venus	Teddy	Cones
Traditional Correlation	32	52	98	98
Our Algorithm	31	44	47	48
Our Algorithm + Refinements	46	74	73	85
Graph-Cuts	> 1000	> 1000	> 1000	> 1000

Table 2: Execution Times at standard data sets in milliseconds. Our algorithm is up to twice as fast as the fastest possible implementation of the traditional disparity computation.

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[2] Heiko Hirschmüller, Peter R. Innocent, and Jon Garibaldi. Real-time correlation-based stereo vision with reduced border errors. *IJCV*, 47 (1-3):229–246, 2002.

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