Accurate Depth Estimation Using Spatiotemporal Consistency in Arbitrary Camera Arrays

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ABSTRACT

Depth estimation is an essential task for natural 3D image generation. In this paper, we estimate an accurate depth map from stereoscopic images captured by arbitrary camera arrays. Usually the depth information is estimated by stereo matching from two input images that are obtained by the parallel camera array. Recently the arc camera array has been widely employed to produce 3D movies. However, in the convergent camera array, it is difficult to apply image rectification by matching correspondence points due to serious image distortion. In this work, we estimate depth data without using image rectification. Once we define a potential energy function for depth detection based on spatial consistency, the energy optimization process identifies mismatching depth pixels. A reasonable depth value is assigned to each mismatched pixel using distance and intensity differences between the mismatched pixel and its neighbors. In addition, we improve temporal consistency and reduce visual discomfort. Experimental results demonstrate that our proposed method provides more accurate depth values than other methods based on image rectification.

Keywords: depth estimation, image rectification, stereo matching, temporal consistency,

1. INTRODUCTION

In recent years, 3D entertainment systems have attracted a lot of attention owing to the success of several 3D films. For 3D image acquisition, multiple cameras are employed to capture multi-view images with a wide viewing angle. Naturally, depth map acquisition is necessary as well to represent the depth information of the 3D scene [1, 2]. For depth image based rendering (DIBR), we can use the depth information to generate non-existing virtual views [3]. The benefit of intermediate view synthesis includes flexibility to render continuous views with a variable baseline and increased compressibility of depth data [4]. The performance of DIBR primarily depends on the quality of the depth data.

Stereo matching [5] is the one of the depth estimation approaches. It extracts depth data using correlation of images captured by two cameras, unlike depth camera based approaches [6]. It directly measures the depth information using a physical sensor. Depth camera based approaches cannot provide accurate depth information of objects that are far away from the sensor, nor depth information of high resolution due to many challenges in measuring systems. Those inherent problems make it more difficult to adopt in various applications.

On the other hand, although stereo matching generally produces somewhat low quality depth images, compared to depth camera based approaches, it can measure the depth information of all objects in the captured scene and be applicable in both indoor and outdoor environments. In addition, the depth map resolution depends on the resolution of video cameras. In stereo matching, both images of the same scene taken from different viewpoints are given and 3D data is acquired by finding the corresponding points in the other image. Most stereo matching methods rectify stereo images for the sake of simplicity and accuracy. In this case, corresponding points are found in the same horizontal line of stereo images. However, image rectification is not always applicable to all kinds of stereo matching algorithms. Furthermore, simple application of stereo matching for depth estimation to individual frames of stereo sequences can produce temporal inconsistency. This is perceived as high frequency flickering effects when the depth sequence is visualized [7].

The objective of this paper is to generate an accurate depth image sequence using a stereo video captured by an arbitrary camera array. In general, stereo-video-based depth estimation is carried out with two input videos that are obtained from the parallel camera array. Recently, the arc camera array has been actively used to create immersive 3D videos. In the arc camera array, it is difficult to adopt image rectification methods for correspondence point matching due to serious image distortion. In this work, we estimate depth data without image rectification. The proposed method includes mismatched
depth pixel detection and handling based on spatial consistency. In addition, we refine estimated depth pixels based on correlation between the current frame and its neighboring frames in the temporal domain.

In this paper, we explain the following processes in details. (1) Initial depth information is measured by an energy function based on Markov Random Field. (2) Mismatched depth pixels are detected by a penalty function modeled by the 3D projection. If projected depth pixels are outside the reference image plane or on the same pixel positions in the reference image, we impose a penalty on these pixels to become mismatched pixels. (3) The mismatched pixel is assigned by a depth pixel chosen by a weighting function exponentially-modeled by the distance and intensity differences between the mismatched pixel and its neighbors. (4) Finally, we improve temporal consistency to resolve a high frequency flickering problem. For this task, a smoothness function is used to minimize the difference between spatial consistency and temporal correlation.

2. SPATIO-TEMPORAL PROBLEMS IN DEPTH ESTIMATION

When we estimate the 3D depth information by stereo matching, we assume that each pair of corresponding points lies in the same horizontal line. Image rectification is necessary for this operation. Image rectification is the transform that makes epipolar lines of the stereo images parallel. The rectified images have the parallel epipolar lines on the coplanar image planes [8]. Thus, each corresponding points of the two images has the same vertical coordinate. As a result, we have only horizontal displacement between two images and we can obtain 3D depth information by transforming the disparity to depth information. Figure 1 explains the image rectification process in the parallel array.

![Image rectification in the parallel camera array](image)

Figure 1. Image rectification in the parallel camera array

Image rectification [8] offers some advantages in a parallel camera array such that we can obtain more accurate 3D depth information by stereo matching. However, it may cause some problems in an arc camera array. Since both image planes are transformed from the original images, they can be distorted significantly. Figure 2 shows the image rectification process in the arc camera array. In this case, the stereo views located on different planes are compulsorily transformed to the coplanar image plane. Thus, although the epipolar lines of the corresponding points become identical, the result of image rectification suffers from the inherent problem. From Figure 2, \( P_L \) and \( P_R \) represent arbitrary corresponding points in the left and right images. The real 3D position of the corresponding point is expressed as \( 'P' \). \( l_L \) and \( l_R \) are epipolar lines of the corresponding point in the left and right images.

Figure 3 shows the stereo images after the image rectification process. In this case, we cannot extract the depth information for the whole pixels in the original image. In Figure 3, some parts in the original images disappear and the shapes of objects are deformed in the rectified images. Therefore, acquiring the 3D depth information by preserving the original images in the arc array cannot be solved by image rectification. Consequently, image rectification generates image distortion and thus image information loss. In this paper, we propose a depth estimation method that excludes the image rectification process.
Figure 2. Image rectification in the arc camera

Figure 3. Image rectification problem

Even with the increased image buffer, we cannot obtain the depth information of lost parts. If we implement the image rectification process based on the base view to prevent its information loss, the parts outside the image cannot be matched. We want to stress again that image information loss is mainly caused by the image plane transformation without proper referencing to the image buffer.

Figure 4. Meaningless of image buffer increase
Since the stereo matching method estimates the depth information at each time frame separately, the depth information can be inconsistent temporally. In other words, we may notice some inconsistent depth values of the same background at different frames [9]. Figure 4 shows depth images of different time frames. Although background depth values should be consistent, the circle part has significantly different depth values in those frames. This problem causes flickering artifacts and it discomforts the users. Therefore, we need to apply temporal smoothing filters to enhance the temporal consistency of the depth information in the whole video sequence.

![Figure 5. Depth inconsistency problem](image)

3. DEPTH ESTIMATION WITH SPATIO-TEMPORAL CONSISTENCY

The main objective of our proposed method is to improve the conventional method using spatio-temporal consistency. Figure 6 represents the overall framework of the proposed method. After we obtain initial depth maps from the left and right images using an energy optimization method based on constant space belief propagation (CSBP), we detect mismatching pixels and perform hole filling using the initial depth maps. Then, we produce the final depth map with post-processing operations.

![Figure 6. Overall framework of proposed method](image)
3.1 Epipolar geometry in stereo images

In the arc camera arrangement, when we find corresponding points in the same horizontal line using image rectification, we can have image distortion, such as object shape deformation. Furthermore, we cannot obtain the depth information of the whole image. If we scan the images in both the horizontal and vertical directions to find corresponding points, it increases complexity and reduces the accuracy of stereo matching. In this case, we can use epipolar constraints to solve this problem. It can reduce the matching operation to one dimensional search. Figure 7 illustrates the basic concept of the epipolar geometry in stereo images.

Figure 7. Epipolar geometry in stereo images

For the stereo view located C1 and C2, we have 3D position P and two image points p1 and p'1, which are corresponding points on each image [10]. p'1 means the corresponding point of p1 in the right image and d means disparity between the corresponding and collocated points of p1 in the right image. p1 is the collocated position of p1 in the right image. The epipolar plane is defined by the three points P, C1, and C2. Thus, p'1, the corresponding point of p1, is on the epipolar plane. The epipolar line is defined as the line that intersects the image plane and epipolar plane. The corresponding point of p1 is located on the epipolar line in the right image plane [10]. Consequently, it is possible to match corresponding points via epipolar lines.

Since common stereo matching has one directional disparity, the disparity information can be easily transformed to depth information by Eq. (1).

\[ Z = f \times l / d \]  

(1)

Z is the depth value, f is the focal length, l is the gap between cameras, and d represents the disparity value. However, to define one directional disparity between corresponding points without rectification is difficult since the direction of disparity is not only horizontal but also vertical, 'x' and 'y', as shown in Figure 5. Furthermore, disparity value may have a negative number. Thus, in the proposed method, we present a direct depth acquisition method without depth transformation of disparity information since detection of corresponding points by epipolar constraints does not have one directional search because of omission of rectification.

3.2 Initial depth map acquisition

In order to extract depth values, we define energy function about matching using Markov Random Field (MRF), solved through an optimization technique. The energy function for matching is defined in Eq. (2).
\[ E(x, y, d) = E_{\text{data}}(x, y, d) + E_{\text{smooth}}(x, y, d) \]  
\[ E_{\text{data}}(x, y, d) = U\{I_l(x, y), I_r(x, y, d)\} \]  
\[ E_{\text{smooth}}(x, y, d) = \sum_{(p, q) \in N} W(p, q) \]  

where \( x \) and \( y \) are horizontal and vertical coordinate of a reference image and \( d \) represents the depth value. Energy function, \( E(x, y, d) \), is comprised of the data term and the smoothness term. The matching costs for data and smoothness terms are defined in Eq. (3) and Eq. (4).

\( U[\star] \) is the pixel value difference between the left and right images, \( N \) is neighbors of pixels, and \( W(p, q) \) represents disparity value difference of neighboring pixels. \( I_l(x, y) \) is pixel value when coordinate is \((x, y)\) in the left image. \( I_{d}(x, y, d) \) is the matched pixel value in the right image when the coordinate is \((x, y)\) and the depth value of the position is \( d \) in the left image. 3D warping is used to find the matched pixel in \( I_{d}(x, y, d) \). The two processes of 3D warping are as follows. 3D warping back-projects the pixel of the left image to the 3D space based on the camera parameters and depth information. The projected pixel in the 3D space is then projected to the right image [11]. 3D warping is performed as follows.

\[ (x, y, z)^T = R_{src}A_{src}^{-1}(u, v, 1)^T du, v + t_{src} \]  
\[ (l, m, n)^T = A_{dst}R_{dst}^{-1}(x, y, z)^T - t_{dst} \]  
\[ (u', v') = (1/n, m/n) \]  

where \( A_{src}, R_{src} \) and \( t_{src} \) are respectively the internal, rotation, and translation parameters in the left image. \( A_{dst}, R_{dst} \), and \( t_{dst} \) are respectively internal, rotation, and translation parameters in the right image and \( d_{src} \) is real depth value. The pixel of the left image is sent to the 3D space by Eq. (5) and is projected to the right image by Eq. (6). \((u', v')\) in Eq. (7) represents the projected coordinate to the right image. Through above processes, \( I_{d}(x, y, d) \) in Eq. (3) is determined and the energy function, \( E(x, y, d) \), is optimized by CSBP considering complexity [12]. CSBP is one of the fastest algorithms for global optimization. Its complexity depends solely on constant space, \( O(1) \). Thus, CSBP is practical for implementation [13]. However, since the result quality by CSBP is not high enough, the obtained depth map can be used as merely initial values to generate more accurate depth information.

3.3 Depth refinement using consistency

As we discussed before, initial depth values are not reliable. Therefore, obtaining an accurate depth map is difficult solely by the energy function of depth extraction defined in Section 3.2. As a solution, wrong matching pixel detection and reasonable depth value assignment are vital.

We propose mismatched pixels detection method. Fundamentally, the proposed mismatched pixels detection method is based on uniqueness constraint which means one-to-one mapping. For this process, we project all pixels in the source image to the reference image using the initial depth map of source image to generate the mismatched parts for the source image. At this time, if pixels in the source image are projected outside image plane of the right image, pixels are regarded as mismatched parts since these does not have any matched pixels in the reference image, that is, one-to-zero mapping, not one-to-one mapping. This is defined by energy function.
\[ E_o(d_{u,v}) = \sum_{u,v} | o_{u,v} - G_o(u,v;d_{u,v}) | \]

\[ G_o(u,v;d_{u,v}) \] is a binary map constructed by the result of one-to-zero. If the pixel is projected inside image plane of right image, the parameter is set to '1', otherwise, the parameter is set to '0'. \( O_{u,v} \) is the value to check whether the pixel is mismatched or not. When the pixel in \((u,v)\) is supposed to the mismatched pixel, \( O_{u,v} \) value is set to '1'.

Furthermore, if many pixels in the source image are projected to the same pixel in the reference image, those pixels have a very high rate of mismatched pixels. This means many-to-one mapping. The energy function regarding this is defined in Eq. (9).

\[ E_w(d_{u,v}) = \sum_{u,v} | o_{u,v} - G_w(u,v;d_{u,v}) | \]

\( G_w(u,v;d_{u,v}) \) is set to '1' in the case of many-to-one mapping. Among the mismatched pixels in the source image, the one which possess the largest depth value is more likely to be matched pixel. Thus, we apply weighting factor \( W_v \) to the pixel of the largest depth value and the other pixels, differently.

Hitherto, we present mismatched pixels detection method using two energy functions. After mismatched pixels detection, the reasonable depth values should be assigned to the mismatched pixels. If we use the depth values from neighboring pixels in the matched pixels region, depth estimation in the mismatched region is possible. The reason is that depth values of mismatched pixels are similar to those of matched pixels in the background. In the proposed method, we perform mismatched hole filling by propagating the depth values of matched pixels to the mismatched pixels. The energy function for mismatched hole filling is defined in Eq. (11).

\[ E_{oh}(u,v,d_{u,v}) = \sum_{(p,q) \in N_v} \left( 1 - p_{o}(q) \right) \frac{1}{\text{dist}[(u,v),(p,q)]} \exp\left( -\frac{\text{diff}[(u,v),(p,q)]}{\sigma^2} \right) \]

\( N_v \) means the neighboring pixels whose distance from current mismatched pixel is smaller than predefined distance \( \text{dist}[(u,v),(p,q)] \) is the distance between mismatched pixel \((u,v)\) and neighboring matched pixel \((p,q)\) and \( \text{diff}[(u,v),(p,q)] \) is color difference. The depth value, which has the maximum value of Eq. (11), is determined as the optimal depth value for the pixel \((u,v)\). We repeatedly apply this process until all mismatched hole are removed. Finally, in order to improve the quality of the depth map, we apply the post-processing to the acquired depth map [14].

Since the depth maps generated in the previous processes are estimated for each frame separately, the results of depth sequences are temporally inconsistent. Therefore, the method generates high frequency flickering problem which is caused erroneously computed abrupt depth changes over time [15]. We add a temporal smoothing to solve this problem. Depth temporal smoothing reduces flickering and visual discomfort to viewer’s eyes by improving depth consistency. At first, we check consistencies of color frames to find the candidates for application of temporal smoothing. Mean absolute difference is used as measure of color consistency. The smoothing candidates obtained through above process are handled by median filter which is a reasonable choice for the desired temporal smoothing.

4. EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed method, we tested four stereo images with two kinds of camera arrangement. These test data are Newspaper and Cafè in the parallel array, and Fitness, and Friends in the arc array. The
resolutions of the test images are 1920×1080 except for Newspaper. Newspaper is captured at 1024×768 resolution. Color correction was applied to these data sets for accuracy of matching. The camera parameters of these images are estimated by camera calibration [16] for image rectification and 3D projective transformation.

Figure 8. Depth map result in the parallel camera array

Figure 8 compares the result of the proposed method with that of convention method with image rectification in the parallel camera array. Image rectification in a parallel camera array has considerable influence on the accuracy of depth map. However, the proposed method without image rectification generates the high quality result as well.

Figure 9. Depth map result in the arc camera array

Figure 9 illustrates the visual comparison of the final depth map obtained from the proposed method with the depth map obtained from conventional method with image rectification in the arc camera array. The conventional method generates
the depth image which transforms disparity map obtained through rectification to depth map. The result in Figure 8(b) and Figure 9(b) is obtained by applying CSBP [12] and post-processing [14].

The proposed method enables us to generate accurate depth values without image rectification regardless of camera arrays. Therefore, our method has an effect that reduces restrictions in camera settings before capturing images. In order to evaluate the performance of the proposed method objectively, we applied view synthesis and calculated PSNR values of the synthesized views for our method and the conventional method. Table 1 represents comparisons of their performances.

Table 1. PSNR comparison of view synthesis result (dB)

<table>
<thead>
<tr>
<th>Sequences</th>
<th>Conventional method</th>
<th>Proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parallel camera array</td>
<td>Newspaper</td>
<td>28.37</td>
</tr>
<tr>
<td>Cafe</td>
<td>32.21</td>
<td>33.42</td>
</tr>
<tr>
<td>Arc camera array</td>
<td>Fitness</td>
<td>20.23</td>
</tr>
<tr>
<td>Friends</td>
<td>18.39</td>
<td>29.91</td>
</tr>
<tr>
<td>Average</td>
<td>24.80</td>
<td>30.63</td>
</tr>
</tbody>
</table>

For evaluation of the proposed temporal consistency method, we tested 50 frames for each sequence using HTM 4.0.1 reference software. Since the proposed method enhanced the temporal consistency of depth sequences without any quality degradation, accurate inter prediction was possible and the coding efficiency was improved.

![Graphs of Newspaper, Cafe, Fitness, and Friends showing R-D curve for evaluation of temporal consistency.](image)

Figure 10. R-D curve for evaluation of temporal consistency

From the experiment with stereo videos captured by an arc camera array, we observe that the conventional depth estimation method using image rectification generates many depth error pixels. In contrast, the proposed method
provides high performance on depth estimation regardless of any kind of camera arrangement. Furthermore, our method reduces visual discomfort to viewer’s eyes.

5. CONCLUSION

In this paper, we have proposed a new method to estimate depth information in an arbitrary camera array. The proposed method finds corresponding points in the epipolar lines, instead of the rectified horizontal lines of stereoscopic images. Besides, our method improves the quality of depth images by refining mismatched depth pixels and considering spatiotemporal consistency. As a result, we have obtained more accurate depth information in the arc array, compared to the conventional method. Consequently, the proposed method has provided more stable results than other methods based on image rectification.

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