RANSAC-based Orthogonal Vanishing Point Estimation in the Equirectangular Images

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ABSTRACT

In this paper, we present an algorithm that quickly and effectively estimates orthogonal vanishing points in equirectangular images of urban environment. Our algorithm is based on the RANSAC (RANdom SAMple Consensus) algorithm and on the characteristics of the line segment in the spherical panorama image of the 360° longitude and 180° latitude field of view. These characteristics can be used to reduce the geometric ambiguity in the line segment classification as well as to improve the robustness of vanishing point estimation. The proposed algorithm is validated experimentally on a wide set of images. The results show that our algorithm provides excellent levels of accuracy for the vanishing point estimation as well as line segment classification.

Key words: Vanishing Point Estimation, Equirectangular Images, RANSAC, Geometric Ambiguity, Distance Function

1. INTRODUCTION

Vanishing point estimation in an image is a major topic in the computer vision since some decades. It has numerous applications ranging from camera calibration, pose estimation, single-view reconstruction, autonomous navigation and rectangular structure estimation and so on [1, 2]. The usefulness of vanishing point estimation in camera calibration and pose estimation has been well understood in the early 90's. For that reason, there have been many attempts that automatically extracting the vanishing point.

Recently, the advancement of optics and computational photography technology have made it easy to create a spherical panorama image by stitching and composing. And online photo-sharing services such as Flickr popularized these types of images. In addition, many map services such as Google Street View provide a 360-degree street-level panorama view, which lets we explore places around the world. Consequently, many conventional image processing techniques on planar image should be adopted into the panoramic image. In this context, vanishing point estimation is also one of the classical image processing work.

In this work, we consider the problem of estimating three orthogonal vanishing point from the equirectangular image of man-made environments. It has not been much studied to estimating the vanishing point from the equirectangular images. It is due to the difficulty in the acquisition of the
equirectangular images. However, obtaining the equirectangular image has become much easier by the advances of the computational photography technology. Therefore, an algorithm that efficiently estimates the vanishing point for the equirectangular image is needed. We propose an algorithm that quickly and effectively estimate orthogonal vanishing points in equirectangular images of urban environment based on the RANSAC (RANdom SAMple Consensus) algorithm and on the characteristics of the line segment in the spherical panorama image of the 360° longitude and 180° latitude field of view.

The remainder of the paper is organized as follows. In Section 2, we review the previous works for vanishing point estimation. The characteristics of the line segment in equirectangular image are summarized in Section 3. Section 4 describes how the proposed algorithm work. Some experimental results are illustrated in Section 5. Finally, we describe the conclusion and future work.

2. RELATED WORKS

This section reviews the existing works that estimate the VPs. There is a significant amount of excellent work on estimating vanishing point in different contexts and for different applications. Existing methods for planar image can be divided into four categories.

The first category is based on the Hough transform (HT) [3–5]. Since Barnard [6], detection was performed on a quantized Gaussian sphere using a HT. The intersection of a line pair is computed and accumulated in the Hough parameter space. These approaches, however, are not reliable in the presence of noise and outliers. And it is sensitive to quantization level of the parameter space.

The second category is Expectation-Maximization (EM)-based methods [7–10]. Given an initial VP, EM alternates between performing an expectation (E) step and a maximization (M) step. The expectation of the line clustering is evaluated for the current VP in the E step. And in the M step, the VPs are computed by the clusters found in the E step. These approaches are sensitive to initialization.

The third category relies on exhaustive search [11]. This method can obtain very satisfying results. However, it is suffered from its computational complexity and large search space.

The fourth category is RANSAC-based algorithms [12–14]. It is simple but efficient general method to distinguish inliers and outliers and also estimates the underlying dominant mode. To detect three orthogonal VPs, RANSAC can be sequentially applied on the remaining outliers [15]. J-linkage algorithm [16] can also be applied, but it is too much computationally expensive.

We now review the panorama case. Most of the studies dealing with the omni-directional images are focused on catadioptric view. Kang and Jo [17] proposed the method to acquire the 3D geometric information of the feature using the geometrical properties of mirror and circle at infinity in a single omni-directional image. They estimate the vanishing points as the intersection points of curves, which meant by horizontal line segments. This method successfully estimates vanishing point, but the assumption that the camera located in a perpendicular against the ground. And they only estimate the horizontal vanishing points. Bosse et al. [18] proposed a method which uses a RANSAC-based method to seed initial clusters for EM-based refinement from omni-directional video. However, the EM-based methods require a precise initialization; otherwise they return unreliable results. Moreover, they need some probabilistic distributions that are complicated to obtain and often based on heuristics. Oh and Jung [19] proposed a RANSAC-based algorithm for the equirectangular image with geometric constraint. However, there exist limitation on the vanishing point estimation.
and ambiguity resolution method due to each of the VPs is estimated independently.

3. LINE SEGMENTS IN EQUIRECTANGULAR IMAGES

In the photography, a panorama is a broad term for an image with elongated field of view. There exists many kinds of panorama image, but we focus on the equirectangular image i.e. a spherical image which has the 360° longitude and 180° latitude field of view. Compared with the traditional images, they provide a couple of advantages such as much wider field of views, a large amount of information shared between images, handling of the ambiguity of rotation-translation inherent to conventional images, etc. The equirectangular image can be taken with a camera cluster. A camera cluster (also known as a polidioptic device) consists of several synchronized cameras each pointing in different directions. The individual images can then be stitched or composed together to build a equirectangular image, as Fig. 1. Probably, Google Street View™ will be the most familiar application based on the equirectangular images.

In the spherical panoramic imaging, a line \( L_i \) in the world is projected onto the unit sphere as an arc segment on a great circle which is represented by a normal vector \( n_i \). The arc segment on a great circle forms a curve segment in the equirectangular image as shown in Fig. 2. Oh and Jung overviews this relationship and introduces GCA representation [21]. GCA representation allows us to estimate vanishing point in a simple way. The great circles of parallel lines intersect in two antipodal points, which correspond to the vanishing point. And they are computed by \( v = n_i \times n_j \) where \( n_i \) and \( n_j \) are the normal vectors of the great circles corresponding two parallel lines in the world. This vanishing point

![Fig. 1. Examples of equirectangular images from Flickr [20].](image1)

![Fig. 2. Line segments in the equirectangular image: a line \( L_i \) in the world is projected onto the sphere as an arc on a great circle \( C_i \) and the projection of parallel lines \( L_i \) and \( L_j \) intersect in two antipodal points \( v \) and \( v' \).](image2)
defines a plane passing through the center of unit sphere, and the points correspond to the normal vectors are exist on this plane. In other words, we can estimate the vanishing point by plane fitting method.

4. VANISHING POINT ESTIMATION

In this section, we explain the algorithm to estimate the three orthogonal vanishing points in equirectangular images. Prior to the explanation our approach, let us fix some notation. Throughout this paper, $N$ denotes the number of detected line segments and $n_j$ is the normal vector of the great circle associated with the $j$th line segment $l_j$. We denote $v_i$ as the $i$th vanishing point, $i = 1, 2, 3$, then $v_1^Tv_2 = v_2^Tv_3 = v_1^Tv_3 = 0$.

We assume a set of the straight-line segment is derived from some image-processing tool. Then, we project the line segments into the unit sphere and compute its corresponding great circle normals. In our experiments, we obtain a set of lines from the equirectangular images using the great circle arc detector [21]. Since the GCA representation gives line as well as its corresponding great circle normal, we can skip this stage. Fig. 3 illustrates the line segments and their corresponding great circle normal. For a better visualization, the line segment and its corresponding normal of the great circle shown as the same color.

Given a set of extracted line segments with corresponding normals, we estimate three orthogonal vanishing points and determine which line is associated to which VP. General RANSAC process is

Fig. 3. Line segments and corresponding great circle normals.
as follows: random selection of data, model fitting and the count of the inliers verifying this model. This process is repeated until a certain number of iterations, and output is the model leading to the highest number of inliers.

The first step for RANSAC process is to determine the number of required samples, which are randomly selected to estimate the model. Intuitively, we have three DOF since each of the vanishing points has a DOF and three orthogonal vanishing points construct complete rotation. Therefore, each RANSAC iteration start with three randomly selected lines. And we set the maximum number of iterations for RANSAC to 169. It is based on a guaranteed accuracy of 99% and a safe outlier ratio of 70%.

Next step is to estimate the model parameter with three lines. The first and second lines (shown in red and green, respectively) intersect at a \( v_1 \) (and its antipodal point \( v'_1 \)). The great circle corresponds to \( v_1 \) (shown in dashed grey) is intersect with the third line (shown in blue) at \( v_2 \) (and its antipodal point \( v'_2 \)). The second vanishing point \( v_2 \) can be defined by cross-product of the vanishing point \( v_1 \) and the great circle normal of the third line. Finally, the third vanishing point \( v_3 \) is determined by the cross-product of \( v_1 \) and \( v_2 \). Fig. 4 illustrates the model estimation process.

Final step is to test all other lines against the model, and count the number of the inliers. We define that the line \( l_j \) is an inlier if its geometric distance is lower than a threshold \( \tau_s \), i.e. \( |n_j \cdot v_i| \leq \tau_s \). The threshold \( \tau_s \) is defined as \( \tau_s = \sin(\tau_a) \) where \( \tau_a \) is an angular tolerance. We fix \( \tau_a = 5^\circ \) for all of the experiments shown in this paper.

However, there is an ambiguity in this approach. There exist the points which are considered as belong to the both of two vanishing points. These misclassified points lead us towards an error of the vanishing points. Fig. 5 shows this ambiguity. The first row shows the line segments classified by the vanishing points and incorrectly classified lines are displayed as the red boxes. The lines which are associated with the same vanishing point are shown as identical color. Unclassified line segments are displayed in grey color. The second row illustrates the normals correspond to the line segments on the first row. The points which cause the ambiguity were marked with red circles.

To avoid this ambiguity, we examine the line segments in the equirectangular image again. As Fig. 5 shows, the problematic line segment has the normal which is quite close to the line of intersection defined by two planes correspond to two vanishing points. The normal of the great circle can be distorted due to the difficulty and inaccuracy of the line extraction. Thus, even if the normal of a great circle is close to the one of two planes correspond to the vanishing points within the unit sphere, it is not necessarily associated with it. Therefore, we consider the constraints on the image space.

Fig. 4. Illustration of model estimation in RANSAC, best seen in color.
In the conventional image case, we can define a distance function as the average orthogonal distance from the endpoints of a line \( l \) to an auxiliary line \( l' \) defined as the line passing through the vanishing point \( v \), and the middle point of the line \( l \). The arc correspond to the line segment in the equirectangular image is similar to pseudo-sinusoidal function. The arc is the part of the great circle in the unit sphere.

Let a set of points on a great circle \( \varphi \) is \( p = (x,y,z)^T \) and its normal vector is \( n_j = [abc]^T \). Then, the points \( p \) satisfies \( n_j \cdot p = 0 \) where \( \| p \| = \| n \| = 1 \). We can represent the points on the unit sphere from Cartesian to Polar coordinates. So, we can formulate the sinusoidal function as

\[
a \cos(\theta) \cos(\phi) + b \sin(\theta) \cos(\phi) + c \sin(\phi) = 0,
\]

where \( \theta \) and \( \phi \) are the horizontal and vertical rotation, respectively. However, it is not easy to compute the endpoints of the line \( l' \) by using this pseudo-sinusoidal function. Thus, we compute the endpoints of the line \( l' \) on the sphere rather than the image, then project them into image space.

Determining the endpoints \( e_1' \) and \( e_2' \) of the given line \( l \) (thick grey, whose middle point is \( e_j \) and endpoints are \( e_1 \) and \( e_2 \)) on the sphere is illustrated in Fig. 6. First, we need to define the normal vector \( n_j' \) of the great circle correspond to the line \( l' \) (black). Since the plane represented by the normal vector \( n_j' \) of the great circle \( C_j' \) corresponds to the line \( l' \) which passing through the vanishing point \( v_i \) and the center \( e_j \) of the arc within the great circle \( C_j' \), the normal can be written as

\[
n_j' = \frac{e_j \times v_i}{\| e_j \times v_i \|}.
\]
Fig. 8. Determination of the endpoints $e_1'$ and $e_2'$ which are orthogonal to $e_1$ and $e_2$, respectively.

The normals of the great circles $n_{e_1}$ and $n_{e_2}$ which are orthogonal to $e_1'$ and passing through $e_1$, and $e_2$ is determined as

$$n_{e_i} = \frac{e_i \times n_j'}{\| e_i \times n_j' \|}, \quad i = 1, 2.$$

where $e_1$ and $e_2$ are the endpoint of the arc within $C'$. Then, $e_1'$ and $e_2'$ can be computed as

$$e_1' = \frac{n_{e_1} \times n_j'}{\| n_{e_1} \times n_j' \|}, \quad e_2' = \frac{n_{e_2} \times n_j'}{\| n_{e_2} \times n_j' \|}.$$

Finally, we obtain the average distance of the endpoints between $e_1'$ and $e_2'$ in image space by projecting them onto the equirectangular image. However, $e_1'$ and $e_2'$ can be their antipodal points on the unit sphere. Therefore, we negate $e_1'$ in order to correct the direction when $e_1 \cdot e_1' < 0$, and it is same as $e_2'$. We choose the vanishing point which is close to the endpoint of the line. This distance function can be used to improve the accuracy of the vanishing point estimation. We performed nonlinear optimization, which minimizes above distance function to obtain more accurate vanishing points.

5. EXPERIMENTAL RESULTS

In this section, we present experimental results using proposed algorithm. We implement our algorithm using RANSAC toolbox for MATLAB [22] and fminsearch function for nonlinear optimization. To illustrate and verify the method, we tested our algorithm on a wide set of images from Flickr. Fig. 7 illustrates an representative result of line clustering and VP estimation obtained by proposed algorithm and ambiguity relieving process. Each curve
Fig. 8. More experimental results for the Flickr images.
corresponds to a line segment and all parallel lines have the same color.

A series of experimental results are shown in the Fig. 8. The images on the left column are the inputs, and the images on the right column are the result of the proposed algorithm. All parallel lines have the same color and unclassified lines are shown in grey color. Most of the lines were correctly classified except for a little. Since these lines are quite close to both two vanishing points within the sphere as well as image space, it is difficult to classify correctly.

Some statistics for images are summarized in Fig. 9 and Fig. 10, using a computer equipped with a hexa-core CPU at 3.2GHz (only one core was used) and 8 GB RAM. All the statistics is the average of 20 trials. Fig. 9 (a) shows the classification ratio of the inliers with respect to the total number of lines. Six items on the left side are corresponded to the images with 640x320 resolution on Fig. 8, and the right two are twice the resolutions. Approximately, 80% of the line segments were classified. Fig. 9 (b) illustrates the execution time for each step and the total execution time. As shown in Fig. 9 (b), the non-linear optimization time accounted for more than half of the total execution time. The total execution time except one is within 1 second on non-optimized MATLAB code. It took 1.06 seconds to the lines exceeding 1700. Since all of the three orthogonal vanishing point samples can be tested independently, it is possible to implement the proposed algorithm on

![Fig. 9](image9.png)

Fig. 9. The classification ratio of the inliers (includes ambiguous lines) w.r.t. the total number of lines, and the execution time for each step (on non-optimized MATLAB code).

![Fig. 10](image10.png)

Fig. 10. Two types of errors for RANSAC and non-linear optimization.
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6. CONCLUSIONS

In this paper, we have presented an algorithm for the vanishing point estimation in the equirectangular images. The proposed algorithm estimates three-orthogonal vanishing points from the equirectangular images by using RANSAC-based approach. And we introduced an efficient distance function that using the geometric constraints of the equirectangular image. The distance function was used to relieve the geometric ambiguity in line segment classification as well as improve the accuracy of the vanishing point estimation. Finally, we performed the experiments on a wide set of images.
The experimental results have demonstrated the accuracy and effectiveness of the proposed algorithm. Although our algorithm effectively classifies and estimates vanishing points, our current implementation may not be applicable to real time environment. Thus, we are currently considering to extend this method into highly parallelized environment such as GPU. And the ambiguity relieving algorithm still has to be improved.

This ongoing attempt is first step towards the reconstruction of the scenes from the panoramic sequences available in online map services. Therefore, we plan to estimate the rotation from a series of panoramic images in the future work.

REFERENCES


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