# Asymmetric post-processing for stereo correspondence

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## Abstract

*This paper presents a novel approach that performs post-processing for stereo correspondence. We improve the performance of stereo correspondence by performing consistency check and adaptive filtering in an iterative filtering scheme. The consistency check is done with asymmetric information only so that very few additional computational loads are necessary. The proposed post-filtering method can be used in various methods for stereo correspondence without any modification. We demonstrate the validity of the proposed method by applying it to hierarchical belief propagation and semi-global matching.*

## 1 Introduction

The correspondence problem has been an important issue in the field of computer vision, and many methods have been proposed to solve this problem. An extensive review of stereo matching algorithms can be found in [1]. Several post-processing methods have been proposed to improve the performance of stereo matching. They detect incorrect correspondences with cross-checking method, and then apply the interpolation technique by using the disparities of the visible pixels. Mattoccia used two-step refinement process which uses the estimated depth border information and mean shift algorithm for the refinement of disparity maps [3]. Hirschmuller proposed the refinement method for semi-global matching which uses intensity consistent disparity selection and discontinuity preserving interpolation with color segmentation [4].

In this paper, we propose a novel approach to efficient post-processing for stereo correspondence. The refinement process is done through an iterative filtering scheme with asymmetric consistency check and adaptive filtering. The proposed method can be used in the various methods without any modification, when suitable cost function is used.

## 2 Proposed post-processing method

The proposed post-processing method consists of two parts, which are consistency check and adaptive filtering. The reliability function of disparity map is estimated through consistency check, and it is used in adaptive filtering for the refinement of disparity map, which is used for the consistency check again. We can improve the quality of disparity map through the iterative filtering scheme as shown in Fig. 1. In this paper, we use asymmetric information for consistency check with minimum amount of additional computational loads. Only the left disparity field needs to be used. The adaptive filtering is done only with the pixels referred to as reliable by the consistency check.

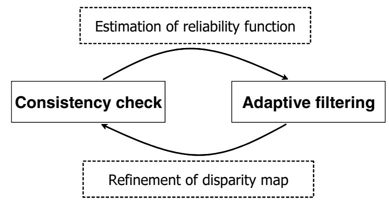


**Figure 1. Iterative filtering scheme**

### 2.1 Asymmetric consistency check

The reliability function is estimated asymmetrically by using consistency check in the proposed post-processing scheme, while other methods use the symmetric matching scheme. If $d_l(p) \neq d_r(p - d_l(p))$ in the symmetric consistency check, the disparity in pixel $p$ can be referred to as invalid. It is possible to classify invalid pixels into occlusion and false matches by determining whether there are depth discontinuities in right image or not, since the depth discontinuities in one image correspond to occlusions in the other image.

In the proposed method, since the invalid pixels are detected with asymmetric information only, the left disparity map is used in the consistency check. We determine a candidate set of invalid pixels, and do not discriminate occlusion and false matches from invalid disparities. The same post-processing method is applied to both occlusion and false matches. It is different from conventional methods which handle the occlusion and false matches in the different manner [3][4]. Although some valid pixels may be contained in the candidate set of invalid pixels, this problem can be solved by using

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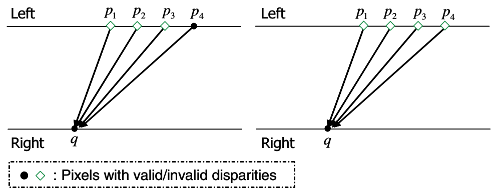


**Figure 2. Asymmetric consistency check**

the proposed post-processing method. For asymmetric consistency check, we use geometric and photometric constraints. To determine whether a pixel is valid or not, we evaluate the disparity values of the neighboring pixels. We define the binary reliability function $R(i)$ as follows:

$$R(p) = \begin{cases} 1, & if\ d(p)\ is\ valid \\ 0, & otherwise \end{cases} \quad (1)$$

where $d$ represent the disparity of the pixel. For estimating the reliability function, we describe the function $S_r(j)$ as a set of pixels in the right image:

$$S_r(j) = \{i | i - d(i) = j,\ \ all\ i\ with\ \ 0 \le i \le W - 1\}$$

where $i$ and $j$ represent the $x$ coordinates of the left and right images, respectively. $W$ represents the width of the image. When there are multiple matching points at pixels in the other image, that is, $\#(S_r(j)) > 1$, the pixel with the largest disparity among $S_r(j)$ is considered as valid and the remaining pixels are considered invalid. This is available only if the valid pixels have reliable disparities. Fig. 2 shows several cases of asymmetric consistency check. We use the photometric constraint to evaluate the reliability of the disparities in the valid pixels. The costs at the invalid pixels are generally larger than those of the valid pixels. If the cost at the pixel, which is determined as valid pixels by geometric constraints, is not smaller than that of the remaining invalid pixels, we can not guarantee the reliability of the valid pixels. Therefore, all the pixels in $S_r(j)$ are referred to as invalid, that is, $R(i) = 0$ for all $i \in S_r(j)$, as shown in Fig. 2. Here, various cost functions can be used to determine the reliability of pixels: aggregated cost function $E_L(p, d)$ computed by local methods such as shiftable window [5] and adaptive support window [6], or cost function $E_G(p, d)$ computed by global methods such as belief propagation [7] and dynamic programming [4] as follows:

$$E_G(p, d) = E_L(p, d) + \lambda \sum_{q \in N(p)} S(d_p, d_q). \quad (2)$$

## 2.2 Adaptive filtering

Given the reliability function $R$ for disparity map, we can refine costs with adaptive filtering technique. It is based on the assumption that the costs should vary smoothly, except at object boundaries. From this observation, we can propose an iterative nonlinear filtering method with adaptive weight $w$ as follows:

$$E^{k+1}(p, d) = \frac{\sum\limits_{m \in N(p)} R(m) w(p, m) E^k(m, d)}{\sum\limits_{m \in N(p)} R(m) w(p, m)} \quad (3)$$

where $w(p, m)$ means the weighting function in the support window $N(p)$. It is similar to bilateral filtering [8], which is the intuitive nonlinear filtering method that smoothes images while preserving edges. The cost function $E(p, d)$ can generally be initialized to $E_L(p, d)$ or $E_G(p, d)$ in Eq. (3).

One reason for slowing down the convergence in Eq. (3) is that the updated components in each pixel are used only after one iteration is complete. We compensate for this problem by using the updated components in each pixel intermediately. We divide a set of neighbor pixels $N(p)$ into two parts: the causal part $N_c(p)$ and the non-causal part $N_n(p)$. Eq. (3) is expressed based on this relationship as follows:

$$E^{k+1}(p, d) = \frac{\sum\limits_{m \in N_c(p)} R(m) w(p, m) E^{k+1}(m, d) + \sum\limits_{m \in N_n(p)} R(m) w(p, m) E^k(m, d)}{\sum\limits_{m \in N(p)} R(m) w(p, m)}. \quad (4)$$

By running the iteration scheme, the cost function $E$ is regularized with the weighted neighboring pixel cost. In the proposed method, the weighting function $w$ used in Eq. (4) can be classified into symmetric weighting function $w_S$ and asymmetric weighting function $w_A$. Before defining the weighting functions $w_S$ and $w_A$, we describe the following Gaussian weight function $w_l$ and $w_r$ in the CIE-Lab color space as follows:

$$w_i(p, m) = \exp\left( - \left( \frac{C_i(p, m)}{2r_c^2} + \frac{S(p, m)}{2r_s^2} \right) \right) \quad i = l, r$$
$$C(p, m) = (L_p - L_m)^2 + (a_p - a_m)^2 + (b_p - b_m)^2$$
$$S(p, m) = (p - m)^2. \quad (5)$$

By using above equation, $w_S$ and $w_A$ can be expressed as follows:

$$w_S(p, m) = w_l(p, m) w_r(p_d, m_d)$$
$$w_A(p, m) = w_l(p, m). \quad (6)$$

$w_S$ is symmetric in the sense that the weighting function is computed by using both the left and right images, while $w_A$ by using only left image. Fig. 3 shows the overall process of the proposed post-filtering method. Symmetric/asymmetric filtering means that the adaptive filtering is done with symmetric/asymmetric weighting functions $w_S/w_A$. In the symmetric filtering, adaptive filtering is performed for all the pixels. The symmetric

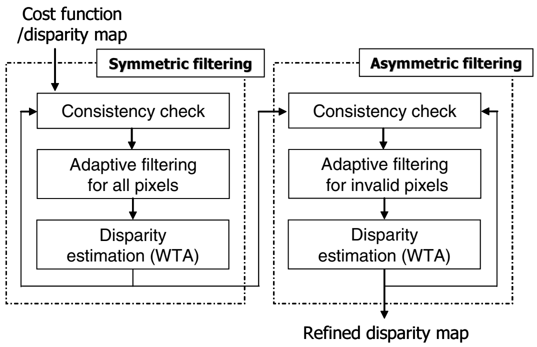


**Figure 3. Proposed post-filtering method**

weighting function is available only when corresponding pixels on both images are visible, since it uses both left and right images. Therefore, asymmetric filtering is performed in order to refine costs of the invalid pixels. The reasonable costs are assigned to invalid pixels through asymmetric filtering. Adaptive filtering is sequentially performed. After adaptive filtering is performed at the invalid pixel, the pixel becomes valid, in other words, $R(p) = 1$. Therefore, the invalid pixels filtered with the valid pixels are used as valid pixels in Eq. (4) again. The information in valid pixels is propagated to estimate the cost function of invalid pixels.

The proposed post-processing method can be applied to several optimization techniques. In this paper, we confirm the validity of the proposed method by applying it to hierarchical belief propagation (HBP) [7] and semi-global matching (SGM) [4]. In SGM, we use 4-pass scanline optimization for computing global cost function, which is different from [4].

## 3 Experimental Results

We evaluate the performance of the proposed method and compared it with state-of-the-art methods in the Middlebury test bed [12]. Since our main goal is to propose the efficient post-processing method, we evaluate the improvement of performance by post-processing method for HBP and SGM. For objective evaluation, we measured the percentage of bad matching pixels (where the absolute disparity error is greater than 1 pixel). The measurement is computed for three subsets of an image: nonocc (the pixels in the non-occluded regions), all (the pixels in both the non-occluded and half-occluded regions), and disc (the visible pixels near the occluded regions). The proposed method is tested using the same parameters for all the test images. The two parameters in the weighting function are $r_c = 8.0$, $r_s = 8.0$, and the size of window for adaptive filtering is $11 \times 11$. In Fig. 3, the number of iterations is 1. We obtained sufficient improvement just after one iteration.

Fig. 4 shows the results of the proposed post-

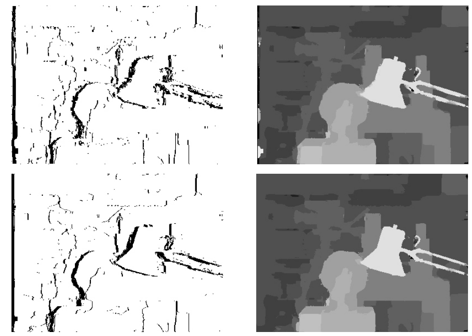

**Figure 5. Intermediate results of proposed method for HBP. Results for (From top to bottom) symmetric/asymmetric filtering**

processing method for HBP and SGM. The proposed method showed accurate results for discontinuity, occluded, and textureless regions. Table 1 shows that the proposed method obtained comparable performance with state-of-the-art methods, although it used the post-processing with asymmetric information only without using color segmentation. We can find that the proposed post-filtering method improved the performance of HBP in nonocc, all, disc region significantly. Fig. 5 shows the intermediate results of the proposed method for HBP. Given the cost function and disparity map, the invalid pixels were estimated with asymmetric consistency check. We could find that consistency check and adaptive filtering compensated each other and improved the performance in the iterative filtering scheme.

## 4 Conclusion

In this paper, we have proposed the asymmetric post-processing method for stereo correspondence. The iterative filtering scheme improves the performance of stereo matching by filtering the cost function with invalid pixel map. Since the asymmetric information is used for estimating the invalid pixel map, minimum amount of additional computational loads are necessary for consistency check. The information at the valid pixels was propagated into the invalid pixels by adaptive filtering. The proposed method can be used in various methods without any modification. The experimental results show that the proposed post-filtering method improved the performance of HBP and SGM, and especially the performance of the post-processing method for HBP is comparable to state-of-the-art methods in the Middlebury stereo datasets.

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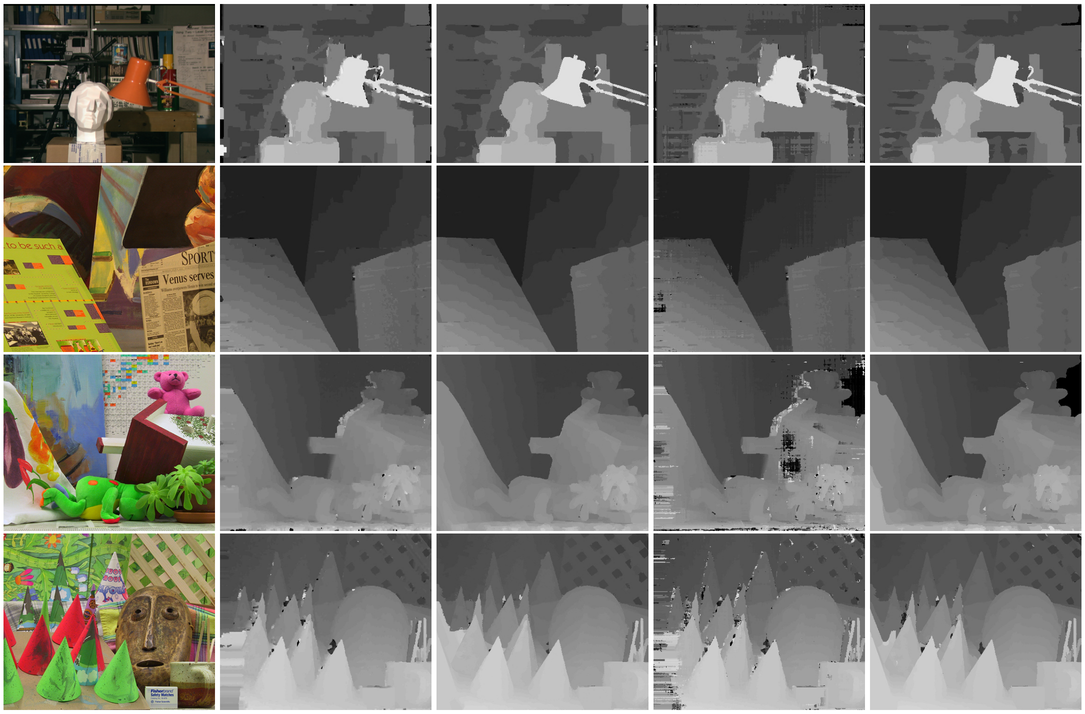

**Figure 4. Results for (from top to bottom) 'Tsukuba', 'Venus', 'Teddy' and 'Cone' image pairs: (from left to right) original images, HBP, HBP+post-filtering, SGM, SGM+post-filtering.**

**Table 1. Objective evaluation for the proposed method with the Middlebury test bed**

| Algorithm | *Tsukuba* | | | *Venus* | | | *Teddy* | | | *Cone* | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | nonocc | all | disc | nonocc | all | disc | nonocc | all | disc | nonocc | all | disc |
| AdaptingBP [2] | 1.11 | 1.37 | 5.79 | 0.10 | 0.21 | 1.44 | 4.22 | 7.06 | 11.8 | 2.48 | 7.92 | 7.32 |
| DoubleBP [9] | 0.88 | 1.29 | 4.76 | 0.14 | 0.60 | 2.00 | 3.55 | 8.71 | 9.70 | 2.90 | 9.24 | 7.80 |
| **HBP + PostFil** | **1.12** | **1.63** | **5.44** | **0.48** | **1.08** | **2.51** | **7.65** | **11.4** | **18.1** | **3.46** | **10.6** | **8.79** |
| OverSegmBP [10] | 1.69 | 1.97 | 8.47 | 0.51 | 0.68 | 4.69 | 6.74 | 11.9 | 15.8 | 3.19 | 8.81 | 8.89 |
| EnhancedBP [11] | 0.94 | 1.74 | 5.05 | 0.35 | 0.86 | 4.34 | 8.11 | 13.3 | 18.5 | 5.09 | 11.1 | 11.0 |
| **HBP** | **2.35** | **4.49** | **11.0** | **1.62** | **2.72** | **11.3** | **8.42** | **14.3** | **21.6** | **5.14** | **13.4** | **12.9** |


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