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SURVEY ARTICLE

Fast Road Tracking for Unmanned Ground Vehicles

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Abstract—***The paper presents a method for vision based road direction detection for Unmanned Ground Vehicles (UGVs). The method relies on finding the optimal local orientation of the image followed by line detection and a soft voting scheme to determine the vanishing point. The proposed method reduces the computational complexity by using less number of Gabor filters and eliminating the sky pixels for detecting the optimal local orientation of the terrain structure, yet achieving comparable results to existing methods. The main relevance of this method is that it can identify the dominant vanishing points in bifurcating roads and also it overcomes the noisy output due to camera vibrations and poor illumination conditions. The method can be used in developing autonomous navigation system (ANS) in either structured urban environments or unstructured off-road conditions.***

Keywords—Sky Line; Gabor Filter; Local Dominant Orientation; Vanishing point; Soft Voting.

I. Introduction

Path findings and navigational control in Unmanned Ground Vehicles (UGVs) are usually accomplished using the road features obtained in the direction of the optical axis of the forward looking cameras.Roads, buildings and other human made structures have a large number of parallel lines in the 3D space. Lane model plays an important role in road/lane detection. The most common approach for constructing the 2D lane model is by assuming that the two sides of the road boundaries are parallel on the ground plane.

The majority of vision-based road detection methods in the literature are grouped into three main categories: edge, region, and texture-based methods. Edge-based methods reduce the road detection to the extraction of road boundaries or lane markings. These approaches were used in navigation system in robotics by avoiding collision, where edges of road seen by a camera are extracted and back projects them on the ground plane in order to compute the appropriate steering commands for the vehicle [1][2]. But in such approaches the strong edges are often the shadow edges whereas road edges are much weaker. Laser [3], radar [4], stereovision [5], color cue [6], Hough transform [7, 8], steerable filters [9], Spline model [10] etc. have been utilized to find the road boundaries or markings. The drawbacks of these methods are that they only consistently work for structured roads with noticeable markings or borders. Methods based on segmenting the road using the colour cue have also been proposed but they do not work well for general road image, especially when the roads have little difference in colours between their surface and the environment. That is most of the existing vanishing-point detection algorithms rely on three steps [10]. The first step performs edge detection on the image in order to extract the most dominant edges such as road borders or lane markings. The next step is to determine if there are any line segments in the image. Once all the line segments are identified, a voting procedure is applied to find the intersections of the lines. The shortcoming of all these methods is that they are based on edge detection followed by line extraction, which may restrain the process of detecting the true vanishing points in unstructured road conditions.

Aside from that, numerous vanishing-point detection methods have been proposed for man-made environments that do not depend on the edge detection step [11], [12]. These approaches search for similar global structures and repeating patterns (e.g., walls, doors, and windows) in the image to define the vanishing-point locations. However, it is unlikely that one can identify such repeating structures in outdoor unstructured environments. To address these drawbacks Rasmussen put forward a method by estimating the orientation of each pixels of the unstructured environment by using several Gabor banks [13,14] or steerable filter banks [15] and the filter with maximum response is chosen as the dominant orientation and a soft voting scheme was followed by it. A location with maximum votes is considered as the vanishing point of the road. However, in order to achieve precise orientation estimation, one needs to apply a large number of oriented filters in all possible directions from 0° to 180°.

Designing and applying a bank of differently rotated filters is computationally expensive. To address this problem, Freeman and Adelson [16] proposed a steerable filter in which each arbitrary oriented filter can be formed by a linear combination of a fixed set of basis-oriented filters. Although the steerable filter is a more efficient approach compared with the bank of oriented filters, it still requires steering the basis-oriented filters in all orientations with a precise angle step size (e.g., 1° interval) and studying the outputs of the filters as a function of their orientations to find the maximum response as the local dominant orientation. Later, in 2012 Peyman Moghadam *et al.* [17] has shown that we need to use only 4 Gabor orientation for extracting the dominant orientation of the environment by achieving more accurate results than the existing methods. However, this method fails in bifurcating roads.In cases of outdoor environments, most of the pixels in the upper parts of the images are related to the sky pixels or off-road regions (e.g, mountains) with no strong points of convergence. Also as the vehicle moves along the road, the road bumps and crevasses can exacerbate vibrations of the mounted forward looking camera on the vehicle and consequently the position of estimated vanishing point v_P max may change drastically from frame to frame.Hence the direct vanishing-point estimation from single image is noisy.

This paper is motivated by three observations of previous approaches: (1) The difficulty in identifying the vanishing points in bifurcating roads (2) The computational complexity while using a higher order Gabor filter bank and the unnecessary processing of sky pixels (3) The noisy output due to camera vibrations. To overcome these drawbacks we propose this method where joint activity of four Gabor filter orientations is used followed by skyline pixel removal, which drastically reduces the computational complexity and also we detect the correct vanishing point from a set of clustered vanishing points over different frames. Finally a new voting scheme method is proposed which can be applied for vanishing point detection in bifurcating roads also. This algorithm is robust to noises, shadows, and illumination variations in the captured road images, and is also applicable to both the marked and the unmarked, dash paint line and solid paint line roads.

The rest of the paper is organized as follows. In section II, skyline detection steps are explained. In section III the procedure for finding the dominant orientation of each pixel in the image using OLDOM and its Hough transform, a new voting scheme which can be applied for vanishing point detection in bifurcating roads also and the method for estimating the most reliable vanishing point over consecutive frames. In section IV some experimental results along with performance evaluation of the proposed method are shown. Finally the conclusion is given in section V.

II. SKYLINE DETECTION

For most of the road images there will be sky pixels which can't be a candidate vanishing point. To enhance the vanishing-point detection process, we can exclude these sky pixels from the OLDOM step and thereafter in the voting scheme. Therefore the detection of the sky line and removing the pixels above it will result in significant computational speed-up.Here we are using an edge based sky line detection algorithm which was proposed by Yang[18]that considers relative differences in appearances of two region. The flow chart of skyline detection algorithm is shown in Figure 2.

Figure 1. Road image showing its vanishing point and horizon line above which are the unwanted sky pixels

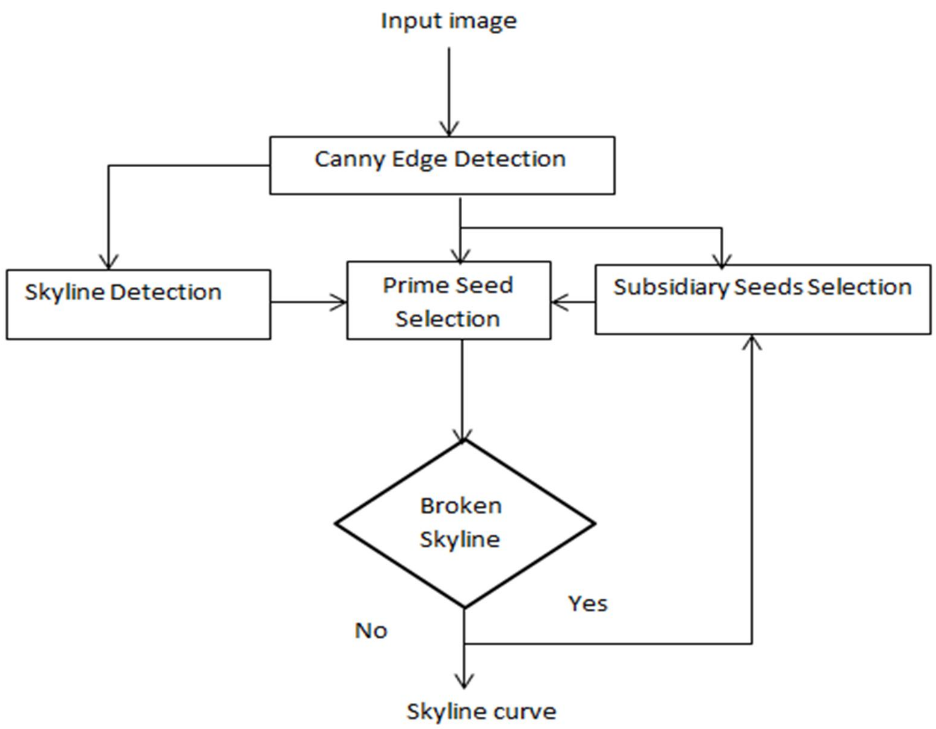

Figure 2. Flow chart of Sky line detection algorithm

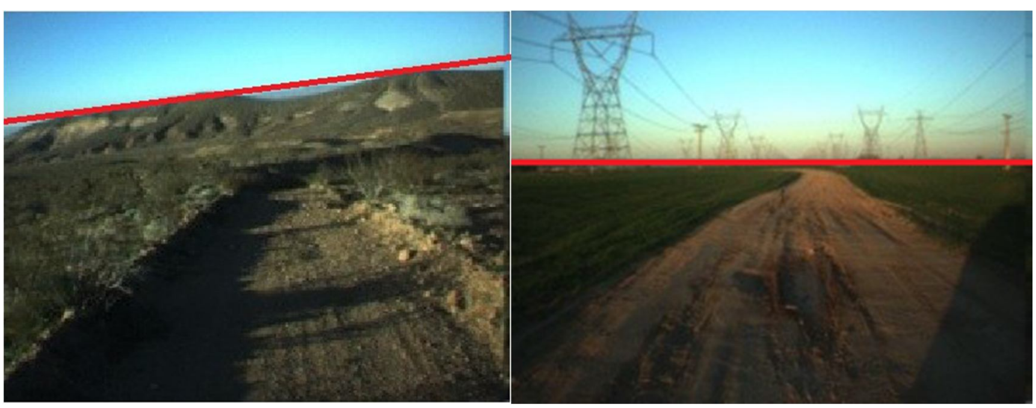

Figure 3. Skyline detected images

III. **DOMINANT ORIENTATION DETECTION AND DOMINANT VANISHING POINT ESTIMATION**

Vanishing point detection algorithm consists of mainly two steps: the dominant orientation estimation in the input image and its Hough transformation for finding the maximally voted point as the vanishing point.

A. Finding dominant orientations

Each pixel in the image say p(x,y) will be having a particular orientation angle. The best method to extract these orientation angles is by using the Gabor filters. The dominant orientation is evaluated using the Gabor kernel for a preferred orientation ψ_n is given by the function

$$g_{\omega,\psi n} = \frac{\omega}{\sqrt{2\pi}\ K} e^{\frac{-\omega}{8K^2}(4a^2+b^2)} e^{i\omega a} e^{\frac{-K^2}{2}} \quad (1)$$

where,

$$a = x\cos\psi_n + y\sin\psi_n \quad (2)$$

$$b = -x\sin\psi_n + y\cos\psi_n \quad (3)$$

ω is the radial frequency , and value of ω is set to $2\pi/\lambda$ and λ is the special frequency which is set to $4\sqrt{2}$ and K is a constant equal to $\pi/2$. The gray scaled input image I(p) is convolved with the Gabor filter bank of predefined orientations ψ_n.

$$Y\psi_n(p) = I(p) * g\psi_n(p) \quad (4)$$

$$\psi_n = (n-1)\pi/N \text{ , for } n=1,2\ldots..N \quad (5)$$

where * represents the convolution operation and $\hat{Y}_{\psi n}(p)$ the convolved image for a particular orientation ψ_n.

N - total number of orientations

Finally the Gabor energy is calculated as

$$E_{\Psi n}(p) = \sqrt{\operatorname{Re}(\hat{Y}_{\psi n}(p))^2 + \operatorname{Im}(\hat{Y}_{\psi n}(p))^2} \quad (6)$$

The outputs of the Gabor filter bank $\hat{Y}_{\psi n}(p)$ is used for finding the dominant orientation $\theta(p)$.That is we can use any number of Gabor filters in parallel with predefined orientations given by equation (5) and only the pixels with corresponding orientation will produce the output. By combining all these orientation and comparing the corresponding energies found using equation (6), we can detect the dominant orientation $\theta(p)$. The orientation corresponding to the strongest Gabor energy response is chosen as dominant texture orientation.

Usually large numbers (N) of orientation kernels are required as the image may have N number of orientations. To reduce the computational complexity here we are using only four Gabor filters. The Optimal Dominant Orientation Technique makes it easier to extract those road features which are useful for vanishing point detection. Here instead of considering the 72 orientation Gabor bank we use 4 Gabor filters, $g_{\Psi n}$, where $1 \le n \le 4$. Let the orientations that we use be Ψ € {0, $\pi/4$, $\pi/2$, $3\pi/4$ } that produces four energy values $E_{\Psi 1}(p)$, $E_{\Psi 2}(p)$, $E_{\Psi 3}(p)$ and $E_{\Psi 4}(p)$, corresponding to these orientations. Select those two energies which are the highest among the four orientations and define a new vector in the 2-D space V(p). Vector V(p) is given by

$$V(p) = \sum_{i=1}^{2} E_{\Psi}^{i}(p) e^{j\Psi si} \quad (7)$$

where $E_{\Psi 1}(p)$ and $E_{\Psi 2}(p)$ represents energy corresponding to two dominant orientations Ψ_1 and Ψ_2 of the image which produces the maximum energy response than the other two orientations. i.e, $E_{\Psi 1}(p) > E_{\Psi 2}(p) > E_{\Psi 3}(p) > E_{\Psi 4}(p)$. The vector V(p) can be represented as

$$V(p) = V_x(p) + jV_y(p) \quad (8)$$

From this we can extract the optimal dominant orientation $\theta(p)$

$$\theta(p) = \tan^{-1}\left(\frac{Vy(p)}{Vx(p)}\right) \quad (9)$$

But this approximation can fail on those which are highly cluttered so that no apparent dominant orientation can be estimated. In such cases the Energy responses from all the 4 filters will be comparable. So we apply a threshold value in this method and if the energies are within this value these energy responses are split into two new vectors S1(p) and S2(p).

$$\text{where } \|S_1(p)\| = E_{\Psi}^{1}(p) - E_{\Psi}^{4}(p) \quad (10)$$

$$||S_2(p)|| = E_{\Psi}^2(p) - E_{\Psi}^3(p) \quad (11)$$

Now the new dominant orientations are $\Psi s_1(p)$ and $\Psi s_2(p)$ corresponding to vectors $S_1(p)$ and $S_2(p)$. The vector V(p) for determining the optimal dominant orientation is now given by

$$V(p)=\sum_{i=1}^{2} S_i(p)e^{j\Psi si} \quad (12)$$

Now using equation (9) the orientation angle θ(p) corresponding to the new vector V(p) can be calculated. Thus the joint activities of all the four Gabor energy responses are used in determining the optimal dominant orientation as described in [17].

B. Detecting vanishing point lines

The dominant pixel orientation θ(p)of each pixel is used for drawing the vanishing point lines. The image will be composed of a set of parallel lines. These lines intersect to a point which is the required vanishing point. Here we use Hough transform for drawing a number of such lines. A straight line y= mx +b can be expressed in polar form as

$$d= x \cos(\theta) + y \sin(\theta) \quad (13)$$

where, θ defines a vector from the origin to the nearest point on the straight line y=mx+b. By converting the polar coordinates back to rectangular coordinates the dominant lines of the cluttered structure can be detected.

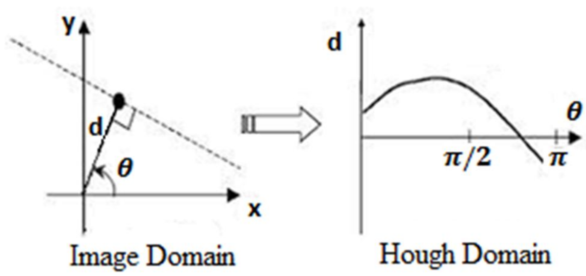

Figure 4: A point in the image domain and corresponding representation in the Hough domain

The Gabor filter output shows all the dominant orientations of the pixels. The problem that arises due to the presence of horizontal orientations of the pixels from Gabor filter bank output is that these horizontal orientations produces parallel horizontal lines in the image as shown in Figure 5.But for vanishing point detection we require only the lines oriented upwards. Hence to avoid the nearly horizontal orientations a weight is applied to each line (ray) based on the trigonometric function of its orientations sin(θ(p).Considering all the lines (after extending them) oriented upwards, the common intersection point of maximum number of lines yields the vanishing point[Figure 6], which is detected using the voting scheme described in the following section.

Figure 5: Line detected output of an image

Figure 6: Image output obtained after applying the trigonometric weight to each pixel orientation angle θ(p) of the line detected image.

C. Voting Scheme

For a straight road segment on planar ground, there is a unique vanishing point associated with the dominant orientations of the pixels belonging to the road. Curved segments induce a set of vanishing points. The voting scheme used here is similar to the one proposed in [17] except that here three maximally voted points are considered. Vanishing point is that point through which maximum number of lines passes through. The existing methods make use of voting scheme to find the coordinates of a single maximally voted point. In this paper, we make use of three accumulator spaces for detecting the first three maximally voted points. These points are required for vanishing point detection in bifurcating roads. The votes obtained for these three coordinates are first compared by taking the absolute differences. If the difference is greater than the threshold value given by equation (14) then the first maximally voted point is taken as the vanishing point indicating that the road is not bifurcating. Otherwise the coordinates of these three points are considered to find the Euclidian distance between them. If the horizontal separation between any two of these three points is greater than one fourth of the image size horizontally, then those two points are detected to be the vanishing points indicating that the road is bifurcating.

$$T=\mu-3\sigma \qquad (14)$$

where μ and σ are the mean and standard deviation of the maximally voted accumulator space respectively.

D. Estimation Of Dominant Vanishing Point

The direct vanishing-point estimation from single image is noisy due to various causes such as irregular illumination conditions, road bumps etc. As the vehicle moves along the road, the road bumps may cause vibrations of the mounted forward looking camera. To reduce impact of such noises a smoother vanishing point is predicted from N vanishing point hypotheses over N frames.Here we first track the entire vanishing point contour throughout a sequence of N voting images.

Consider the set X^t of the t-th time.This set may contain N-hypothetical regions (frames).

ie, X^t={X_i}

where, X_i : X_1,X_2,X_3,……..X_N

Smoother vanishing points are estimated by considering the full road posterior {X^t} by searching for a path with highest weight over a sequence of frames. For the computational simplicity we considered 30 frames for a particular set ofX^t.

IV. RESULT ANALYSIS

The proposed algorithm has been applied to 40 digital images captured from both structured as well as unstructured environments under different illumination conditions for performance evaluation and comparison with the other techniques. This section contains some results as well as discussion about the performance of the proposed algorithm. To determine the quality of vanishing point estimation of the proposed method the vanishing points estimated experimentally is compared against the vanishing-point ground truth manually determined through human perspective perception.

A. Performance Analysis

For a quantitative analysis approach, a performance metric is used which is defined as,

$$D = \frac{||P-P0||}{diag(P(x,y))} \qquad (15)$$

where $P(x_0,y_0)$ is the estimated vanishing point and $P_0(x_0,y_0)$ the centre pixel of the ground-truth vanishing point location P(x,y) represents the image and "diag(P(x,y))" represents the diagonal size of the image. D value near to 0 shows correct detection of vanishing point.

B. Experimental Results

The performance of proposed method is evaluated both qualitatively and quantitatively in 40 images of different terrain conditions.. For the quantitative comparison we have used the classical edge-based (Canny/Hough) vanishing point detection method [10] and the best known texture based vanishing point algorithm [14].Figure 7.shows the results of error computed with these three methods of vanishing point detection. Some of the experimental results are shown in Figure 8. Here unstructured and non-bifurcating roads are considered. Vanishing points detected in bifurcating roads are shown in Figure 9.

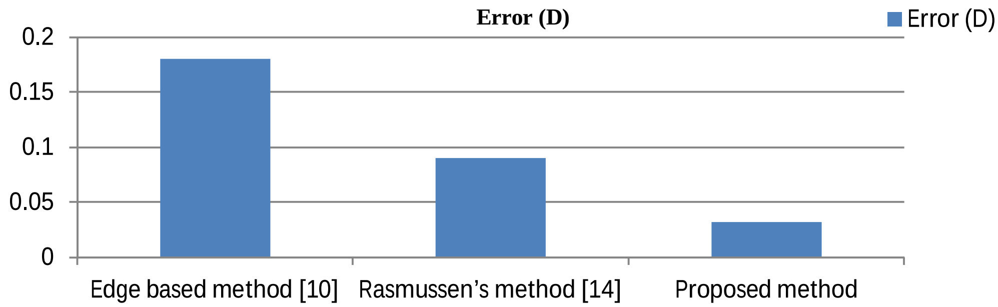

Figure 7.Graphical representation of error from Edge based, Rasmussen's and the proposed method.

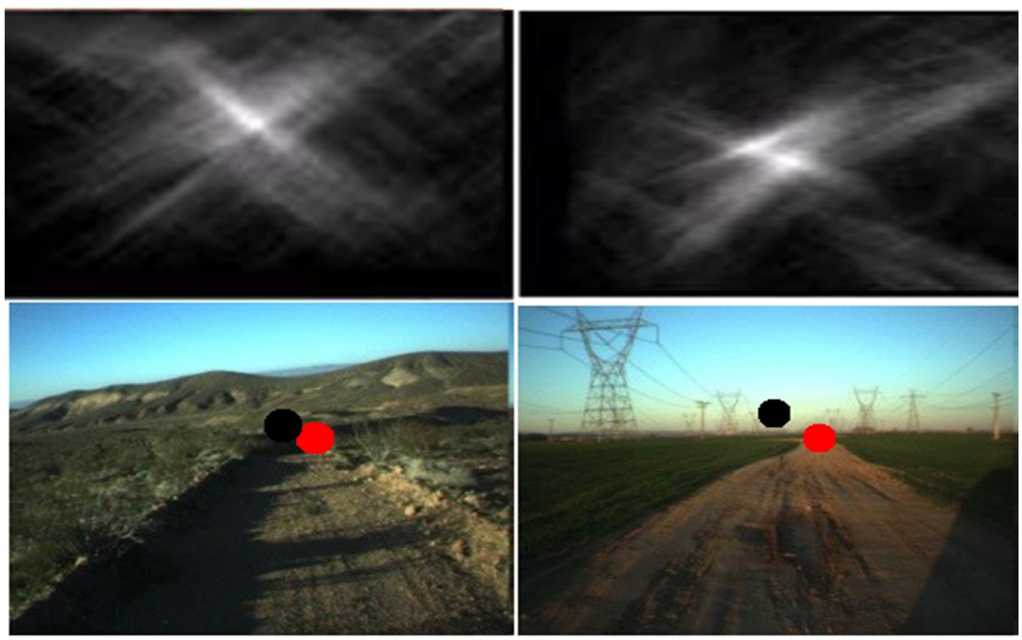

Figure 8: Experimental results of vanishing point detection.First row shows the accumulator spaces of two road images and second row shows the corresponding vanishing point detected images where black dot represents estimated vanishing point and red dot represents the ground-truth vanishing point.

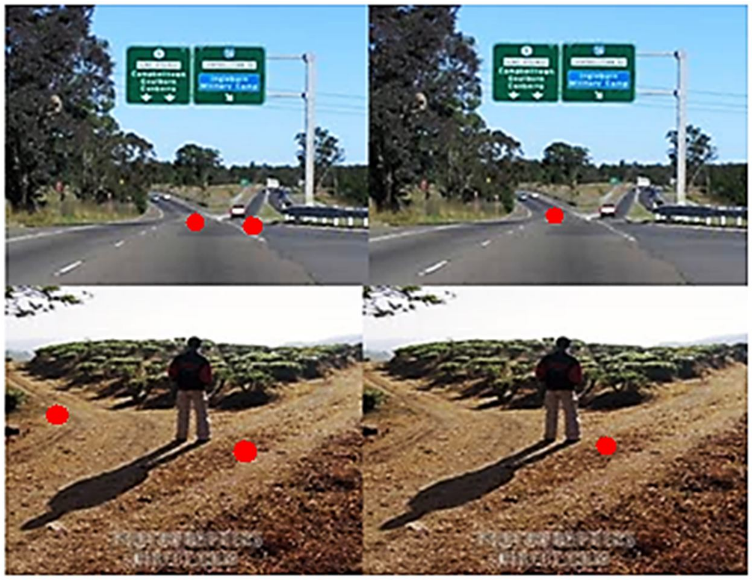

Figure 9: Vanishing points detected in Bifurcating roads using the proposed method is shown in first column and the detection using one of the existing methods[17] is shown in second column.The proposed method detects both the vanishing points

V. CONCLUSION

A novel method for simultaneous vanishing point detection in bifurcating roads is proposed in this paper and the results were evaluated in 40 images. The experiments have shown that the method produced less noisy results, even for images with a cluttered environment such as poorly delineated roads and works equally well for non-bifurcating roads. The method can be used for unstructured as well as structured roads. The estimation is more accurate in the case of structured roads. The results are not affected by noise and varying illumination of the image.To remove the effect caused by noisy pixels, each Gabor texture orientation is given a weighting score. Also the removal of sky pixelsand the voting of only upward direction pixels whose confidence is high,drastically reduces the computational complexity and improves the accuracy.

However this approach is found to be sensitive in certain unstructured road cases where a road scene consists of some obstacles with strong edges than the tracks left by previously passed vehicles. Then these strong boundaries will induce the voter to an incorrect estimation of vanishing point. In our future task we will see, if this method is sufficient for detecting vanishing points in roads leading to multiple tracks. If not, the transition from our simple framework to a more complex and probabilistic framework might be necessary. We believe the knowledge of the road network is essential in this case.

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