Principal Orientation and Generalized Vanish Point Based Road Detection

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***Abstract*—With the development of road detection related applications, higher performance is required on the accuracy, robustness and time efficiency. Road detection algorithm based on vanishing point estimation has been paid lots attention on for its adaptability when processing complicated situations. However, the existing algorithms based on vanishing point estimation have two shortcomings: 1) unable to handling images with no internal vanishing point, 2) high computational complexity. This paper proposes an improved road detection algorithm based on principal orientation and generalized vanishing point estimation. Proposed method reduce amount of calculation by select effective voting pixels with the principal orientation constraint, and improved the algorithm robustness by handling cases that vanishing point located external of images with the concept of generalized vanishing point. Quantitative and qualitative experiment results donate that the proposed method is both accurate and efficient in road detection.**

Keywords- Road Detection; Vanishing Point Estimation; Generalized Vanishing Point; Principal Orientation; Multidimensional Voting Strategy

I. INTRODUCTION

It has been decades that researchers focused on road detection, literatures on this field proposed various methods have been widely applied in recent research. Compared with other sensors like laser or radars[1][2], vision sensors contain more information, several vision based branches should be mentioned.

Methods based on machine learning such as SVM [3] and Neural Network [4] are highly intelligent, but limited to artificial training samples. Branch of Vanish Point estimation based algorithms known for its outstanding performance when original proposed by N. Simond [5] using 2D Gabor Filter to calculate the texture orientation and estimated the VP by Hough Transform. Rasmussen [6] proposed a new voting strategy to estimate the vanish point which regard all pixels below candidate vanishing point as voters, result in too large amount of calculation algorithm efficiency is not high. H. Kong [7] proposed an optimized method by considering the distance between the candidate vanishing point and voters. This strategy ensures the fairness in numbers of voters but remains the problems of computing complexity. The latest literature suggests that real time property become a crucial demand, many methods using extra hardware to improve the speed, such as GPU [8], FPGA [9]. Moghadam [10] proposed the conception of Optimal Local Dominant Orientation Method (OLDOM) to speed up the vanishing point estimation by decreasing stages of the Gabor filters. Although these algorithms made progress in reducing the computational complexity, there are still much more room for improvement. In addition, the existing algorithm based on vanishing point estimation had ignored situations that if the intersection point of road boundaries is not exist inside the image, existing algorithms remain processing as normal situation which certain lead to a wrong output.

To conquer the defect, we propose a novel vanishing point estimation algorithm by introducing the concept of generalized vanishing point. We use multidimensional voting strategy to estimate vanishing point and determine whether the vanishing point located inside of the image, finally segment the road region according to estimation result. In addition, we optimized the voting area selection strategy to improve the efficiency.

II. ESTIMATION OF GENERALIZED VP

N. Simond [5] original propose the vanishing point method using image texture information, and proved to be effective and feasible in vanishing point estimation by many literatures. C. Rasmussen [6] regards all the pixels below the candidate vanishing point as voters without filtering lead to a high computation complexity. H. Kong [8] introduced the definition Confidence Coefficient to improve this situation. Only Confidence Coefficient of pixels more than a certain value is considered to be effective voters. However, Confidence Coefficient can only eliminate pixels of low texture feature, but not noise points with strong local texture feature, such as trees, pedestrians beside the road.

A. Selection of Effective Voters

While texture of effective pixels presents consistency, texture of noise points often chaotic. As shown in Figure 1, the second column presents distribution statistic histograms of pixels in different texture orientation. To most images, texture orientation of pixels of highest percentage always consistent with the principal direction of road. Interference points were not obviously reflected in the statistical figure for they are not of orientation consistency.

Therefore, we use the principal orientation constraints for the filtering image pixels, eliminating redundancy pixels which of discrete texture concentration or weak texture feature. If orientations whose sum of pixels accounted for over 80% of the whole image, we mark them as candidate Principal Orientation. Then eliminate the rest of pixels retain pixels whose texture orientation in accordance with road principal orientation as effective voters.

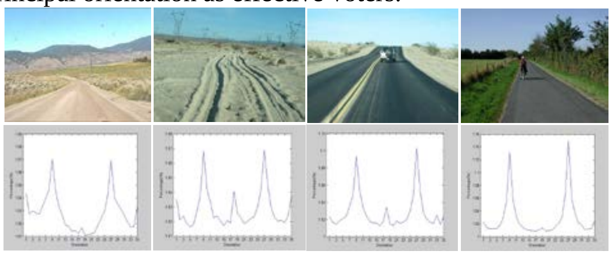

Figure 1. Statistical figure of pixels distributed on 36 texture orientation.

B. Improvement of Voting Area

Through the statistical analysis, we found that the strategy of vote area selection [8] could be optimized. According to the projection shape of most roads, the effective voters tend to located below the diagonal, voters in the left and right sides of candidate pixel have less contribution for the voting. As shown in Fig 2, soft voting strategy uses lower a half circle as a vote area, Point *v* stands for the candidate vanishing point to be voted, the radius *R* of the semicircle region in the figure will be voting area of Point *v*.

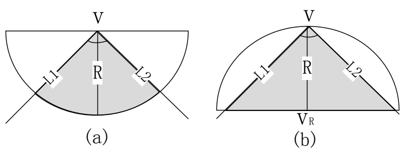

Figure 2. Two different voting area: (a) Method proposed By H. Kong[8]. (b) Our improvement.

With the same voting radius, voting area should be no different (i.e., the same number of voting pixels), the wider real road area (that is, the effective area) covered by voting area shows the higher efficiency of voting strategy. In two different voting area selection strategies, if define F (θ) Optimization Ratio of the improved strategy, there are:

$$F(\theta)=\frac{s_2-s_1}{s_1}=\left(\tan\frac{\theta}{2}-\frac{\theta}{2}\right)\bigg/\frac{\theta}{2}. \tag{1}$$

When the road boundary angle equals 90°, the real road coverage area of our improvement strategy is 27% more than the original strategy. In the actual situation, the road boundary is commonly 60°, even so, the optimal proportion still reach 20%. More effective voting pixels mean higher processing efficiency and more accurate results. In addition, improved voting strategy will enable the candidate vanishing point to accept more support voters below the diagonal, rather than the left and right side, which tend to be more in line with the actual situation.

C. Generalized vanishing point estimation

As the problem that existing algorithms generate incorrect estimations when vanishing point is not inside image, we proposed the concept of *Generalized Vanishing Point*. Generalized Vanishing Point, means never assume the vanishing point is always present within the image. In processing, road images are divided into two categories according to whether vanishing point can be found inside image. In the follow-up road segmentation process, respectively specific segmentation methods were applied. Combined with Multidimensional Voting Strategy, we can easily decide whether the vanishing point exist within the image.

Multidimensional Voting Strategy records not only the location of the vanishing point candidate, but also records the direction of the road boundary information. Define a multidimensional voting vector for every candidate vanishing point $\boldsymbol{Vector}=(n_1,n_2,\dots,n_k)$, k represent road orientation number, n_i means vote number that candidate vanishing point gain at orientation *i*. Road orientation collection $\boldsymbol{C}=\{\gamma_1,\gamma_2,\dots,\gamma_k\}$ corresponding to component n_i of multi-dimensional voting vector. The improved voting function as follows:

$$mp(i)=\begin{cases}1\big/1+\left[\theta d(p,v_R)\right]^2, if\ \theta\le 5\big/1+2d(p,v)\ \&\overline{\mathbf{OP}}=\gamma_i\in C_i\\ 0, otherwise\end{cases}. \tag{2}$$

Of which, $d(p,v_R)$ means distance between voter P and candidate vanishing point V_R (shown in Figure 2(b)) divided by the diagonal length of the image, $d(p,v)$ means distance between voter P and candidate vanishing point *v* divided by the diagonal length of the image, θ is the intersection angle between texture orientation $\overline{\boldsymbol{OP}}$ of voter P and vector $\overline{\boldsymbol{PV}}$, $m_p(i)$ means the number of votes in the i_{th} orientation that candidate vanishing point receive from voter p. γ_i corresponding to the texture orientation of voter P. Then we have the total votes of candidate vanishing point in dimension *i* by adding together all the votes whose orientation is γ_i, that is,

$$n_i=\sum_{\mathbf{OP}\in C} m_p(i). \tag{3}$$

The total votes of the candidate vanishing point given by the sum of votes in every dimension:

$$Votes_{\mathrm{multi}}(v)=\sum_{i=1}^{k} n_i. \tag{4}$$

We can determine whether the vanishing point inside the image by the process description as follows:

a) Search for the pixel which has the largest amount of votes, define it as candidate vanishing point. Find the first two direction (vector) which have most votes among all voting vectors, define it as the way of the main boundary direction;
b) If the candidate vanishing point is located right in the intersection point of road boundaries, regard it as reliable one, the following process can be primarily based on the estimation result;
c) Otherwise, estimation location of vanishing point is not reliable, real vanishing point isn't inside the image, the follow-up road boundary fitting process should mainly rely on the principal road orientation.

III. ROAD SEGMENTATION

We adopt the way of fusion texture feature and color feature for road segmentation [8]. *Orientation Consistency Rate* (OCR) is defined as the ratio between the number of points within consistent orientation and the number of total points on the line. OCR can well describe the texture feature of linear road boundary. In our experiment, orientation consistent means the angle between the texture orientation and the line is not more than 5˚. Color Feature of the line is measured by the color difference between two wedge areas near the line:

$$diff(A_1, A_2) = \max\{diff(A_1, A_2)_C \mid C = R, G, B\}. \quad (5)$$

Where A_1, A_2, respectively represent for the two adjacent wedge area in each side of the line, color difference is defined as the maximum value of a single color channel. Define the Color and Texture Features (CTF) as follows:

$$CTF_i = diff(A_1, A_2) \times \sum_{j=i-1}^{i+1} OCR_j. \quad (6)$$

Calculate the CTF of every candidate boundary and reserve the one with maximum CTF as the estimated road boundary. We use different segmentation method according to two situations of vanishing point position respectively:

a) *Situation with internal vanishing point.* Firstly, initial voting vectors of the estimated vanishing point are divided into two parts by orientation angle 90˚. Then, search for the one with maximum vote number in each part respectively. Finally update vanishing point location and search for the second road boundary in the same way.

b) *Situation with no internal vanishing point.* According to the concept that road principal orientation is independent to the location of vanishing point, firstly select out the former *N* sorted texture orientation vectors represent for road principal orientation, then two parallel lines are drawn on both sides of each texture orientation vector 10 pixels away. Finally the candidate road boundary set consist of texture orientation vectors and their parallel lines are separate into two parts by the vertical line, search for the lines with maximum CTF line in each part as road lanes.

Finally, wedge region between two road boundaries is the road region estimated by our segmentation algorithm.

IV. EXPERIMENT & ANALYSIS

In this paper, the experimental dataset including 213 road images, exhibit large variations in road conditions, light intensity and climate conditions, of which 110 images with vanishing point inexistence or invisible. Part of them are taken from the Grand Challenge route hold by the DARPA which mention in literature [7], rest of them are provided by Carnegie Mellon University robotics laboratory [11] and Google Map. To be objective, all images are used resolution of 240*180. Algorithms mentioned in the experiment are implemented on X86 personal computer platform with a 3.2 GHz Pentium Dual Core CPU.

We implement the algorithm proposed in this paper in MATLAB and compare the performance with algorithms Hard Voting strategy proposed by Rusmussem [7] and Soft Voting strategy by Kong [8]. For brevity, the hard voting strategy and soft voting strategy is denoted by “Hard-Vote” and “Soft-Vote” respectively.

A. Qualitative Analysis

Figure 3 shows vanishing point detection results of the algorithms in different illumination, whether and road conditions. Column 1-3 present detection results under different illumination, column 4-6 are results under different whether, columns 7-8 show detection results when vanishing point not inside the image. As shown, our proposed algorithm has better robustness and accuracy than other algorithms. In addition, in the case of the vanishing point outside of image, while Hard-Vote, Soft-Vote generating wrong results, our proposed show well performance.

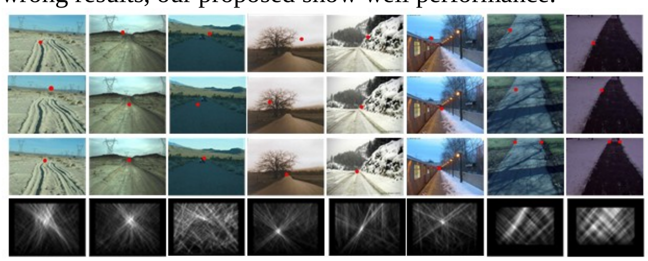

Figure 3. Vanishing point detection results. From top to bottom is Original, Hard-Vote, Soft-Vote, Proposed and the principal orientation results correspondingly.

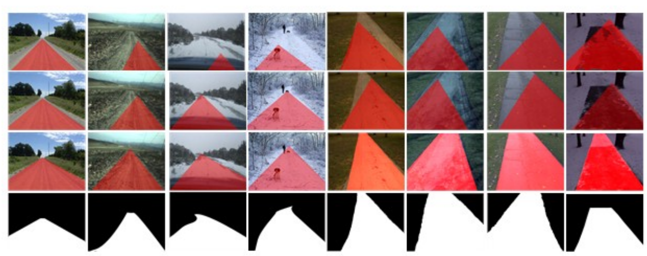

Figure 4. Road segmentation result. Fom top to bottom is original image, Hard-Vote, Soft-Vote, proposed algorithm and Ground Truth (extracted binary image by artificial calibration) correspondingly.

Images shown in Figure 4 containing two cases: with internal vanishing point (column 1-4) and external vanishing point (column 5-8). For the former, although Soft-Vote and our proposed algorithm both generate satisfactory segmentation results, distinguishable higher precision of our algorithm can be seen compared to Soft-Vote. When handling the latter situation, segmentation results generated by Hard-Vote and Soft-Vote are unreliable due to previous mistake in vanishing point position estimation. However, our proposed method remains robust performance.

B. Qualitative analysis

Our quantitative analysis methods are based on literature [8], respectively vanishing point location estimation precision and road segmentation accuracy evaluation. For the vanishing point position precision analysis, we measure the Euclidean distance between estimated vanishing point and Ground Truth. For convenience, we normalized the distance value to domain [0, 1] by image diagonal length. For the reason that Ground Truth of images without internal vanishing point are unable to determine, we use only 103 images with internal vanishing points for vanishing point estimation precision analysis. For the accuracy of road segmentation results, we compare segmentation results with the Ground Truth at pixel-wise level, more overlap means higher segmentation accuracy. Literature [8] introduced an evaluation measure named *recall*, defined as follows:

$$recall = \frac{B_t \cap B_s}{B_t \cup B_s}. \tag{7}$$

Where B_t and B_s respectively represent for road area of Ground Truth and segmentation result by algorithm. According to its definition, recall is a linear function in domain [0, 1]. Only when the algorithm segmentation result and Ground Truth completely consistent, where $B_t = B_s$ and $recall = 1$.

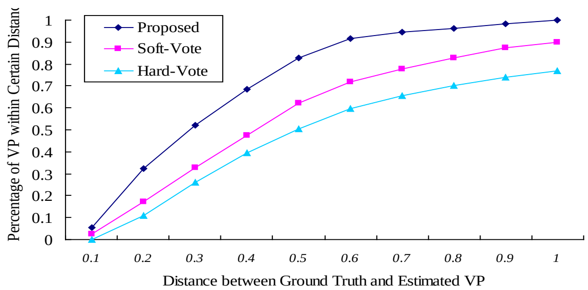

Figure 5. Comparison of vanishing point estimation accuracy. X-axis is the normalized Euclidean distance and the Y-axis is percentage of estimated vanishing points of which the Euclidean distance to the Ground Truth is not greater than the corresponding value.

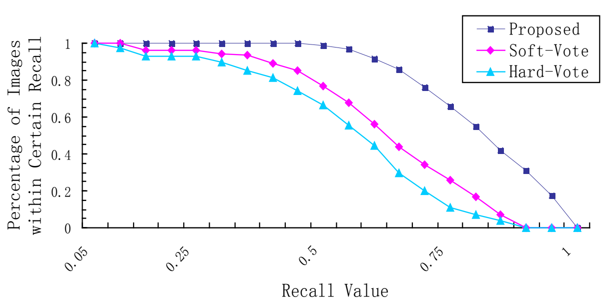

Figure 6. Comparison of road segmentation accuracy. X-axis is recall value and Y-axis is percentage of images within recall not greater than the corresponding values. Higher Y-axis value means more images with the segmentation result not more than a certain threshold, the greater the road and the better the segmentation algorithm is.

The experiment data generate from segmentation results of 213 images (including cases that vanishing point located internal and external the image). As shown in figure, the algorithm on vanishing point location estimation precision and road segmentation accuracy is always better than the other two algorithms. In time efficiency, more than 5 times speed up is attributed to the effective voter selection based on constrain of principal road orientation.

V. Conclusions

The concept of generalized vanishing point and principal orientation constrained road detection algorithm is proposed in this paper. Experimental implement and quantitative analysis donates that our method effectively solves the problem of existing algorithms in handling images with no internal vanishing point. Time efficiency is also improved without reducing accuracy of algorithm.

Acknowledgment

This work was partially supported by the National Natural Science Foundation of China (Grant No. 91320103, No.61272062 and No.61300037), Hunan Provincial Natural Science Foundation of China (Grant No. 12JJ4057) and the Fundamental Research Funds for the Central Universities. These supports are gratefully acknowledged.

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