Robust Horizon and Peak Extraction for Vision-based Navigation

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Abstract

Most vision based UAV (Unmanned Aerial Vehicle) navigation algorithms extract features such as horizons and mountain peaks from 2D input images, and match the extracted features with features obtained from DEM(Digital Elevation Map) by process of registration. The difficulties of the horizon and peak extraction originate from the variations of input images such as noise, viewing direction, and scale. Moreover to prove the existence of horizon is also difficult. Therefore the success of the feature extraction will depend on its ability to cope with these variations. In this paper, we present a new feature extraction method, which is robust to these variations and verified throughout the following experiments.

1 Instructions

UAV has used GPS (Global Positioning System) or INS (Inertial Navigation System) for self-localization. But GPS is sensitive to signal dropout and to hostile jamming. The drawback of INS is that their position error compounds over time and causes large localization errors when the UAV is matching the acquired images with DEM. In order to overcome main disadvantages of both methods, many researchers suggested the vision-based navigation, which helps estimating localization of UAV when GPS or inertial guidance is not available. [3][5][4]

This paper considers the problem of accuracy in extracting horizon and peaks -they are useful for vision-based navigation because a horizon is the longest edge line in mountain scene containing abundant information and a peak is invariant about viewing directions- from infrared images of a mountain scene. The problem of accuracy regarding extraction of horizon and peaks is important since these features determine the pose.

The difficulties of the horizon and peak extraction originate from the variations of input images such as noise, viewing direction, scale, and existence of horizon. So the success of the feature extraction will depend on its ability to cope with these variations.

Yet previous researches have often required limited and good environments, such as noiseless images, good weather, or high computation power. They also could not guarantee the existence of extracted horizon. [5, 6, 7, 8]

We propose a robust horizon extraction method under noisy images and bad weather, based on characteristics of human visual system such as binding, which is a main process of the visual perception. Binding is a process to bind two different properties by a series of attention. And Gwan Sung Kim^{*}, In Cheol Kim^{**} LG Electronics^{*} Agency for Defense Development^{**} 16, Woomyon-dong, Seocho-gu, Seoul, Korea^{*} Yuseong P. O. BOX 35, Daejeon, Korea^{**} kimgs@lge.com^{*} cheol@add.re.kr^{**}

with a such method, we verified existence of a horizon in the input image.

For the peak extraction, previous approach has used SDG (Second Derivative of Gaussian), which searches for Gaussian characteristics in the second derivative of the extracted horizon. But we use the CSS (curvature scale space)[5] corner detection algorithm, which is stable to scale, viewing direction, and noise variation. We compared those two methods and demonstrated that CSS is better in consequence. The process of extracting a peak that corresponds with the image sequence is developed by the use of curvature matching.

2 Horizon Extraction

The performance of human visual system is more outstanding than computer vision system. So we can upgrade recognition efficiency of computer vision system by using human biological recognition process.

2.1 Human Visual System

Neurons in human brain respond not only to object's shape but also to color and texture as well. So there is abundant information about color, shape and texture in perceived images. The information is analyzed by distinguished neurons and integrated into one object of which we want to recognize. Neuroscientists call the former part, an attention process and the latter, a binding process. [2]

Figure 1 shows an example object. There are three boundaries in figure 1. The first one divides homogeneous region from non-homogeneous region, the second one, yellow region from white region, and the last one, white region from blue region. If we want to recognize the second boundary, which divides yellow region from white region, we should, at first, extract all boundaries, which constitute a border map, from the image and then find the region in which yellow contrasts with white very much in the segmented region map.



Figure 1 Example image [2]

2.2 Horixel

The horizon is a strong edge boundary, which segments sky region and mountain region. In figure 2, the difference in temperature between sky and mountain is so large that the intensities of both regions are different. The figure 3 shows the variation of image intensity at 50^{th} , 200^{th} and 400^{th} column in the figure 2. So to find horizon, we focus on two factors. One is strong edge-ness and the other is region segmentation. Using the attention and binding process, we can obtain borders and homogeneity maps in figure 3.

We formulated attention and binding process in the equation 1 and defined 'Horixel' which means a pixel on the horizon. In the equation 1, the energy in a pixel (x, y)is E(x, y). It tells us about two things. One is the edge-ness and the other is similarity: each characteristic corresponds to border and homogeneity maps respectively in figure 3. The edge-ness is computed by a canny edge operator, and the similarity is computed by considering how many similar intensity pixels exist in the upper and lower direction group and how different the intensity of the two groups are. The pseudo code for calculation D(x, y) is described in figure 4. Or, we focused on the boundary of two clustered regions. When a pixel has higher energy than the threshold value, we can define it as horixel (Equation 2). Figure 5 shows the horixel distribution in figure 2.



Figure 2 Infrared Image (MWIR sensor, PM 2)



Figure 3 Variation of column's intensity in figure 2

$$E(x, y) = \alpha \cdot |\nabla G_{\sigma} * I(x, y)| + \beta \cdot \frac{D(x, y)}{H}$$
(1)

(H: Height of the image, pseudo code for D(x, y) is in figure 4)

Horixel = {
$$(x, y) | E(x, y) > \mu$$
} (2)



Figure 3 Border maps and Homogeneity maps in figure 2



Figure 4 Pseudo-Code for calculation D(x, y)



Figure 5 Horixel Distribution in figure 2

2.3 ROI(Region Of Interest) extraction

It is unnecessary to search all pixels in the image because it takes up large computation power. So we calculated the region of interest, using horixel. Horizon has many horixels and links along horizontal direction. We define vertical projection of horixel in equation 3. E(x, y) denotes the horixel energy in pixel (x, y) (equation 2).

$$VP(y) = \sum_{x=1}^{H} E(x, y)$$
 (3)

The region of interest covers the area from the first local minimum, which is higher than the global maximum, to the other first local minimum, which is lower than the global maximum. Figure 6 shows the ROI and vertical projection of horixel energy.



Figure 6 ROI extraction and Vertical Projection

2.4 Boundary Extraction using Dynamic Pro-

gramming

Reliable extraction of the mountain skyline under the widely varying light conditions of outdoor scenes is not a trivial task. An usual approach to similar problems involves dynamic programming for the edges or graph searching techniques[3].

Amini[6] proved that a dynamic programming is efficient for energy minimization problems in vision. Each pixel in an input image has horixel energy. We formulate this energy term as that for active contour model's energy.

2.5 Verification of Horizon Existence

Verifying extracted horizon is important. When the false alarm occurs, UVA misunderstands its location because of false horizon information, but when missing occurs, UVA calculates horizon just in the next input image. Accordingly, UVA must be capable of avoiding the false alarm. We verify horizon by using the characteristics of human visual system, the Helmholtz principle. Or, non-casual alignments are automatically detected by the Helmholtz principle as a large deviation from uniform randomness. It was implemented by partial Gesutalt theory. [7]

Figure 7 shows horizon and horixel distribution. The horixel must be aligned on the horizon. The probability of horixel existence in the image is H(x, y) which is described in the equation 6. If the horizon contains n pixels, and k pixels of n pixels are horixels then the probability is shown as B in the equation 4.





$$B(H(x, y), n, k) = \binom{n}{k} H(x, y)^{k} (1 - H(x, y))^{n-k}$$
(4)

$$H(x, y) = P[E(x, y) > \mu] = \frac{1}{M} \#\{(x, y) \mid E(x, y) > \mu\}$$

M: number of pixels E(x, y) which is non-zero n: number of pixels, which compose extracted boundary k: number of horixels, which are on extracted boundary

If the extracted boundary is meaningful, the expectation value must be small. So if the probability B in equation 4 is under the threshold, a horizon exists in the input image.

2.6 Peak Extraction

Previous works used SDG for peak extraction [3]. This algorithm is simple to implement and runs quickly. But SDG assumes that the shape of mountain is Gaussian, so when this assumption fails, we cannot extract a peak. We selected CSS for peak extraction. In CSS corner detector, the corner points are detected at a high scale of the CSS and tracked through multiple lower scales to improve the result of localization. So this method is very robust to noise and we believe that it performs better than SDG. [5]

3 Experimental Results

3.1 Extraction with various environments

We consider global energy minimization for which we calculated all available paths in order to make it robust to various environmental factors such as image noise level, weather, and atmosphere condition.

Figure 8 shows the horizon extraction from noisy images with various standard deviations. Our model can even endure a very extreme situation where the standard deviation of noise reaches about 20. Figure 9 shows various atmospheric conditions about power of sunlight and the humidity.



Figure 8 Horizon Extraction with noise level increasing



(c) Fog in atmosphere (humidity: 70%) Figure 9 Horizon with various atmosphere conditions

3.2 Verification result

Figure 10 shows that the ROC curve of our system. We tested the proposed system for 80 IR images. We set α and β to 1 in equation 1.



Figure 10 ROC curve of proposed system

3.3 Peak Extraction

Figure 11 compares the robustness to noise level between SDG and CSS. When the deviation of gaussian noise is 11, the peaks move within 3 pixels in CSS method.



Figure 11 Comparison with SDG about noise level

Table 1 shows the mean shift of peak when image is enlarged twice. CSS is less sensitive than SDG. And table 2 shows the repeatability of SDG and CSS when viewing direction increases from 0 to 20 degree. In case of CSS, about 90% peaks can be repeated so we can use CSS for feature tracking.

Table 2.	<u>Mean shift of</u>	peak
	CDC	000

	SDG	CSS
Mean of	1.9	0.7
Peak's shift (pixel)		

Table 3. Repeatability with viewing direction			
	SDG	CSS	
Repeatability	67%	90%	

4 Conclusion

In this paper we have proposed a new system for practical horizon and peak extraction from infrared images.

First, we integrated region and edge based horizon extractions and defined a novel model, horixel. This approach is robust to noise and weather variation. And we verify the extracted horizon by using characteristic of human visual system so that we can reduce false alarm.

Second, we applied CSS to mountain peak extraction and have shown its robustness to viewing point, scale, and noise. Finally, we demonstrated that our approach is feasible in real infrared images.

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