Sheared EPI Analysis for Disparity Estimation from Light Fields

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SUMMARY Structure tensor analysis on epipolar plane images (EPIs) is a successful approach to estimate disparity from a light field, i.e. a dense set of multi-view images. However, the disparity range allowable for the light field is limited because the estimation becomes less accurate as the range of disparities become larger. To overcome this limitation, we developed a new method called sheared EPI analysis, where EPIs are sheared before the structure tensor analysis. The results of analysis obtained with different shear values are integrated into a final disparity map through a smoothing process, which is the key idea of our method. In this paper, we closely investigate the performance of sheared EPI analysis and demonstrate the effectiveness of the smoothing process by extensively evaluating the proposed method with 15 datasets that have large disparity ranges.

key words: epipolar plane image, light fields, disparity estimation

1. Introduction

Depth (disparity) estimation from images has attracted much research interest for many years. One of the most common conventional configurations is stereo matching using two images [1]–[5], for which many sophisticated techniques have been developed. Recent advances in image acquisition techniques [6]–[11] have brought about a new trend in this research field: depth estimation from a set of multi-view images or a light field. The most straightforward approach is called multi-view stereo (MVS) [12]–[16], 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.

Another approach is to analyze the structure of an epipolar plane image (EPI) that is obtained from the light field [17]–[24]. 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 [20], [22] have applied structure tensor analysis to EPIs. 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. However, we found that the accuracy of their method is quite limited for relatively sparse light fields where neighboring images have non-small disparities.

To overcome this limitation while keeping computational cost low, we have developed a method called sheared EPI analysis [25], where EPIs are transformed with several shear values before the structure tensor analysis. Then, the results of analysis obtained with different shear values are integrated into a final disparity map through a smoothing process, which is the key idea of our method.

We have found that an idea similar to ours had been presented as EPI refocusing [21]. However, our study has several nontrivial differences. First, our method is applied to 2-D viewpoint arrangements, while that of Diebold and Goldluecke [21] was limited to 1-D ones. Second, our method includes a smoothing process during the integration process, which significantly increases the accuracy of disparity estimation. Moreover, we extensively evaluated 15 datasets that have large disparity ranges to closely investigate the effectiveness of shearing EPIs and the smoothing process. We also prove that our method is comparably accurate to and much faster than a multi-view stereo method.

2. Epipolar Plane Image Analysis

2.1 Outline of Epipolar Plane Image Analysis

We assume that a set of multi-view images, such as that shown in Fig. 1 (a), is given. These images constitute a 4-D light field \( f(s, t, x, y) \), 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 plane image (EPI). For example, \( f^{y'}(x, s) = l(s, t', x, y') \) is an EPI on \((x, s)\) plane where \(t\) and \(y\) are fixed to \(t'\) and \(y'\).

![Fig. 1 Multi-view images and EPI](image-url)


\( y^* \), respectively, as shown in Fig. 1 (b). 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 depth [17]–[23].

On the basis of this idea, Wanner and Goldluecke [20], [22] have developed a depth estimation method using structure tensor analysis. A structure tensor on an EPI \( l(x, s) \) is defined as

\[
J(x, s) = \begin{bmatrix}
G \ast (l_x l_x) & G \ast (l_x l_y) \\
G \ast (l_y l_x) & G \ast (l_y l_y)
\end{bmatrix},
\]

where \( G^* \) denotes convolution with a Gaussian filter kernel. In this paper, the filter size is fixed to the default value of [26]: a \( 3 \times 3 \) kernel with \( \sigma = 1 \). Symbols \( l_x \) and \( l_y \) 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 [20], [22]) can be obtained from principle component analysis of matrix \( J \).

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

\[
c(x, s) = \sqrt{\left( J_{11}(x, s) - J_{22}(x, s) \right)^2 + 4J_{12}^2(x, s)}
\]

\[
J_{11}(x, s) + J_{22}(x, s),
\]

where larger \( c(x, s) \) means more 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

\[
\left( d^{t^*y^*}(x, s), c^{t^*y^*}(x, s) \right) = \text{EPIAnaly}\left( l^{t^*y^*}(x, s) \right).
\]

To obtain a disparity map from a specific viewpoint \((s^*, t^*)\), we perform EPI analysis for both the horizontal and vertical directions and combine the results in accordance with the point-wise confidence.

\[
d^{t^*r^*}(x, y) = \begin{cases} 
\frac{d^{t^*y^*}(x, s^*)}{c^{t^*y^*}(x, s^*)} & c^{t^*y^*}(x, s^*) \geq c^{r^*y^*}(y, t^*) \\
\text{otherwise.} & 
\end{cases}
\]

The disparity map \( d^{t^*r^*}(x, y) \) is further refined using a fast denoising or a more sophisticated global optimization. The former is given as:

\[
d^{t^*r^*}(x, y) = \arg \min_{d(x,y)} E(d(x,y), d^{t^*r^*}(x,y))
\]

\[
E(\alpha, \alpha_0) = \int_{\Omega \subset \mathbb{R}^2} \left| h D_{\alpha y} \alpha + \frac{1}{2\rho} |\alpha - \alpha_0| d\Omega
\]

\[
h(x, y) = 1 - \max\left( c^{t^*y^*}(x, s^*), c^{r^*y^*}(y, t^*) \right)
\]

\[
\text{where} \ \Omega \ \text{is the 2-D pixel domain,} \ \rho \ \text{is a smoothing strength, and} \ D_{\alpha y} \ \text{is a 2-D derivative operator.} \ \text{The first term of} \ \text{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.}

2.2 Comparison to 4-D Analysis

A light field has originally a 4-D structure. If a pixel \((x, y)\) at a specific viewpoint \((s_0, t_0)\) has a disparity \( d \),

\[
l(s_0, t_0, x, y) = l(s, t, x - d(s - s_0), y - d(t - t_0))
\]

should be satisfied except for occluded regions. Several methods use this 4-D constraint directly to obtain accurate disparity values from the light field [11], [27]–[29]. This constraint can be used for multi-view stereo matching where the point correspondence is evaluated across all the images arranged in a 2-D grid, or to derive defocus cues by taking the average of disparity-compensated multi-view images. Generally, these methods are computationally heavy due to the complexity of analysis that is performed on the 4-D space.

Meanwhile, the EPI analysis presented in [20], [22] works in 2-D; only the 2-D subspaces, i.e. \((s, x)\) and \((t, y)\) planes, extracted from the original 4-D light field, are analyzed to obtain disparities. This analysis is computationally much more simpler than the 4-D methods. This fast 2-D analysis is used as the basic building block of our method. As a result, our method can achieve a good performance in terms of the trade-off between the accuracy and computational cost, as will be shown in Sect. 4.

3. Proposed Method

3.1 Sheared EPI Analysis

EPI analysis has been proven to be fast and accurate for a dense light field where the range of disparities among the viewpoints is small [20], [22]. However, this does not hold true for the images that have a larger range of disparities. For example, Fig. 2(b) shows a disparity map estimated from \( 3 \times 3 \) viewpoint images where disparities between neighboring viewpoints are from \(-2.54\) to \(4.86\) pixels. This disparity map is quite erroneous compared with the ground truth in Fig. 2(a).

To identify the reason for this erroneous result, we closely observe several EPIs in Fig. 3, where the original EPIs are visualized in the row of \( \delta = 0 \). As mentioned earlier, the direction of each line corresponds to its disparity. If the disparity is near zero, the line direction is almost vertical. However, as the disparity diverges from zero, the line becomes more slanted and finally separates into discontinuous dots. In such cases, the dominant gradient direction obtained by the structure tensor analysis no longer corresponds correctly to the line direction. In fact, the most erroneous parts in Fig. 2(b) originally have disparities that diverge from zero.

To fix these errors, we introduce shear transforms to EPI analysis. Specifically, a sheared EPI is written as

\[
l_0^{t^*y^*}(x, s) = l^{t^*y^*}(x + s\delta, s),
\]
where $\delta$ is the amount of shear, which is called the shear value in this paper. Examples of sheared EPIs with $\delta = 2$ and $-2$ are shown in Fig. 3. It can be observed that thanks to the shear transforms, the directions of several lines become closer to vertical. These directions can now successfully be estimated by the structure tensor analysis.

Disparity estimation from a sheared EPI is formulated using Eq. (4) as

$$
\begin{align*}
(d'_{s}(x, y), c'_{s}(x, y)) = \text{EPIAnaly}\left(f'_{s}(x, y)\right) \\
d'_{s}(x, s) = \delta + \tan d'_{s}(x, s),
\end{align*}
$$

where the shear value $\delta$ is compensated for in Eq. (12). Similarly to Eq. (5), a disparity map from a specific viewpoint $(s^*, t^*)$ is obtained as

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

Here, $d_{s}^{s*t*}(x, y)$ denotes a disparity map obtained through a shear transform with $\delta$. Such disparity maps with $\delta = -2$ and 2 are presented in Figs. 2(c) and 2(d). We observed that the shear transforms partly improve disparity estimation; with $\delta = 2$, the nearer regions become accurate, while with $\delta = -2$, the farther regions become accurate. These results validate the effectiveness of introducing shear transforms to EPI Analysis.

### 3.2 Integration of Multiple Disparity Maps

Shear transform of EPIs helps improve the accuracy of disparity estimation where and only where the original disparities are close to the shear value $\delta$. To cover a large range of disparities in a target light field, we need to perform sheared EPI analysis several ($N$) times while changing the value of $\delta$ and combine the results. Here, we describe how to integrate multiple disparity maps obtained with different shear values.

The $n$-th shear value is denoted as $\delta_n$ ($n = 1, \ldots, N$). First, for each $\delta_n$, we obtain a disparity map $d_{\delta_n}^{s*t*}(x, y)$ using Eq. (13) and a confidence map $c_{\delta_n}^{s*t*}(x, y)$ using

$$
c_{\delta_n}^{s*t*}(x, y) = \max\left(c_{\delta_n}^{s*t*}(x, s^*), c_{\delta_n}^{s*t*}(y, t^*)\right).
$$

Next, we integrate $N$ disparity maps, $d_{\delta_n}^{s*t*}(x, y)$ ($n = 1, \ldots, N$). For this purpose, the most confident value of $\delta$ for each $(x, y)$ is selected as

$$
\delta^{s*t*}(x, y) = \arg\max_{\delta_n \in [\delta_1, \delta_N]} c_{\delta_n}^{s*t*}(x, y),
$$

which is called a $\delta$ map. A straightforward method of integration is to use it directly as

$$
d^{s*t*}(x, y) = d_{\delta^{s*t*}(x, y)}^{s*t*}(x, y),
$$

which is the same as in the work of Diebold and Goldluecke [21] except for the arrangement of viewpoints. However, this straightforward integration results in a noisy disparity map. We found that this noisiness comes from the noisiness of the $\delta$ map visualized in Fig. 4(a). The true $\delta$ map is expected to be locally smooth because it is ideally a quantized version of the continuous disparity map and the continuous disparity map is locally smooth for a natural scene in general. Therefore, we smooth the $\delta$ map with weights in accordance with the per pixel confidence.

$$
\hat{\delta}^{s*t*}(x, y) = \arg\min_{\delta_n} \left(\arg\min_{\delta_n} E(\delta(x, y), \delta^{s*t*}(x, y))\right) \\
E(\alpha, \alpha_0) = \int_{\Omega \subset \mathbb{R}^2} g|D_{xy}\alpha| + \frac{1}{2\lambda}(\alpha - \alpha_0)d\Omega,
$$
where $\Omega$ is the 2-D pixel domain, $\lambda$ is a smoothing strength (when $\lambda = 0$, no smoothing is performed), and $D_{xy}$ is a 2-D derivative operator. Symbol $g$ denotes a weighting function described as

$$g(x, y) = 1 - \max_{\delta \in [0, \lambda]} c^e_{\delta} (x, y) / \sum_{\delta \in [0, \lambda]} c^e_{\delta} (x, y).$$  \tag{19}$$

Function $g(x, y)$ takes larger values where the corresponding disparities are less confident as visualized in Fig. 4 (b). Larger values of $g(x, y)$ lead to a stronger smoothing effect for the pixel $(x, y)$. Finally, the smoothed $\delta$ map $\hat{\delta}^e_{\delta} (x, y)$, which is shown in Fig. 4 (c), is used to integrate $N$ disparity maps as

$$\hat{d}^e_{\delta} (x, y) = d^e_{\delta} (x, y).$$  \tag{20}$$

As shown in Fig. 4 (d), the disparity map obtained by Eq. (20) is quite accurate. It is further refined by the additional denoising given by Eqs. (6)–(8), where $\rho$ was fixed to 5 throughout this paper and the weight function $h$ was defined as

$$h(x, y) = 1 - \max_{\delta \in [0, \lambda]} c^e_{\delta} (x, y).$$  \tag{21}$$

4. Experiments

We examined the performance of our method and the effect of several parameters using light field datasets obtained from other studies [30], [31]. All of the original datasets have $9 \times 9$ viewpoints, but except for a few datasets the disparity ranges are too small to show difference between the original EPI analysis and our method. Therefore, from each dataset, we selected $3 \times 3$ viewpoints images with constant intervals and used them as an input light field. As for the datasets horses, medieval, and stillLife, we also used the original $9 \times 9$ viewpoints because these datasets have originally large disparity ranges. The input data and the disparity ranges between the neighboring viewpoints are listed in Table 1. To implement our proposed method, we used cocolib and light field suite software available online [26], [31]. The cocolib software includes a fast implementation of the continuous minimization for Eqs. (7) and (18). For each dataset, the disparity map at the central viewpoint was evaluated against the ground truth.

In Sects. 4.1–4.5, we evaluated the performance of our method. In Sects. 4.1–4.3, we present the effects of the three parameters: the shear range $\Delta$, the shear step $\tau$, and the smoothing strength $\lambda$ (in Eq. (18)). For example, when $\Delta = [-3, 5]$, the candidate shear values are given as $\delta_n = \{-3, -2, -1, 0, 1, 2, 3, 4, 5\}$ with $\tau = 1$, and $\delta_n = \{-2, 1, 4\}$ with $\tau = 3$. The performance of our method also depends on the target disparity ranges $D$ and disparity-map denoising, which are analyzed in Sects. 4.4 and 4.5. For the experiments described in Sects. 4.1–4.5, we used the buddha dataset. The disparity-map denoising was omitted in Sects. 4.1–4.4 but was enabled in Sects. 4.5 and 4.6. In Sect. 4.6, we compare our method with other methods over all datasets and discuss the trade-off between the accuracy and computational cost for disparity estimation.

4.1 Effect of the Shear Range $\Delta$

First, we explain how the shear range $\Delta$ affects the performance of our method. In this experiment, the shear range $\Delta$ was changed while the target disparity range $D$ was fixed. The shear step $\tau$ was fixed to 1, and the smoothing strength $\lambda$ was optimized for each condition. We compared the cases with and without $\delta$-map smoothing. The performance was measured by using the accuracy of disparity estimation (PSNR against the ground truth) and is summarized in Fig. 5.

It can be seen that the $\delta$-map smoothing significantly
improves the accuracy. We can also see that the accuracy becomes low when the shear range $\Delta$ is much narrower than the target disparity range $D$. This indicates that the shear range $\Delta$ should cover the target disparities $D$ to fully exploit the potential of the sheared EPI analysis. Meanwhile, making the shear range $\Delta$ wider than the target disparity range $D$ also negatively affects the accuracy. However, this negative effect is greatly mitigated by using the $\delta$-map smoothing. Therefore, if we use the $\delta$-map smoothing, $\Delta$ does not need to be selected strictly. Several resulting disparity maps are presented in Figs. 6–8.

### 4.2 Effect of the Shear Step $\tau$

Second, we examined the effect of the shear step $\tau$ on the performance of our method. Here, we fixed the shear range $\Delta$ to $[-3,5]$ and varied the shear step $\tau$, where the smoothing strength $\lambda$ is optimized for each condition. The accuracy and computational time were evaluated and are presented in Figs. 9 and 10, respectively. As expected, increasing the shear step $\tau$ results in a lower accuracy. However, decreasing the shear step $\tau$ results in more candidate shear values, which leads to a longer computational time. Meanwhile, the computational time for the $\delta$-map smoothing is moderate and independent of the shear step $\tau$. Therefore, in terms of the trade-off between the accuracy and the computational time, using $\delta$-map smoothing is often more beneficial than using a smaller shear step $\tau$. 

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**Fig. 5** PSNR and Shear range $\Delta$

**Fig. 6** Disparity maps with $\Delta = [-6, 8]$

**Fig. 7** Disparity maps with $\Delta = [-3, 5]$

**Fig. 8** Disparity maps with $\Delta = [0, 2]$

**Fig. 9** PSNR with different shear steps $\tau$

**Fig. 10** Computational time with the shear steps $\tau$
4.3 Effect of the Smoothing Strength $\lambda$

To see how the smoothing strength $\lambda$ affects the performance of our method, we show a performance curve along $\lambda$ in Fig. 11, where $\Delta$ and $\tau$ were fixed to $[-3, 5]$ and 2, respectively. Moreover, the $\delta$ maps and the disparity maps with $\lambda = 0.01, 10, 10000$ are represented in Figs. 12 and 13, respectively. As shown in those figures, the performance of our method depends greatly on the value of $\lambda$; when $\lambda$ is too small, the $\delta$ map is still noisy; meanwhile, when $\lambda$ is too large, the information on the $\delta$ map is lost due to smoothing being too strong. In this case, the best performance was obtained with $\lambda = 10$.

4.4 Effect of the Target Disparity Range $D$

Next, we analyzed how the target disparity range $D$ affects the performance. The disparity range was controlled by changing the viewpoint intervals of input images because the disparity range is proportional to the viewpoint interval. The viewpoint intervals were varied from 1 to 4. The shear range $\Delta$ was changed in accordance with the viewpoint interval while the shear step $\tau$ was kept to 2. Therefore, as the target disparity range increased, the number of the candidate shear values also increased. Specifically, we used $\delta_n = \{0\}$ for the target range $D = [-0.85, 1.62]$, $\delta_n = \{-2, 0, 2, 4\}$ for $D = [-1.70, 3.24]$, $\delta_n = \{-3, -1, 1, 3, 5\}$ for $D = [-2.54, 4.86]$, and $\delta_n = \{-4, -2, 0, 2, 4, 6\}$ for $D = [-3.38, 6.48]$.

We compared our method with the original EPI analysis [20], [22] denoted as “plain,” and our method without $\delta$-map smoothing in Fig. 14. The plain EPI analysis significantly deteriorated as the disparity range increased, prevention of which was the original motivation of our study. In contrast, our method can maintain or even increase the accuracy with a large disparity range, especially when combined with $\delta$-map smoothing.

4.5 Effect of Disparity-Map Denoising

Now, the disparity-map denoising given by Eqs. (6)–(8) was applied to the bare outputs of plain/sheared EPI analysis. The results are presented in Fig. 15, where the denoising improved all the results. Especially, our method without $\delta$-map smoothing was significantly improved by the denoising but it was still below our method with $\delta$-map smoothing. Consequently, we can conclude that our method should be combined with both the $\delta$-map smoothing and disparity-map de-
4.6 Comparison with Other Methods

We compared our method with three other methods as follows. The first one, “plain + denoising”, is the original EPI analysis without shear transform combined with the disparity-map denoising. The second, “plain + global optimization”, is similar to the first one but combined with a more sophisticated global optimization. The above two are the proposed method in Wanner et.al. [22]. The third one, “MVS”, is a multi-view stereo, the detail of which is described as Eqs. (11)–(13) in [22]. This method is categorized as 4-D analysis methods mentioned in Sect. 2.2. The implementation of this method is also available online [26]. Our method was configured as follows. The shear step $\tau$ was fixed to 2 and the smoothing strength $\lambda$ was fixed to 10.

The shear range $\Delta$ are summarized in Table 2. Both the $\delta$-map smoothing and disparity-map denoising were enabled to show the best performance of our method.

The PSNR values of the estimated disparity maps against the ground truth are presented in Fig. 16. The average PSNR values for the datasets with 3 $\times$ 3 viewpoints and those with 9 $\times$ 9 viewpoints are also reported. For sev-
Fig. 18  Results from buddha dataset

Fig. 19  Results from couple dataset

Fig. 20  Results from cube dataset

Fig. 21  Results from medieval (a) dataset

Fig. 22  Results from statue dataset

Fig. 23  Results from stillLife (a) dataset
eral datasets among them, the input images, the ground truth disparity maps, and the estimated disparity maps using the four methods mentioned above are shown in Figs. 18–23. As can be seen from Fig. 16, our method consistently achieved better quality than the other methods in almost all the datasets, which shows the effectiveness of our method. The disparity maps produced by our method are also visually compelling as shown in Figs. 18–23. Note that for the datasets couple, cube, maria, pyramid, and statue, the ground truth disparities are obviously missing for the part of the stand; therefore, the PSNR values for those datasets are not trustworthy. However, as seen from Figs. 19, 20, and 22, our method obviously achieved better quality than the other methods with those datasets.

We can also observe from Fig. 16 that the methods using EPI analysis (ours, plain + denoising, and plain + global optimization) performed better for the datasets with 9 × 9 viewpoints than for those with 3×3 viewpoints. This reflects the fact that the datasets with 9 × 9 viewpoints have smaller disparity ranges than those with 3 × 3 viewpoints. As the disparity range decreases, the advantage of our method over the other two methods reduces, as was also shown in Fig. 14.

Finally, we show the trade-off between the accuracy and computational cost of disparity estimation among the four methods, all of which were implemented using GPU. We used a desktop computer equipped with GeForce GTX 970. As clearly seen from Fig. 17, “plain + denoising” needed extremely short computation time thanks to the simple algorithm that works in the 2-D EPI domains combined with a fast denoising method. This simple algorithm was used as the building block of our method. The computation time required for our method increases as the target disparity range D increases because the computational cost is proportional to the number of candidate shear values. The δ-map smoothing requires additional computational time. However, the total computation time for our method is still moderate, and at the cost of this increased computation, our method achieves better accuracy. Meanwhile, 2-D EPI analysis with the sophisticated optimization (plain + global optimization) and 4-D light field stereo matching (MVS) required significant amounts of time due to their complexities, but did not always yield accurate results.

5. Conclusion

Aiming to estimate an accurate disparity map even from a non-dense light field, we proposed sheared EPI analysis where EPIs are transformed with several shear values before the structure tensor analysis and the results of analysis are integrated into a final disparity map. We carefully examined how the parameters of our method affect the result to fully exploit the performance of our method. Moreover, we demonstrated the effectiveness of our method by comparing our method with three other methods over 15 datasets. Experimental results proved that our method achieves significant accuracy especially when combined with the δ-map smoothing step. Moreover, using the simple and efficient EPI analysis as the building block, our method requires much less computational cost compared to the complex multi-view stereo method. In the future work, our method will be further improved by combining it with appropriate handling of occlusions and weakly textured regions.

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† The missing parts are included in the PSNR values for these datasets because we treated the data as they were. However, these untrustworthy PSNR values, which are marked with +, are not included in the average PSNR values reported in Fig. 16.
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