Vanishing-Point Detection Based on a Fuzzy Clustering Algorithm and New Clustering Validity Measure

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Abstract

This paper proposes an image-preprocessing method combined with a fuzzy clustering algorithm and new validity measure to detect the vanishing point in an image. The proposed method segments the object in an image by using the clustering algorithm and then extracts critical vanishing lines. By examining the intersection of the vanishing lines, the vanishing point is located. To locate the vanishing point accurately, the initial cluster number of the fuzzy clustering algorithm should be provided correctly. Therefore, the study proposes a new clustering validity measure, the area measure, to estimate the initial cluster number according to the information of cluster areas. Experimental results on 29 images show that the proposed preprocessing method and validity measure can accurately identify the location of the vanishing point and vanishing lines. In addition, compared with several validity measures, the new validity measure achieves satisfactory experimental results and outperforms six other validity measures.

Key Words: Fuzzy Clustering, Clustering Validity, Vanishing Point, Vanishing Line, Depth Map

1. Introduction

Three-dimensional (3D) images play an increasingly crucial role in the future of science and technology. The development and application of 3D images are therefore currently a major research focus. This paper focuses on converting a single 2D image into a 3D image by using the depth-estimation method. The objective of a depth-estimation method is to estimate the depth map of a scene from one signal image; left-eye and right-eye images can then be produced using the original image and depth map [1–4]. Two critical steps are included in this process. The first step segments the foreground objects and background; the second step assigns an appropriate depth value to all objects. A virtual view of the 3D scene can then be synthesized in real time by applying the depth image-based rendering (DIBR) technique [5]. Figure 1 shows the main flowchart for converting a 2D image into a 3D image. However, designing a general method to segment foreground objects and generate depth maps for all types of images is difficult.

Establishing the correct depth map from the information provided by a single image is called the monocular depth cue [6–13]. The research method for the monocular depth cue can be categorized into as following:

Figure 1. Main flowchart of converting one single 2D image into one 3D image.
(1) Linear perspective: As distance increases, the outlines of rooms or buildings converge. The lines never meet but they appear to from a distance [6,7].

(2) Texture gradient: Fine details on nearby objects can be seen clearly, whereas such details are not visible on distant objects [8,9].

(3) Shape and shading: Objects cast shadows that give observers a sense of their 3D form [10].

(4) Overlapping and the atmospheric perspective. This study mainly uses the linear-perspective method [6,7] to locate vanishing lines and the vanishing point. Most researchers extract the image edge first, and then locate the vanishing lines from the image-edge information by using the Hough transform. The possible position of the vanishing point is located at the intersection of the vanishing lines. However, when the image contains a complex object or background, the edge information extracted from the original image is complex. After the Hough transform, numerous line segments are recognized as vanishing lines, therefore generating many intersections in the image. This makes determining the correct position of the vanishing point among these intersections difficult. Consider the following example: there is one bus in Figure 2(a); Figure 2(b) is obtained by using Canny edge detection. In Figure 2(b), edge information is complex; therefore, applying the Hough transform (Figure 2(c)) generates a number of possible vanishing lines (red line segments). Because some red line segments are not actually vanishing lines, more than one intersection appears. In Figure 2(d), seven obvious intersections (blue circles) appear. Because of the interference from these false vanishing lines, rules must be designed to determine the intersection that is the correct vanishing point.

The most intuitive solution is to adjust the parameters (e.g., mask size) of Canny edge detection to reduce the exposed-edge information, and adjust Hough transform parameters to reduce the number of found line segments. However, in practical application, because information such as brightness, contrast, and the category of each image is not identical, setting appropriate parameters for all possible cases is not feasible. To solve these problems, the first contribution of this study is the design of a simple and intuitive preprocessing method that employs the concept of image segmentation and a fuzzy clustering algorithm. The preprocessing method can extract the critical edge information of an image, enabling increased accuracy in the detection of the correct vanishing lines and vanishing point. Details of the preprocessing method are provided in section 2.

The main purpose of image segmentation [14–20] is to label foreground objects and the background. If the objects and background are correctly labeled, critical edge information can be gained by retrieving the object contour, which benefits locating vanishing lines and the vanishing point. After determining the vanishing point, image segmentation also labels the regions of the object and background. This is essential to produce the correct depth map.

The clustering algorithm is the most common method of dealing with image segmentation problems [17–20]. However, correctly labeling object and background regions for any image is not easy. Figure 3 is the reproduced image obtained after dividing entire pixels according to their RGB values into two groups by applying the fuzzy c-means algorithm (FCM) [21]. The objects and background are not correctly classified in this case, illustrating the difficulty of image segmentation. In addition, an initial cluster number should be determined in advance by using the clustering algorithm for image segmentation. Different initial cluster numbers generate various segmentation results. Therefore, the second contribution of this paper is the design of a new cluster measure, the area measure, to estimate the initial cluster number according
to the information of cluster areas. Details of the area measure are provided in section 3.

2. Detecting Vanishing Lines and the Vanishing Point

To detect vanishing lines and the vanishing point, the proposed preprocessing method consists of five steps:

Step 1: First, blur the image by using a mean filter with a $5 \times 5$ mask size. Figure 4(a) shows the image resulting from the blurring process.

Step 2: After blurring, transfer the image pixels from the RGB color space to the YCbCr color space. Subsequently, divide the original image into several nonoverlapping image blocks of $8 \times 8$ pixels. Calculate the mean values of Cb and Cr from the pixels within the image block and use the mean values of Cb and Cr to typify the color information of this image block.

Step 3: Consider each image block as a data pattern, and use the Cb and Cr mean values as features of the data pattern. Generate the dataset that contains the data pattern of each image block. Subsequently, group the dataset into two clusters by using the fuzzy c-means (FCM) algorithm. Figure 4(b) shows that the blue data patterns and red data patterns represent two different clusters, and position X represents cluster center $C^*$. For each pixel, only the Cb and Cr values are changed, whereas the Y value remains unchanged. Subsequently, transfer the image pixels from the YCbCr color space to the RGB color space. Figure 4(c) shows the reproduced image. This step can be considered as a type of color quantization processing.

Step 5: Use Canny edge detection to generate edge information, and use the Hough transform to generate a number of possible vanishing lines. In Figure 4(d), three red line segments represent the possible vanishing lines. Finally, the intersection of the vanishing lines is the vanishing point.

Comparing Figures 4(d) and 2(c), the proposed preprocessing method extracts only critical edge information to locate vanishing lines. The proposed method can therefore locate the correct vanishing point more easily.

3. Proposed New Cluster Validity Measure

Results of the proposed preprocessing method are satisfactory; however, clustering using the FCM algorithm

Figure 3. Reproduced image after dividing entire pixels (according to their RGB values) into two groups by applying fuzzy c-means algorithm.

Figure 4. (a) Image after blurring operation; (b) Clustering results achieved by FCM algorithm; (c) Reproduced image; (d) Vanishing lines and vanishing point retrieved after applying Canny edge detection and Hough transform.
requires setting up the initial cluster number in advance. The initial cluster number for Figure 4 is set at two. However, the optimal initial cluster number is usually different for different images. For example, Figure 5(a) contains three main color regions, namely the red toy car (region A), ivory floor (region B), and blue wall (region C). The cluster number should reasonably be set to three. Figures 5(b) and 5(c) show results of using cluster numbers of two and three, respectively; Figures 5(d) and 5(e) show reproduced images processed using the proposed method. In Figure 5(d), the red toy car and ivory floor (regions A and B) are grouped into the same cluster, whereas the blue wall (region C) is grouped into another cluster. Such clustering results affect the retrieved edge information; more importantly, mistakenly grouping the red toy car (object) and ivory floor (background) into the same cluster may lead to serious mistakes when producing the depth map.

The evaluation of the appropriate cluster number in the dataset is the cluster validity. Many studies present different cluster validity measures to assess the appropriate cluster number [22–29]. However, further analysis of the data distribution in Figures 5(b) and 5(c) shows all data patterns pooled into one cluster in the CbCr 2D space. The dataset in Figure 4(b) is also pooled into an apparent cluster. According to the design concept in most cluster validity measures, the most reasonable cluster number for datasets in Figures 4 and 5 should be one. This means that most cluster validity measures are not suitable for this problem. Therefore, a new cluster validity measure should be proposed to solve this problem.

Comparing the clustering results in Figures 5(b) and 5(c) reveals one interesting phenomenon. In Figure 5(c), three clusters are located in the CbCr 2D space; the area covered by each cluster is extremely close. However, in Figure 5(b), the red cluster covers a relatively large area, whereas the blue cluster covers a relatively small area. Figure 4(b) shows that the area covered by both clusters is extremely close when grouped into two clusters. The cluster number may thus be considered reasonable when the result shows a close area covered by each cluster.

Figure 5 is analyzed to explain the rationale of this idea. In the proposed preprocessing, the original image is divided into nonoverlapping image blocks. Each block represents a data pattern in a 2D color space based on Cb and Cr values. After clustering by using the FCM algorithm, if a cluster has a larger area, it usually contains image pixels with more colors compared with other smaller clusters. In Figure 5(a), most image blocks in Region A (toy car) are red. The corresponding data patterns are mainly located in the top cluster in Figure 6 according to their Cb and Cr values (greater Cr value). Image blocks of the wall (Region C) are blue and located mainly in the bottom cluster in Figure 6 (greater Cb value). Most image blocks of the floor (Region B) are ivory and inside the middle cluster. The area covered by each cluster is closer. Therefore, setting a smaller cluster number (e.g. two clusters in the case) may make one cluster cover a larger area than other clusters. As illustrated in Figure 5(b), the top cluster contains most blocks within regions A and B, therefore covering a larger area compared with the other cluster. However, by increasing the cluster number to three, the area covered by each cluster is more similar compared with setting two clusters. The object (toy car) can be labeled successfully in the reproduced image.
method is to set a large cluster number (e.g., ten clusters) to reduce the area of each cluster after clustering. This approach, however, results in a reproduced image similar to the original image, thereby repeating the negative results in Figure 2. With a large cluster number, correctly labeling the clusters according to the image objects or background is difficult, and therefore establishing the correct depth map is also difficult.

In brief, if the cluster result shows that the area covered by each cluster is similar, then the presumed cluster number should be considered reasonable. Achieving favorable performance by using a large cluster number is also difficult. Therefore, a new cluster validity measure is necessary to assess the similarity of the area of each cluster.

In the proposed validity measure, the first step is to calculate the area of a cluster. Three clusters in Figure 6 are used as an example to estimate the area. First, treat the CbCr data space as a new image and set the background color black (Figure 7). According to the position of each data pattern in the CbCr space, calculate a corresponding coordinate position in the new image. Then, generate a white circular area around the corresponding coordinate position. In this study, the radius of the circular area is set at 5 pixels. By performing the same process on all the data patterns, the result shown in Figure 7 can be realized. In according to this image, the area of the white region is finally summed to represent the area for each cluster. After obtaining the area of each cluster, the formula of the area validity measure (A) is proposed as follows:

\[
A(c) = \frac{1}{c} \sum_{i=1}^{c} \left(1 - \frac{\text{Area}_i}{\text{Area}_{av}}\right)^2
\]

where \(c\) is the cluster number, \(\text{Area}_i\) is the area of the \(i\)th cluster, and \(\text{Area}_{av}\) is the average area of all clusters. The smallest value of \(A(c)\) indicates a valid optimal partition; in other words, the area of each cluster is most equivalent.

4. Experimental Results

This paper proposes a preprocessing method to find correct vanishing lines, and a new area measure to determine the appropriate cluster number. In two experiments, a total of 29 images [30,31] were used to assess the proposed method. The first experiment verifies whether the vanishing lines and vanishing point can be found effectively by combining the proposed preprocessing method and area measure. The second experiment compares the area measure with other validity measures to find the optimal cluster number.

4.1 Detecting the Vanishing Lines and Vanishing Point

In the first experiment, 29 images were used to assess the proposed preprocessing method and area measure. For comparison, Canny edge detection was applied directly to the test images to extract their edge information; subsequently, the Hough transform was used to generate the vanishing lines. The experimental results are tabulated in Table 1. The experimental results are cate-
gorized into three scales. “Good” means the user can easily detect the critical vanishing lines and correct vanishing point. “Average” means the tested method generates more than one intersection, one of which is the correct vanishing point. If the correct position of the vanishing point does not appear in any detected intersection,

Table 1. Experimental results of two methods

<table>
<thead>
<tr>
<th>Scale</th>
<th>Good</th>
<th>Average</th>
<th>Bad</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apply the proposed method</td>
<td>24</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Apply canny edge detection</td>
<td>7</td>
<td>22</td>
<td>0</td>
</tr>
<tr>
<td>and hough transform</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 8. Experimental results of five “Good” test images by the proposed method.
the experimental result would be denoted as “Bad.”

Several experimental results of the proposed method are provided in Figures 8–10. In Figures 8–10, the image on the left is the original image; the image in the middle is the reproduced image; and the image on the right is the detection result of vanishing lines and the vanishing point. Twenty-four images are “Good” (Figures 8–9), three images are “Average” (Figure 10), and only two images are “Bad” for the proposed method (Table 1). For most test images (Figures 8 and 9), critical edge information is retained on these images, which is the main advantage of the proposed method. This helps the user to easily locate vanishing lines and the correct vanishing point. Because there is more than one intersection presented in the three

Figure 9. Experimental results of five “Good” test images by the proposed method.
images (Figure 10), the user must identify the correct vanishing point from these intersections.

Some experimental results of the other comparison method are shown in Figure 11. These images contain substantial edge information. Therefore, the Hough transform may find a number of possible vanishing lines and generate several intersections. For example, 47 obvious intersections appear in Figure 11(e). This makes identifying the correct vanishing point among these intersections difficult. Experimental results of the other comparison method also illustrate this situation (Table 1). Only seven images are “Good,” but 22 images are “Average.” Comparing the two methods, the proposed method extracts more critical edge information and enables users to locate correct vanishing lines and the vanishing point more easily.

4.2 Comparison of Area Measure with Other Cluster Validity Measures

The second experiment attempted to verify whether the area measure can find the appropriate cluster number. The optimal cluster number of a test dataset is known in most cluster validity studies. However, this study did not have the prior information of each test dataset (image). Hence, the optimal cluster number for each test image is determined in advance by applying the following process. First, assess possible cluster numbers from two to six; subsequently, find the smallest cluster number that can successfully segment the main object and background in the reproduced image after applying the proposed preprocessing. Assign the identified smallest cluster number as the optimal cluster number. For example, to successfully segment the main object (toy car) and background (floor and wall) in Figure 5(a), use at least three clusters to cluster the dataset (Figures 5(c) and 5(e)). Hence, the optimal cluster number of Figure 5(a) is three. In Figure 2(a), the use of two clusters can successfully segment the main object (bus) and background (Figure 4(c)); hence, the optimal cluster number of the image is two.

The optimal cluster numbers of 13 test images (Figures 8–10) and experimental results are shown in Table 2. In addition to the proposed area measure, the experi-

![Figure 10. Experimental results of three “Average” test images by the proposed method.](image)
ments compare six cluster validity measures including Partition coefficient (PC), Partition entropy (PE), Separation measure (S), Dunn’s measure (Dunn), Davies-Bouldin’s measure (DB), and fuzzy hypervolume (FHV) [22–26]. In Table 2, the table block with a gray background indicates that the optimal cluster number determined using the validity measure is wrong. The main results and observations obtained from the simulations are summarized as follows:

### Table 2. The experimental results of seven validity measures

<table>
<thead>
<tr>
<th>Test image</th>
<th>Optimal cluster number</th>
<th>A</th>
<th>PC</th>
<th>CE</th>
<th>S</th>
<th>Dunn</th>
<th>DB</th>
<th>FHV</th>
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<tbody>
<tr>
<td>Figure 8 (a)</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>2</td>
<td>3</td>
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<tr>
<td>Figure 8 (b)</td>
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<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Figure 8 (c)</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>2</td>
<td>2</td>
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<tr>
<td>Figure 8 (d)</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>2</td>
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<tr>
<td>Figure 8 (e)</td>
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<td>2</td>
<td>2</td>
<td>6</td>
<td>6</td>
<td>5</td>
<td>2</td>
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<tr>
<td>Figure 9 (a)</td>
<td>4</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>6</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Figure 9 (b)</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>2</td>
<td>3</td>
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</tr>
<tr>
<td>Figure 9 (c)</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
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<tr>
<td>Figure 9 (d)</td>
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<td>3</td>
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<td>2</td>
<td>2</td>
<td>6</td>
<td>3</td>
<td>3</td>
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<tr>
<td>Figure 9 (e)</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>5</td>
<td>2</td>
<td>2</td>
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<tr>
<td>Figure 10 (a)</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>5</td>
<td>5</td>
<td>4</td>
<td>4</td>
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<tr>
<td>Figure 10 (b)</td>
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<td>2</td>
<td>2</td>
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<tr>
<td>Figure 10 (c)</td>
<td>2</td>
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<td>2</td>
<td>2</td>
<td>6</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

1. For the proposed area measure, only one out of the 13 test images (Figure 9 (e)) failed to estimate the optimal cluster number; the performance of the area measure is significantly more favorable than other validity measures.

2. The color of the vessel (object) in Figure 9(e) is not clear; therefore, the area measure selects only two clusters (the white sky and green ground) as the optimal cluster number.

3. Regarding the other six validity measures for comparison, the performance of PC, CE, and DB is more favorable than that of the other three measures.

### 4.3 Limitations of the Proposed Method

The proposed method performs well in simulation results, especially for outdoor images simultaneously containing the sky, buildings, and the ground. However, the proposed method also has limitations. For the two indoor images (Figure 12), results of the proposed method are not favorable because the interior ceiling, walls, and floors in these two indoor images are of similar color. In this case, segmenting the image by using the clustering algorithm is difficult.

### 5. Conclusions

Combined with the clustering algorithm and new va-
lidity measure, the proposed preprocessing can easily locate the position of vanishing lines and the vanishing point in an image (especially outdoor images). In addition, the proposed area measure can provide a suitable initial cluster number in this research. Compared with six validity measures, the area measure achieves satisfactory experimental results and outperforms the other six validity measures.

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Reference


[30] Some Images are Available on the Following Web-


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