Segment-Tree Based Cost Aggregation for Stereo Matching with Enhanced Segmentation Advantage

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I. Introduction

Segment-tree (ST) based cost aggregation algorithm [1] successfully integrates the information of segmentation with non-local cost aggregation framework. However, the original strategy performs unreasonable, so we propose a novel segmentation algorithm for constructing a more faithful ST with enhanced segmentation advantage according to a robust initial over-segmentation. Then we implement non-local cost aggregation framework on this new ST structure and obtain improved disparity maps. Performance evaluations on all 31 Middlebury stereo pairs show that the our algorithm outperforms other five state-of-the-art algorithms and also keeps time efficiency.

II. Proposed Algorithm

For the original ST based stereo matching algorithm, the tree structure is represented by:

$$o = \min \{ \min \{ \text{left}(T), \max \{ \text{right}(T) \} \} \}$$

(1)

However, in formula (1) the original segmentation algorithm performs underwhelming for the following reasons:

1) Large k leads to a much relaxed threshold at the beginning of grouping and performs under-segmentation regions with inconsistent boundaries.

2) Small l performs better at the beginning of grouping but inevitably leads to consistent over-segmentation and too many boundaries.

3) As the region size [2] grows, 4(l) decreases dramatically which becomes increasingly unreliable for discriminating between regions of the same type.

4) When |p| increases, the connecting decision function would perform much too constrained. It will break the homogeneous regions into different segments and contrary to the disparity consistency assumption.

More importantly, while implementing non-local cost aggregation on this imperfect ST structure would lead the substandard utilization of segmentation advantage.

Based on these reasons, an algorithm is proposed for constructing a new ST structure by us. The connected decision function can be formulated as follows:

$$o = \min \{ \min \{ \text{left}(T), \max \{ \text{right}(T) \} \} \} + k \cdot \text{left}(T) \cdot \max \{ \text{right}(T) \}$$

(2)

Here we choose k as 0.02. We perform it mainly on the following considerations:

1) It begins with a more constrained threshold while grouping. The choice of k keeps most of the boundaries coincide with true region borders.

2) When |p| increases, the proposed segmentation algorithm performs a more relaxed threshold: It could enforce more similar regions merged and perform more compatible with disparity consistency assumption.

With formula (2), an Improved-ST (IST) based non-local cost aggregation algorithm for stereo matching can be implemented, which is described:

Algorithm 1. Improved-ST Algorithm

1. for each p = 1

2. Compute Matching cost with method of (2)

3. end for

4. Construct updated ST with Color-Depth weight:

$$\text{left}(T) = \min \{ \text{left}(T) + k \cdot \text{left}(T) \ \text{left}(T) \}$$

$$\text{right}(T) = \max \{ \text{right}(T) + k \cdot \text{right}(T) \ \text{right}(T) \}$$

5. Aggregate costs and set D as an updated result.

III. Experimental Results

Performance Evaluations on all 31 Middlebury Stereo Pairs in non-occluded Regions without Disparity Refinement

IV. Conclusion

We improved the ST based stereo algorithm by using a novel segmentation algorithm. Firstly, it provides an enhanced segmentation advantage and constructs a more faithful ST structure. Secondly, it also better meets the disparity consistency assumption. Based on this new tree structure, an Improved Segment-tree (IST) non-local cost aggregation algorithm can be performed. Performance evaluations show that the proposed algorithms outperforms than other five aggregated based algorithms on all 31 Middlebury stereo pairs and time consuming does not increase too much.

V. Reference


Fig. 1. Results of Baby3,Cone and Dolly by six algorithms with Disparity refinement.

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Performance Evaluations on all 31 Middlebury Stereo Pairs in non-occluded Regions with Disparity Refinement

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