Fast and Robust Disparity Estimation from Noisy Light Fields Using 1-D Slanted Filters

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SUMMARY Depth (disparity) estimation from a light field (a set of dense multi-view images) is currently attracting much research interest. This paper focuses on how to handle a noisy light field for disparity estimation, because if left as it is, the noise deteriorates the accuracy of estimated disparity maps. Several researchers have worked on this problem, e.g., by introducing disparity cues that are robust to noise. However, it is not easy to break the trade-off between the accuracy and computational speed. To tackle this trade-off, we have integrated a fast denoising scheme in a fast disparity estimation framework that works in the epipolar plane image (EPI) domain. Specifically, we found that a simple 1-D slanted filter is very effective for reducing noise while preserving the underlying structure in an EPI. Moreover, this simple filtering does not require elaborate parameter configurations in accordance with the target noise level. Experimental results including real-world inputs show that our method can achieve good accuracy with much less computational time compared to some state-of-the-art methods.

key words: light field, epipolar plane image, denoising, disparity estimation

1. Introduction

Due to recent advances in image acquisition techniques [1]–[5], depth (disparity) estimation from a set of multi-view images or a light field has attracted much research interest. The most straightforward approach is called multi-view stereo [6]–[12], where the classical stereo matching methods for two images are extended directly to a set of multi-view images. The basic idea is to find corresponding points across the images. Defocus and correspondence cues [13], [14], which were recently developed for light fields, also fall into this category. Another approach [15]–[20] is to analyze the structure of an epipolar plane image (EPI) [21]–[23] that is obtained from the light field. This approach is based on the fact that an EPI consists of many line patterns, and the slopes of those lines are directly related to the depth information. Wanner and Goldluecke [15], [19] have applied structure tensor analysis to EPIs to estimate the slopes. Their method has been proven to be fast and accurate when the light field is sufficiently dense, i.e., the disparity range between the neighboring viewpoints is sufficiently small, as is often the case with those taken by light field cameras [24].

In this paper, we focus on how to handle a dense but *noisy* light field for disparity estimation, because if left as it is, the noise degrades the accuracy of estimated disparity maps. Several researchers have worked on this problem, e.g., by introducing disparity cues that are robust to noise [25], [26]. However, it is not easy to break the trade-off between the accuracy and computational speed. To tackle this trade-off, we proposed a method in [27]^{*}, which combines a fast disparity estimation framework developed in [19] with a fast denoising scheme. Specifically, we found that a simple 1-D slanted filter is very effective for reducing noise while preserving the underlying structure in an EPI. Moreover, this simple filtering does not require elaborate parameter configurations in accordance with the target noise level. Experimental results including real-world inputs show that our method can achieve good accuracy with much less computational time compared to some state-of-the-art methods.

In the remainder of this paper, we first mention disparity estimation through the EPI analysis in Sect. 2. We will then introduce our method that incorporates denoising with 1-D slanted filters into the framework of the EPI analysis in Sect. 3. Experimental validations are presented in Sect. 4, followed by conclusion in Sect. 5.

2. Disparity Estimation through EPI Analysis

We assume that a set of multi-view images, such as that shown in Fig. 1 (left), is given. These images constitute a 4-D light field $l(s, t, x, y)$, where (s, t) denotes a viewpoint and (x, y) denotes a pixel position. A 2-D subspace of the 4-D light field with a fixed (s, x) or (t, y) is called an epipolar

Fig. 1 Multi-view images (left) and EPI (right)

^{*}This paper is an extension of our conference paper [27], with more thorough experimental evaluations. Several experimental results were revised, because we noticed that some conditions were not consistent among different methods in [27].

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Fig. 2 EPIs (top) and confidence maps (bottom). The insets show filter kernels applied to noisy EPI.

plane image (EPI). For example, $l^{t^*y^*}(x, s) = l(s, t^*, x, y^*)$ is an EPI on the (x, s) plane where t and y are fixed to t^* and y^* , respectively, as shown in Fig. 1 (right). The EPI consists of many lines, each of which is a trace of an object point, and its direction (slope) corresponds to the depth of the object point. Therefore, analyzing the line direction is equivalent to estimating the depth [15]–[17], [19]–[21].

Based on this idea, Wanner and Goldluecke [15], [19] have developed a depth estimation method using structure tensor analysis. A structure tensor on an EPI $l(x, s)$ is defined as:

$$J(x, s) = \begin{bmatrix} G * (l_x l_x) & G * (l_x l_s) \\ G * (l_x l_s) & G * (l_s l_s) \end{bmatrix}, \quad (1)$$

where $G*$ denotes convolution with a Gaussian filter kernel. In this paper, the filter size is fixed to the default value of [28]: a 3×3 kernel with $\sigma = 1$. Symbols l_x and l_s denote gradients of the EPI along x and s directions. The dominant gradient direction $\theta(x, s)$ and its confidence $c(x, s)$ (coherence in [15], [19]) can be obtained from principle component analysis of matrix J .

$$\theta(x, s) = \frac{1}{2} \arctan \left(\frac{2J_{12}(x, s)}{J_{11}(x, s) - J_{22}(x, s)} \right) \quad (2)$$

$$c(x, s) = \frac{\sqrt{(J_{11}(x, s) - J_{22}(x, s))^2 + 4J_{12}^2(x, s)}}{J_{11}(x, s) + J_{22}(x, s)}, \quad (3)$$

where larger $c(x, s)$ means stronger confidence. The disparity $d(x, s)$ is given by $d(x, s) = \tan \theta(x, s)$. For simplicity, we describe these processes as a function $\text{EPIAnaly}(\cdot)$. For fixed t^* and y^* , this function is written as:

$$(d^{t^*y^*}(x, s), c^{t^*y^*}(x, s)) = \text{EPIAnaly}(l^{t^*y^*}(x, s)). \quad (4)$$

To obtain a disparity map for a specific viewpoint (s^*, t^*) , we perform the EPI analysis for both on (x, s) and (y, t) EPIs and combine the results in accordance with the point-wise confidence values.

$$d^{s^*t^*}(x, y) = \begin{cases} d^{t^*y^*}(x, s^*) & c^{t^*y^*}(x, s^*) \geq c^{s^*x^*}(y, t^*) \\ d^{s^*x^*}(y, t^*) & \text{otherwise.} \end{cases} \quad (5)$$

The disparity map $d^{s^*t^*}(x, y)$ is further refined using a fast denoising or a more sophisticated global optimization method. The former, which was used in this paper, is given as:

$$\hat{d}^{s^*t^*}(x, y) = \arg \min_{d(x, y)} E(d(x, y), d^{s^*t^*}(x, y)) \quad (6)$$

$$E(\alpha, \alpha_0) = \int_{\Omega \subset \mathbb{R}^2} h(x, y) |D_{xy} \alpha| + \frac{1}{2\lambda} |\alpha - \alpha_0| d\Omega \quad (7)$$

$$h(x, y) = 1 - \max(c^{t^*y^*}(x, s^*), c^{s^*x^*}(y, t^*)), \quad (8)$$

where Ω is the 2-D pixel domain, λ is a smoothing strength, and D_{xy} is a 2-D derivative operator. The first term of Eq. (7) penalizes non-smoothness on the disparity map, and its strength is controlled by the per pixel confidence of the initial disparity value; less confident disparities are more strongly smoothed.

3. Proposed Method

3.1 Denoising an EPI with 1-D Slanted Filters

Figure 2 illustrates an essential problem in depth estimation on an EPI and our idea as a remedy for this. As shown in (a), the noiseless EPI (top) exhibits clear line patterns, with which stable disparity estimation is possible, as indicated by the high confidence values (bottom). However, if the EPI is contaminated by noise as shown in (b), the line patterns become obscure, so we can no longer estimate disparities confidently. To solve this problem, we should somehow remove or soften the effect of noise before applying the EPI analysis.

In doing so, we focus on an inherent structure of the noiseless EPIs: the pixel values are almost the same along the intrinsic line patterns. To fully exploit this structure for denoising, we propose using a simple averaging filter whose kernel has only 1-D support, as shown in the insets of (c) and (d). Specifically, the denoising process on $l(x, s)$ is described as

$$\text{Denoise}(l(x, s); a) = \frac{1}{2r + 1} \sum_{|s'| \leq r} l(x + as', s + s'), \quad (9)$$

where a and r determine the direction (slope) and length of the filter kernel. For a non-integer pixel position, we apply linear interpolation. Different from the *edge-preserving* or *edge-aware* filters [29]–[32], our filter does *not at all* destroy the underlying line patterns if the lines in a local region have a constant slope and a is chosen correctly. Moreover, our filter does not require fine parameter tuning in accordance with the noise level. In fact, parameter r was fixed to 2 for all noise levels in our research.

In Fig. 2 (c) (d), we used two different values for a in

applying this denoising filter to the noisy EPI. When a corresponds to the intrinsic line patterns in the target EPI ((c)), we can successfully remove the noise while preserving the underlying line patterns. Meanwhile, when a takes an inappropriate value ((d)), the noise can be removed, but at the same time the intrinsic line patterns are blurred out. Importantly, we can identify which value of a is suitable to this EPI by observing the confidence values; they are high in (c) but low in (d). This observation leads to a simple but effective algorithm that will be presented in the next subsection.

3.2 Algorithm

We first determine the candidate slope values a_n for denoising as

$$a_n = a_{\min} + \frac{a_{\max} - a_{\min}}{N - 1}n \quad (n = 0, 1, \dots, N - 1). \quad (10)$$

where a_n changes from $a_{\min}$ to $a_{\max}$ in N steps. For all pixels on the EPI $l^{t^*y^*}(x, s)$, we perform denoising along the slope a_n as

$$l_n^{t^*y^*}(x, s) = \text{Denoise}(l^{t^*y^*}(x, s); a_n), \quad (11)$$

followed by the structure tensor analysis as

$$(d_n^{t^*y^*}(x, s), c_n^{t^*y^*}(x, s)) = \text{EPIAnaly}(l_n^{t^*y^*}(x, s)). \quad (12)$$

We repeat the processes of Eqs. (11) and (12) for all the slope values a_n and merge the results in accordance with the confidence values.

$$(d^{t^*y^*}(x, s), c^{t^*y^*}(x, s)) = \text{Merge}(\{d_n^{t^*y^*}(x, s), c_n^{t^*y^*}(x, s)\}). \quad (13)$$

The function Merge is given as follows:

Algorithm 1 Joint denoising and disparity estimation

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Input:  $l(s, t, x, y)$ ,  $s^*$ ,  $t^*$ ,  $a_{\min}$ ,  $a_{\max}$ ,  $N$ 
Output:  $\hat{d}^{s^*t^*}(x, y)$ 
// Pre-processing
Obtain  $\{a_n\}$  by Eq. (10)
// Processing on  $(x, s)$  EPIs
for all  $y$  do
   $l^{t^*y}(x, s) = l(s, t^*, x, y)$ 
  for  $n = 0$  to  $N - 1$  do
     $l_n^{t^*y}(x, s) = \text{Denoise}(l^{t^*y}(x, s); a_n)$ 
     $(d_n^{t^*y}(x, s), c_n^{t^*y}(x, s)) = \text{EPIAnaly}(l_n^{t^*y}(x, s))$ 
  end for
   $(d^{t^*y}(x, s), c^{t^*y}(x, s)) = \text{Merge}(\{d_n^{t^*y}(x, s), c_n^{t^*y}(x, s)\})$ 
end for
// Processing on  $(y, t)$  EPIs
for all  $x$  do
   $l^{s^*x}(y, t) = l(s^*, t, x, y)$ 
  for  $n = 0$  to  $N - 1$  do
     $l_n^{s^*x}(y, t) = \text{Denoise}(l^{s^*x}(y, t); a_n)$ 
     $(d_n^{s^*x}(y, t), c_n^{s^*x}(y, t)) = \text{EPIAnaly}(l_n^{s^*x}(y, t))$ 
  end for
   $(d^{s^*x}(y, t), c^{s^*x}(y, t)) = \text{Merge}(\{d_n^{s^*x}(y, t), c_n^{s^*x}(y, t)\})$ 
end for
// Post-processing
Obtain  $\hat{d}^{s^*t^*}(x, y)$  by Eq. (5)
Obtain  $\hat{d}^{s^*t^*}(x, y)$  by Eq. (6)

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$$c(x, s) = \max_n c_n(x, s) \quad (14)$$

$$n(x, s) = \arg \max_n c_n(x, s) \quad (15)$$

$$d(x, s) = d_{n(x,s)}(x, s). \quad (16)$$

The idea behind this merging process is that the disparity value estimated with the highest confidence over all a_n should be preserved.

To obtain a disparity map for a given viewpoint (s^*, t^*) , we perform the processes of Eqs. (11)–(13) both on (x, s) and (y, t) EPIs. Finally, we integrate the disparity values using Eq. (5) and Eq. (6). The entire procedure of our method is described in Alg. 1.

4. Experiments

In Sect. 4.1, we present the effect of the parameter N (in Eq. (10)). In Sects. 4.2 and 4.3, we compare our method with other denoisers and other state-of-the-art disparity estimation methods that are robust to noise. Finally, in Sect. 4.4, we apply our method to real-world inputs.

We used a PC running Ubuntu 14.04 LTS, equipped with an Intel Xeon (R) 3.10 GHz central processing unit (CPU), 16 GB main memory, and a GeForce GTX 660 Ti graphics processing unit (GPU). To implement our method fully utilizing the GPU, we used a continuous global optimization library (cocolib) and light field suite software, both of which were available online [28].

We used computer-generated light field datasets that are available from [33], [34]. Each light field consists of 9×9 views. Table 1 shows the disparity range of datasets. We evaluated the accuracy of the estimated disparity maps against the provided ground truth using the mean squared errors (MSE). To simulate a noisy condition, artificial zero-mean Gaussian noise (the standard deviation is denoted by σ) was added to the input light fields.

4.1 Trade-Off between Accuracy and Processing Time

We first evaluated the effect of the parameter N in Eq. (10). We fixed $a_{\min} = -2.0$ and $a_{\max} = 2.0$ because the range of slopes should cover the disparity range. We used the “buddha” dataset with the noise of $\sigma = 10$. As can be seen from Fig. 3, the accuracy of the estimated disparity increases as the number of steps N becomes large. However, the processing time also increases along with N . Considering the trade-off, we determined to use $N = 5$ in the experiments later. This value will be appropriate for other datasets if

Table 1 Light field datasets used in Sect. 4

Datasets	Disparity range
buddha	[-0.85, 1.62]
monasRoom	[-0.79, 0.72]
stillLife	[-2.71, 2.62]
boxes	[-2.20, 1.40]
museum	[-1.50, 1.30]
dino	[-1.90, 1.90]

they have similar ranges of disparities, as was the case in our experiments.

4.2 Comparison with Other Denoisers

We next evaluated our idea of denoising along the slopes. We compared five scenarios including those using the standard denoisers before applying the EPI analysis: (i) EPI analysis on the noise-free input (noise-free), (ii) EPI analysis directly applied on the noisy input (noisy), (iii) image domain denoising followed by the EPI analysis (spatial denoising), (iv) EPI domain denoising followed by the EPI analysis (EPI denoising), and (v) our method. For all the cases, the EPI analysis was implemented with GPU acceleration.

For scenarios (iii) and (iv), we used a non-local means

Fig. 3 Accuracy and processing time with different N .

filter [30] implemented without GPU acceleration. We chose this filter because it has a similar order of complexity to our method, and it is also known to be edge preserving, reducing the risk of erasing the underlying line patterns while removing the noise. The kernel size and search range for the non-local means filter were set to 3×3 and 5×5 pixels. In this case, the number of neighboring pixels involved in the filtering operation for a pixel was 25. This number was close to that of our method, where 21 neighboring pixels were used for denoising a pixel in the case of $N = 5$ and $r = 2$. It should be noted that in this evaluation, we only verified the idea of denoising along the slopes on an EPI in comparison with standard denoising approaches on the spatial and EPI domains under the similar order of complexity. We did not intend that our method would achieve better denoising performance than more sophisticated (but inevitably computationally-complex) methods [35], [36], because our method was designed rather simple for fast computation.

Figure 4 shows the accuracy of the disparity maps obtained at different noise levels from six datasets. Figure 5 shows disparity maps estimated with $\sigma = 10.0$. It can be seen that our method produced more accurate disparity maps than the simple edge-preserving denoisers that were applied on both the image and the EPI domains.

The computational time for each scenario is presented in Fig. 6. Most of the computational time of our method was devoted to the EPI analysis operation, which was repeated N times. Although this repetition induces additional computational cost, our method can still be executed in a moderate time compared to the bare EPI analysis (the noisy case).

Fig. 4 Noise level and disparity accuracy for six datasets.

Fig. 5 Visual comparison of disparity maps estimated with $\sigma = 10$. From top to bottom, we used buddha, monasRoom, stillLife, boxes, museum, and dino datasets.

Fig. 6 Processing time for scenarios (ii)–(v).

Note also that the non-local means filter for the spatial/EPI denoising was implemented without GPU acceleration, and thus, the computational time reported here should be considered only for reference.

Another advantage of our method is that it does not require elaborate parameter configurations. In fact, we used the same parameters for our method for all the conditions in Fig. 4. Meanwhile, for the non-local means filter, we adjusted the parameter (h in [30]) for the target noise level

Fig. 7 Noise level and disparity accuracy with the “monasRoom” dataset. This graph is different from Fig. 4 (b) in that the noise level was simply assumed to be $\sigma = 5$ for EPI denoising.

to achieve a good performance. For instance, as shown in Fig. 4 (b), EPI denoising performed well if it was provided with the target noise levels. However, as shown in Fig. 7, its performance became poor if the noise level was simply assumed to be $\sigma = 5.0$. Note that in practical applications, we rarely know the exact noise level.

Fig. 8 Computational time and disparity accuracy. See Table 2 for legends.

Fig. 9 Visual comparison of disparity maps. From top to bottom, the noise level was $\sigma = 10$, $\sigma = 15$, and $\sigma = 10$.

4.3 Comparison with Other Disparity Estimation Methods

We compared the performance of our method with other state-of-the-art methods in terms of accuracy and computational time, as shown in Fig. 8. We used three datasets with non-identical noise levels, to show that our method did not overfit a specific dataset or a noise level. In addition to the baseline EPI analysis [19], dubbed as “baseline”, we obtained an authors’ implementation of Williem’s method [25], [26], which was stated as being robust to noise. Their method was tested with and without global optimization, which is time-consuming but can improve the accuracy. We plotted all the values obtained with our environment in red. Moreover, we added the plots in black for other state-of-the-art methods on the basis of the reported values in [25] (see Table 2 for the legends)[†]. The method indicated by

[†]For the methods of [13], [14], only the total computational time was reported while the accuracy was evaluated individually for the defocus and correspondence costs.

Table 2 Legends for Fig. 8

Methods	Legends
Jeon’s data cost [11]	1
Tao’s correspondence cost [13]	2
Tao’s defocus cost [13]	3
Wang’s correspondence cost [14]	4
Wang’s defocus cost [14]	5
Williem w/o optimization [25]	6

“6” is the same as “Williem w/o opt.”, but the MSE values were slightly different, seemingly, due to some difference of the experimental conditions. It was reported in [25] that they used a PC with an Intel i7 4770 3.4 GHz CPU and 12 GB main memory, which resulted in faster computation than ours for the same method.

As can be seen from these graphs, our method achieved good accuracy compared to the state-of-the-art methods. Although our method induced an additional computational cost in the baseline EPI analysis [19], it was still a few orders of magnitude faster than the other methods. It should

Fig. 10 Real world results with “Books”, “Poppies” and “Mirabelle” datasets [37] from top to bottom.

Fig. 11 Real world results with a light field obtained by ourselves.

be noted that most of the methods did not put importance on the computational time; the baseline EPI analysis and our method were implemented with GPU acceleration, but it seems that the other methods were not optimized for speed, nor implemented with GPU acceleration.

Figure 9 shows disparity maps including ones estimated by Williem’s method. Our disparity maps are visually better than those of Williem’s method.

4.4 Real-world Results

We also tested several real-world light field datasets, which are inherently somewhat noisy depending on the shooting condition, to validate the effectiveness of our method. We used some datasets taken by Lytro Illum cameras that were available from [37]. We estimated disparity maps with the baseline EPI analysis [19], our proposed method, and

Williem's method [25], [26], and presented the results in Fig. 10. We also used a light field taken by ourselves using a Lytro Illum camera, whose disparity ranges between the neighboring viewpoints were from -1.5 to 1.5 . The results are presented in Fig. 11, where a depth map obtained with Lytro Desktop ver. 5.0.1 is also presented for reference. As shown in those results, our method produced visually compelling disparity maps even from noisy real-world light fields.

5. Conclusion

We addressed the problem of fast and accurate disparity estimation from a dense but noisy light field. In constructing our method, we incorporated a fast denoising scheme using simple 1-D slanted filters into the fast disparity estimation framework in the EPI domain. Experimental results show that our method can achieve good accuracy with much less computational time compared to some state-of-the-art methods. In future work, we will extend our method to larger disparity ranges as in [20] and less-textured objects that are common in natural scenes.

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