REAL-TIME CLASSIFICATION METHOD FOR DETECTING ROAD REGION IN VARIANT ENVIRONMENT

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Abstract: This paper intends to propose a real-time and robust to noise classification method for extracting the road region in complex environments. A new approach is presented aiming the reduction of the classification area and time. The process starts from road region seeds and stops when the road region borders are identified. In order to increase accuracy of classification, a more powerful discrimination function is proposed based on the local difference probability. This method behaves like a supervised classification. However, it extracts the prior information from each processed image providing better tuning of the discrimination threshold to the image features.

Key words: supervised-like classification, seed extension, local difference probability, and parameters learning

1. Introduction

Many classification methods appeared so far related to road region detection. Computationally high algorithms, from mathematical point of view, are used in order to obtain more polished classification results by the time expensive applications: wavelet-based [1], [2], [3], [4] and filter-bank-based classification [5], [6], [7]. These methods use the frequency domain in order to extract the texture features from the image.

In the time-critical applications, the K-Mean family is used with time domain features: K-Mean, Fuzzy-K-Mean, and Contiguity-K-Mean [8]. These methods can considerably reduce classification time as opposed to frequency-based classification. However it still doesn't satisfy the real-time condition.

In our previous works, we used the K-Mean and the local threshold method [9] in the combined feature space [10], color/gray and texture, basically, in order to classify the pixels in road or non-road. In these cases, after the classification is finished, we have to decide which class is the road. Especially, in the highway case, it is a challenge to obtain well-defined road region, pavement region, because of the limited classifying ability of the discrimination function in the case when we use two classes classification. However, if we increase the class number to obtain abundant road classes, the classification time is increased, and more, the procedure of class merging is required.

In this paper we focus our attention on reducing classification time and on obtaining accurate classification results in real-time conditions. A new approach is presented aiming the reduction of the classification area and time. The process starts from road region seeds and stops when the road region borders are identified. In order to increase accuracy of classification, a more powerful discrimination function is proposed based on the local difference probability.

In a learning phase, carried out for each image, the local difference probability is estimated on well-established road sample areas, corresponding to the initial seeds also, and discrimination thresholds are established.

In the classification process, each candidate pixels LDPs is computed, and compared against discrimination threshold. The detailed procedure of the classification method based on the LDP is described in Section 2.

The advantages of this method compared to generic methods, e.g. the K-Mean family, Gabor filters, and GMRF are the following:

1) It doesn't use recursive operation; each pixel is used only one time in the classification procedure. The algorithm iteration cost is $\{O(n_p) \mid 1 \le n_p \le (n_r \times n_c)\}$. Where n_p is the total pixel count used in the image space, n_r and n_c are row and column size of image. Running the above-mentioned generic algorithm takes $O(n_c \times n_r \times c)$, where c is the classifier classes number. The saved classification time is $O(n_c \times n_r \times c) - O(n_p)$.

2) It is not necessary to extend features in order to overcome the noise factors: shadow and high illumination. It has strong discrimination power that is based on the LDP. This discrimination threshold is obtained by averaging the distances among the LDPs inside randomly sampled road regions.

2. Local-Difference-Probability-Based Classification

2.1 Randomly selected sample road area

The proposed LDP-based classification is a sort of supervised classification. The difference between the proposed LDP-based classification and the prevailed supervised classification, namely Bayesian classification, is that the LDP-based classification uses current state information for prior knowledge, and the features aren't classified by the similarity of the pixel values, but by the distance range of the similarity among the pixels based on the local probability. To perform of this, we need to decide on a sample road region in order to extract prior information. We assume that this area is placed in front of the ego vehicle. To decide the size of randomly selected sample area, we use assumption that road and non-road area have the same percentage in the image.

The distance value (range) of the similarity is obtained according to following procedure.

1) *The initial seed ($x_{i(r,c)}$) is selected*, and it is located in center of a 3x3 window. where r, c are row and column of the input image.
2) *N9 neighborhood averaging is applied on the 3x3 window*. It provides correct value for LDP and avoids false classification due to the noise.
3) *The four neighborhood of the current pixel is:*
$N_i = \{x_{i(r,c-1)}, x_{i(r-1,c)}, x_{i(r,c)}, x_{i(r,c+1)}, x_{i(r+1,c)}\}$, *and the LDP is computed at each position.*

Each pixel of N_i has to satisfy the following condition.

$$p_j \geq 0 \text{ and } \sum_{k=1}^{5} p_{jk} = 1 \tag{1}$$

where p_{jk} is the probability of neighborhood member.

and

$P_i(x) = \{p_j(x) \mid j \in \{1, \cdots, 5\}\}$ or

$$P_i(x) = \{p_1(x \mid x_{i(r,c-1)}), p_2(x \mid x_{i(r-1,c)}), p_3(x \mid x_{i(r,c)}), p_4(x \mid x_{i(r,c+1)}), p_5(x \mid x_{i(r+1,c)})\} \tag{2}$$

where i is the neighborhood identifier.

The one of LDPs of N_i is following.

$$dp_{(r,c)} = p_1^{'}(x \mid x_{i(r,c)}) = (x_{i(r,c)} - \mu_{(r,c)})^2 p_1(x \mid x_{i(r,c)})$$
$$\vdots$$
$$dp_{(r,c-1)} = p_1^{'}(x \mid x_{i(r,c-1)}) = (x_{i(r,c-1)} - \mu_{(r,c-1)})^2 p_1(x \mid x_{i(r,c-1)}) \tag{3}$$

It comes from the first order derivative of the probability inside the sub-window around (r,c), and we emphasize the distance between the central points and the mean around the central points using their power of 2 because we are interested in the probability distance between two pixels. The LDPs are computed at each four direction inside the 3x3 window. The initial seed moves to one of the neighbors after the computation of the LDP is finished.

4) *The distances among the LDPs are computed.*

The four distances around (r,c) are :

$$d_i = \{d_{(r,c)\to(r,c-1)}, d_{(r,c)\to(r-1,c)}, d_{(r,c)\to(r,c+1)}, d_{(r,c)\to(r+1,c)}\} \tag{4}$$

Where $d_{(r,c)\to(r,c-1)} = \left|dp_{(r,c)} - dp_{(r,c-1)}\right|$, $d_{(r,c)\to(r-1,c)} = \left|dp_{(r,c)} - dp_{(r-1,c)}\right|$,

$d_{(r,c)\to(r,c+1)} = \left|dp_{(r,c)} - dp_{(r,c+1)}\right|$, $d_{(r,c)\to(r+1,c)} = \left|dp_{(r,c)} - dp_{(r+1,c)}\right|$.

These sets of distances are computed inside randomly selected road region.
We discard the smallest and largest distance values in the sets of distances corresponding to the randomly selected road area. The average of distances is:

$$d_{th} = \frac{\sum_{i=1}^{M}\sum_{k=1}^{4} d_i(k)}{4*M - r} \tag{5}$$

where M is the number of sets, and r is the number of discarded distances.
"d_{th}" will be used as the discrimination threshold (distance range of similarity).

2.2 Road pixel classification

Sometimes the road pixels aren't classified on the entire road region because the discrimination threshold is computed by randomly sampling the road area.
It means that the discrimination threshold doesn't satisfy all variance of the distance between two local pixel probabilities in the selected sample area. Therefore we need initial seed acceptance/rejection procedures. It is achieved by the following constraint condition. The number of expanded points in the contour has to be greater than the number of pixels of the selected sample area. The seed position that satisfies equation (6) becomes the starting position of the seed.

$$\oint_{i \in M} x_i > X \tag{6}$$

If the initial seed satisfies Equation (6), the extension procedure is performed. If it doesn't satisfy Equation (6), Section 2.1 is repeated in order to obtain a new randomly selected road sample. Extending some directions mean that the classification is performed in those directions because the LDP-based classification is the extension-based classification. In order to decide the evolution from this position, the distance obtained from Equation (5) is compared to the discrimination threshold.

$$E(x_i)=\begin{cases} 1 \quad if \quad (\overleftarrow{d}_{(r,c)\to(r,c-1)} \le d_{th}) \| (\overset{\uparrow}{d}_{(r,c)\to(r-1,c)} \le d_{th}) \| (\overrightarrow{d}_{(r,c)\to(r,c+1)} \le d_{th}) \| (\overset{\downarrow}{d}_{(r,c)\to(r+1,c)} \le d_{th}) \\ 0 \quad if \quad (\overleftarrow{d}_{(r,c)\to(r,c-1)} > d_{th}) \| (\overset{\uparrow}{d}_{(r,c)\to(r-1,c)} > d_{th}) \| (\overrightarrow{d}_{(r,c)\to(r,c+1)} > d_{th}) \| (\overset{\downarrow}{d}_{(r,c)\to(r+1,c)} > d_{th}) \end{cases} \tag{7}$$

The result "1" represents that the seed can extend toward that direction. The pixel that is used for extension belongs to the road cluster. Otherwise, the seed stops the evolution. The pixel at which the extension is stopped belongs to the border of the non-road cluster. Finally, road area is constructed by the contour of the border.

3. Experiments

In this section, we present the results obtained from the classification comparison among the K-Mean family, GMRF, Gabor filter, and the proposed LDP-based classification. The K-Mean family consists of K-Mean, Fuzzy K-Mean, and Contiguous K-Mean. The main focus of the comparison is:

i) Classification ability and classification robustness: The proposed method uses two classes classifier. The visual comparison results are presented in Figure 1. The quantitative analysis is presented in Table1.

ii) Classification time cost: This elapsed time is obtained from relative time. We used a Pentium-IV 2.1Ghz CPU, 256 Mbyte memory, and 4 Mbyte graphic memory. The results are presented in Table 1. The results displayed in Table 1 come from a highway image sequence of about 3000 images. The chosen images of Figure 1 consist of the high illumination, the shadow, and many clusters.

Table 1. The quantitative analysis of the classification ability and the relative time cost of the classification. (256x256 size image).

Comparison Item	Used classes	K-Mean	Fuzzy K-mean	Configuous K-Mean	Proposed Method
Error (%) (average)	2 classes	44.82	43.51	43.3	13.6
	4 classes	27.96	25.21	23.5	No necessity
Time cost (average)	2 classes	55.7 ms	500 ms	125 ms	31 ms
	4 classes	125 ms	2104 ms	250 ms	No necessity

Following the results from Figure 1 and Table 1, the proposed LDP-based classification is more efficient than the generic classification method in both time-cost and classification robustness point of view. The error rate includes the under classified classification and the over classified classification. In four-class classification, we select the classes belonging to the road, manually, in order to compute the error rate. However, in the real application, the automatic selection of the road class is very difficult for the four-class classification. And more, the classification of the proposed method doesn't depend on the image resolution. However the generic classification method produces higher error rates in the low-resolution image than in the high-resolution image. The only controversial thing of the proposed method is the selection of the sample road region. However, the suggested method in this paper is reasonable in the case of the autonomous driving system. We only present the classification result in the highway images. But it can be applied in another kinds of possible moving areas: rural roads and desert environment. GMRF and the Gabor filter are presented as results of the classification comparison of Figure 1. However we can't consider a time comparison because they aren't real-time methods, obviously. But they are useful if we want to extend the features in order to obtain the dedicated classification results. The contiguity K-Mean, sometimes, fails to classify the features in high-illumination condition and in the low-resolution image. This is presented in Figure 1.

4. Conclusion

We proposed an efficient classification method for the autonomous driving system compared to generic classification methods in the aspects of the classification ability and of the relative classification time cost. We obtained much improved classification results and time-cost then in the generic classification method. If we apply the 4-class classification, at least, a more correct road region is obtained. However, the time for classification also increases. In the future works, we will compare the extension ability to the level set and active contour and geodesic algorithm. In the simple test, we also obtained good extension results in shady environment and in environments featuring many clusters.

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Figure 1. The classification ability comparison in changing environments