Hole-Filling for DIBR Based on Depth and Gradient Information

Abstract

Depth image-based rendering (DIBR) is a method for generating new virtual images from known viewpoints. However, holes often appear in the rendered virtual images due to occlusion and inaccurate depth information. In this paper, we present a novel hole-filling algorithm to improve the image quality of DIBR. In the proposed method, depth information is added to the priority calculation function when determining the order of hole-filling. Then, the gradient information is used as auxiliary information when searching for the optimal matching block. Experimental results show that the proposed algorithm achieves better objective quality and also improves the subjective quality of the rendered images.

Keywords hole-filling, depth, gradient, depth image-based rendering

1. Introduction

By using monoscopic colour video and its associated per-pixel depth information, the DIBR technique is able to generate an arbitrary video view through the three-dimensional image transform technique (3D image warping) [1]. However, holes may appear unexpectedly due to inaccurate depth maps and changes in occlusion resulting from the transformation of viewpoints. Therefore, an effective hole-filling algorithm is the key to obtaining high quality images of virtual views. Various methods have been proposed for hole-filling in DIBR [2]. Layered depth images (LDIs) [3-5] have been proposed as a method to remove holes. In this instance, several layers of depth image are needed to provide sufficient information. However, the LDIs method is computationally expensive. An approach that combines the technology of preprocessing depth maps and the method of targeting image postprocessing [6, 7] is therefore proposed to render the depth value smoothly. However, this approach does not work well when the virtual viewpoint is far away from the source reference point. Filling holes with multiple reference images and their associated depth maps is proposed in [8], which uses two viewpoints nearest to the virtual view as reference images to create target images. Then, holes are reduced by applying image fusion. Obviously, hole-filling using multiple reference images and depth maps is computationally expensive. Hierarchical hole-filling and depth adaptive hierarchical hole-filling approaches are proposed in [9], which can avoid geometric distortion in the rendered image through the use of a pyramid-like approach for estimating the hole pixels from the lower resolution estimation of the 3D wrapped image. Holes in the scene are filled using the temporal correlation of texture and depth.
information from one view, while the regions along the static objects are filled using the inpainting technique in [10]. The algorithm in [10] is more suitable for 3D video systems with single-view-plus-depth format. In [11], a novel multidirectional extrapolation hole-filling method, which uses neighbour pixels’ texture features to estimate hole-filling direction in a pixel-by-pixel manner, is proposed. This method has better visual quality for the synthesis of virtual views with a high-quality depth map. A classic exemplar-based hole-filling method, which is referred as the EBI algorithm in this paper, is proposed in [12]. The EBI algorithm focuses on filling both structural and textural information, and it pays more attention to the effects caused by filling order. It avoids producing discontinuous and uncompleted results by using image isophotes for determining the filling order. Therefore, the EBI algorithm is widely used in a large number of applications such as image inpainting, video inpainting and film stunts, due to its better performance. A similar method, referred to as the DAII algorithm in this paper, is provided in [13], where the calculating priority is modified and aided depth is used to enhance discovering the best matching patch.

The rest of this paper is organized as follows. As the basis of the proposed algorithm, works related to the EBI and DAII algorithms are introduced in section 2. Section 3 provides the proposed algorithm. Experimental results are given in section 4 and the paper is concluded in section 5.

2. Related works

2.1 EBI algorithm

There are three primary steps in the EBI algorithm: (i) calculating the priority of each point at the hole boundary; (ii) finding a matching patch with the best filling priority; (iii) updating priority and repeating the step (ii) until every hole point is filled.

2.1.1 Calculating priority

As shown in Figure 1, the image to be inpainted is denoted by I. The target region is denoted by Ω and its contour is denoted by ∂Ω;ϕ is referred to as the known region (source region), p is a point on ∂Ω and Ψ_p is a target patch centred at point p. Priority in the EBI algorithm is defined by:

\[ P(p) = C(p)D(p) \]  

where \( C(p) \), which represents the reliability of \( \Psi_p \), is called the confidence term and usually defined by:

\[ C(p) = \frac{\sum_{q \in \Psi_p \cap \phi} C(q)}{\text{area}(\Psi_p)} \]  

2.1.2 Finding the best matching patch

The hole pixel \( \hat{p} \), which has the greatest priority and the most optimal target block \( \Psi_{\hat{p}} \) will be obtained after calculating the priority of all points at the hole boundary. Then, the best matching patch \( \Psi_q \) for \( \Psi_{\hat{p}} \) will be found in the image of the source region. The best matching block \( \Psi_q \) usually satisfies:

\[ \Psi_q = \arg\min_{\Psi_q \in \phi} d(\Psi_{\hat{p}}, \Psi_q) \]  

where \( \Psi_{\hat{p}} \) and \( \Psi_q \) are referred to as pixel blocks with centred points \( \hat{p} \) and \( q \), respectively. The pixel similarity \( d(\Psi_{\hat{p}}, \Psi_q) \) between the target block \( \Psi_{\hat{p}} \) and the matching block \( \Psi_q \) is calculated by the sum of squared difference (SSD), which is defined by:

\[ SSD = \sqrt{\frac{\sum_{i=1}^{N} \sum_{j=1}^{M} (p_{ij} - q_{ij})^2}{N \times M}} \]  

Figure 1. Illustration of the EBI algorithm

where \( area(\Psi_p) \) is the area of \( \Psi_p \) and \( C(p) \) is often initialized to:

\[ C(p) = \begin{cases} 0, & \forall p \in \Omega \\ 1, & \forall p \in I - \Omega \end{cases} \]  

\[ D(p) = \left\| \nabla I_p \right\| \cdot n_p \]  

where \( n_p \) is the normal vector at point \( p \), \( \nabla I_p \) is the gradient term, \( \perp \) is the orthogonal operator and \( \alpha \) is a normalizing factor.

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\[ SSD = \sqrt{\frac{\sum_{i=1}^{N} \sum_{j=1}^{M} (p_{ij} - q_{ij})^2}{N \times M}} \]
Additionally, the pixel colours are represented in the colour space of CIE Lab, due to the nature of perceptual uniformity.

2.1.3 Updating priority

After $\Psi_p$ has been filled, the priority of $p$ will be updated to:

$$C(p) = C(\hat{p}) \quad \forall p \in \Psi_p \cap \Omega \quad (7)$$

Additionally, the boundary involved will be updated and the process is repeated until the entire region is completed.

2.2 DAII algorithm

According to the analysis in [12], the confidence term $C(p)$ in (1) will gradually become smaller or even zero, so that no matter how large $D(p)$ is, the product $P(p)$ will likely remain zero. This will lead to negative impacts on the spreading of the isophote, as well as the inpainting effect. Therefore, in the DAII algorithm, (1) is modified to:

$$P(p) = C(p) + D(p) \quad (8)$$

Furthermore, in the DAII algorithm, depth-aided texture estimation is used to search for the best matching patch and the definition of pixel similarity is changed to:

$$d(\Psi_p, \Psi_q) = SAD(\Psi_p, \Psi_q) +$$
$$\lambda \left| \text{ave} \left( \sum \text{depth}(p_i) \right) - \text{ave} \left( \sum \text{depth}(q_i) \right) \right| \quad (9)$$

where $p_i$ denotes the non-hole pixel point and $q_i$ in the source block corresponds to the point of the unknown part in the target block; $SAD(\Psi_p, \Psi_q)$ represents the sum of absolute difference (SAD) between the target block $\Psi_p$ and the matching block $\Psi_q$:

$$SAD = \sum_{i=1}^{n} \sum_{j=1}^{m} |p_{ij} - q_{ij}| \quad (10)$$

$\lambda$ is a Lagrange multiplier, which is defined by:

$$\lambda = \begin{cases} \lambda_0 & \text{ave} \left( \sum \text{depth}(p_i) \right) \leq \text{ave} \left( \sum \text{depth}(q_i) \right) \\ \lambda_1 & \text{ave} \left( \sum \text{depth}(p_i) \right) > \text{ave} \left( \sum \text{depth}(q_i) \right) \end{cases} \quad (11)$$

where $\lambda_0$ and $\lambda_1$ are two constants and $\lambda_1 > \lambda_0$.

3. Proposed algorithm

3.1 Calculating priority

In the EBI algorithm, the amount of structural information in the hole region is measured by the gradient or variation of the grey level. The greater the $D(p)$, the higher the priority will be. However, the data term $D(p)$ may not fully reflect the complex edge structural information when the variation of the grey level is not large, which will bring about error texture growth. The depth information reflects the distance between objects in the scene and the camera. The depth values of objects at different positions are different. Additionally, depth values will change dramatically at the edge of the two objects with different distances. Therefore, depth factor $Z(p)$ is used as auxiliary information for determining the edge structure when calculating priority in the proposed algorithm. Even if the variation of the grey level is not obvious, which means the data term $D(p)$ is not good enough to reflect the information around hole points, a more reasonable priority can be obtained for each hole point with the help of depth factors. In the proposed algorithm, the priority is redefined by:

$$P(p) = C(p) + D(p) + Z(p) \quad (12)$$

where $Z(p)$ is the depth term, which reflects the change rate of the average depth of the pixels in the target block and $Z(p)$ is defined by:

$$Z(p) = \sum_{q \neq p, q} \left( \frac{|\bar{z}_p - \bar{z}_q|}{\alpha} \right)^2 \quad (13)$$

where $|\bar{z}_p|$ represents the average depth value of the pixels known in the target block and $\alpha$ is a normalizing factor.

3.2 Searching for the best matching patch

The sum of squared difference (SSD) is the criterion for selecting a best source patch in the EBI algorithm, which puts particular importance on the colour difference between pixels. However, it cannot distinguish the structure and texture information in the image very well, which results in mismatching and makes the hole-filled image look unnatural. In terms of an image, structural information reflects its macroscopic features, while textural information reflects its microscopic features. Inaccurate texture growth will appear during the process of filling if only the SSD is considered.

The DAII algorithm has a better effect for regions containing natural texture (weak structure) than for those with strong complex structural information and might therefore naturally lead to structural fracture. Furthermore, the DAII algorithm assumes that all hole points appear in the background region, which is not true for all cases. In other words, when using the DAII algorithm, all of the hole pixels will be filled by the background pixels, even if they belong to the foreground or the junction between foreground and background. Therefore, it may inevitably cause unexpected discontinuity and distortion at the object’s edge.
To solve this problem, we combined the gradient information into the definition of pixel similarity in the proposed method, which is given by:

\[
d(\Psi_p, \Psi_q) = \text{SSD}(\Psi_p, \Psi_q) + \text{Grad}(\Psi_p, \Psi_q)
\]

(14)

Generally, the warped image is processed in YUV space and the image is often provided in 4:2:0 format. Thus, \(\text{SSD}(\Psi_p, \Psi_q)\) and \(\text{Grad}(\Psi_p, \Psi_q)\) are simplified by considering only the Y component:

\[
\text{SSD}(\Psi_p, \Psi_q) = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} (p_{ij}^{Y} - q_{ij}^{Y})^2}
\]

(15)

\[
\text{Grad}(\Psi_p, \Psi_q) = \sum_{i=1}^{n} \sum_{j=1}^{n} \left| p_{ij}^{Y} - q_{ij}^{Y} \right|
\]

(16)

where \(\text{SSD}(\Psi_p, \Psi_q)\) represents the sum of squared difference between \(\Psi_p^{Y}\) and \(\Psi_q^{Y}\) and \(\text{Grad}(\Psi_p, \Psi_q)\) represents the sum of absolute difference of gradient between \(\Psi_p^{Y}\) and \(\Psi_q^{Y}\).

4. Experimental results

In order to evaluate the proposed method, we compared the performance of the proposed algorithm with that of the EBI algorithm, DAI1 algorithm and the algorithm in [11], which is referred to as the MDE algorithm in the comparison results. In the experiments, the multiview video sequence Breakdancers, with camera parameters and depth maps provided by Microsoft Research, were used for the performance evaluation. There were eight views in total and each view had 100 frames of image at a resolution of 1024×768. In our proposed algorithm, the block size was 9×9 and the same Lagrange multipliers were used as those in the DAI1 algorithm. The normalizing factor in (13) was 255 in our experiments.

In the first experiment, we took the first frame of view 3 or camera 3 as reference and generated view 4. Experimental results are shown in Figure 2. Figure 2 (a) shows the original image of view 4; (b) is the DIBR generated image; (c) to (f) are the hole-filled images created by using different hole-filling algorithms. Comparing the results of the left side of the middle individual (region A) in Figure 2 (c), 2 (d) and 2 (f), we can see clearly that at the left shoulder position, the EBI and DAI1 algorithms chose to fill the hole with a weak structure and texture information according to the edge of the white scarf, rather than the foreground of the left shoulder. The reason for this is that the variance of the grey level between the white scarf and the black sleeveless cloth was greater than that between the black sleeveless cloth and the background wall. Only the variance of the grey level can misguide the priority algorithm based on isophotes, especially for texture areas with large contrasts around the to-be-filled target. Therefore, the EBI and DAI1 algorithms could not identify the real important structural edge, which finally resulted in the wrong extension of image structure. The priority calculating in our proposed algorithm changed the filling order and gave filling preference to the target with the maximum mixed priority by adding depth information. Consequently, the proposed algorithm restricted the wrong texture growth to some extent, as shown in Figure 2 (f). Regarding the results of the MDE algorithm in Figure 2 (e), the visual effect of region A looked better than those provided by the EBI and DAI1 algorithms; however, the pixels in the regions of the white scarf and the black sleeveless cloth around the left shoulder position were wrongly extended to the background. In addition, comparing the results of region B in Figure 2 (c), 2 (d) and 2 (f), the image quality of hole-filling by using the proposed method was significantly better than those produced using the EBI and DAI1 algorithms, because the structure and texture information could be considered in full by adding the gradient factor.

The corresponding PSNR comparisons are shown in Table 1. The results show that the proposed algorithm was superior to the EBI, DAI1 and MDE algorithms.

![Figure 2](image-url)
In the second experiment, we took the first frame of view 5 as reference for generating view 6. The comparisons of partially enlarged images are shown in Figure 3. We can see from Figure 3(c) and 3(d) that the grey-white strip edges of the corner show an obviously fractured phenomenon, while the fracture phenomenon is avoided in the image shown in Figure 3(f), further illustrating the advantages of the proposed algorithm.

In the final experiment, we included all of the different views of frame 2 in order to evaluate the performance of the proposed algorithm in more depth. The frame of view 2 was rendered from the corresponding frame of view 1; the frame of view 3 was rendered from the corresponding frame of view 2; the frame of view 4 was rendered from the corresponding frame of view 3; the frame of view 5 was rendered from the corresponding frame of view 6; the frame of view 6 was rendered from the corresponding frame of view 7.

| Algorithm | EBI   | DAII  | MDE   | Proposed |
|-----------|-------|-------|-------|----------|
| PSNR(dB)  | 31.3651 | 31.7728 | 31.2711 | 32.3714  |

Table 1. PSNR comparisons of the first frame of view 4

Table 2 provides detailed PSNR (dB) results for the different views of frame 2. From these results, we can clearly see that the objective performance of the proposed hole-filling algorithm outperformed the EBI, DAII and MDE algorithms in all instances.

5. Conclusion

This paper proposed a novel exemplar-based hole-filling algorithm for improving virtual images in a DIBR system. Based on the widely used EBI algorithm, depth information was added to the priority computation to obtain a more accurate order of hole-filling and gradient information was introduced to the searching process for finding best matching blocks. The comparative experimental results showed that our proposed algorithm exhibited advantages in terms improving both the objective quality and subjective effect over the traditional exemplar-based hole-filling algorithms. The fracture areas in the rendered image were effectively reduced and the texture around the holes was more reasonably extended. Furthermore, the experimental results also showed that changing the priority and taking the depth and gradient information into consideration were efficient for improving the performance of image hole-filling. In future work, the proposed algorithm can be further optimized in order to reduce mismatching and its efficiency can be improved by using adaptive methods.

| Algorithm | EBI   | DAII  | MDE   | Proposed |
|-----------|-------|-------|-------|----------|
| View 2    | 29.5082 | 28.9963 | 29.3939 | 30.7612  |
| View 3    | 30.3584 | 30.9452 | 30.0759 | 31.9389  |
| View 4    | 29.3829 | 29.2462 | 29.2323 | 30.8589  |
| View 5    | 28.4823 | 28.3633 | 25.8721 | 28.8059  |

Table 2. PSNR (dB) results of frames 2 of different views

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