MI tech

Multimedia Imaging Technology

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Inclusion of a Second-Order Prior into Semi-Global Matching

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Outline and Objective

Abstract

We consider different parameter settings for SGM, suggest to include a second order prior into the smoothness term of the energy function, and propose and test a new cost function. Some preprocessing (edge images) proves to be of value for improving SGM stereo results on real-world data.

Our Approach

We evaluate variants of the SGM algorithm of [H. Hirschmüller] both on stereo images of the Middlebury stereo website as well as on real-world image sequences of the *.enpeda..* image sequence analysis test site. We highlight differences in behavior on different data sets.

Modified SGM Cost Function

Cost-Function of Semi-Global Matching

For a digital line in direction **a**, processed between image border and pixel p, we only consider the segment $p_0p_1 \ldots p_n$ of that digital line, with p_0 on the image border, and $p_n = p$. The cost at pixel position p (for a disparity d) on the path $L_\mathbf{a}$ is recursively defined as follows (for $i = 1,2, \ldots, n$):

$$\begin{aligned} L_\mathbf{a}(p_i, d) = \; & C(p_i, d) + \min\big[L_\mathbf{a}(p_{i-1}, d), \\ & L_\mathbf{a}(p_{i-1}, d-1) + c_1, L_\mathbf{a}(p_{i-1}, d+1) + c_1, \\ & \min_{\Delta} L_\mathbf{a}(p_{i-1}, \Delta) + c_2\big] - \min_{\Delta} L_\mathbf{a}(p_{i-1}, \Delta) \end{aligned}$$

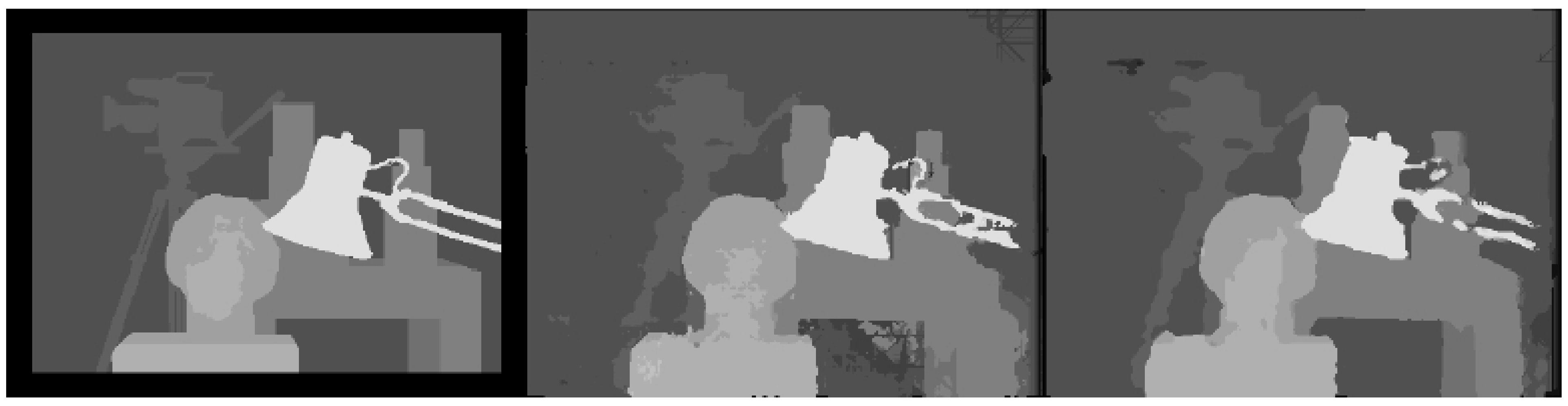
where $C(p,d)$ corresponds to the data term and is the similarity cost of pixel p for disparity d. The costs of paths $L_\mathbf{a}$, for all (say, eight) directions **a**, are accumulated at a pixel p, for all disparities d with $0 \leq d \leq d_{max}$, and the disparity d_{opt} with the lowest cost is finally selected.

Modified SGM Cost-Function

Let d_{mp} be the disparity with the current minimum cost on the path at previous position p_{i-1}, and c_3 be a `disparity smoothness' parameter:

$$\begin{aligned} L_\mathbf{a}(p, d) = \; & C(p, d) + \; \min\big[L_\mathbf{a}(p_{i-1}, d), L_\mathbf{a}(p_{i-1}, d-1) + c_1 + c_3(d-1), \\ & L_\mathbf{a}(p_{i-1}, d+1) + c_1 + c_3(d+1), \min_{\Delta} L_\mathbf{a}(p_{i-1}, \Delta) + c_2 + c_3(d_{mp})\big] \\ & - \min_{\Delta} L_\mathbf{a}(p_{i-1}, \Delta) \end{aligned}$$

Results



Above: ground truth of Tsukuba, SGM reference result, and result with modified costfunction and optimized preprocessing.

Right: example of an *.enpeda..* stereo sequence and Sobel image (top), SGM on orihginal and Sobel sequence, and modified SGM (with optimized preprocessing) on original and Sobel sequence.

We included an additional penalty to the accumulation step, based on a second order prior. Results indicate that there is a poten–tial for performance gain, justifying more experiments for this subject in future. We also tested SGM on Sobel images of the Tsukuba image sequence on the Middlebury stereo page. Results indicate that edge preoprocessing can improve the quality of the algorithm (see Table 8). Especially the outcome of our experiments on real-world sequences suggest that processing SGM on edge images can also result in a big performance gain. Performance gains are much better on real world sequences than on engineered data. Therefore it would be interesting to quantify how much real world stereo analysis actually benefits by optimizing for engineered data (only).