ROBUST CLASSIFICATION BASED ON PRIOR OF LOCAL DIFFERENCE PROBABILITY FOR THE UNMANNED GROUND VEHICLES

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Abstract: The aim of this paper is to propose a new classification method based on the noise tolerant LDP (Local Difference Probability) prior-based discriminator for the unmanned ground vehicles. This proposed classification has three characteristics, namely, probability features space instead of Gray intensity features space, Bimodal Gaussian discriminator (noise tolerant discriminator), and single class cluster center based classification (only road class). Based on these components, the classification ability and classification time-cost are better than in generic classification method; K-Mean, Fuzzy K-Mean, Contiguity K-Mean, K-Mean applied on the texture features obtained from GMRF and from Gabor filter bank. The core of the proposed classification is a discriminator (prior density), and it is obtained from the mean of the distances of Local Difference Probabilities (LDPs) in the randomly selected road area. The road area is randomly selected in front of ego vehicle, and the initial class cluster center is employed inside the sampled road area. The road features are classified from around single cluster center to the entire image space.

1 INTRODUCTION

The technology of road detection and recognition has dramatically developed during the last 20 years (C. Thorpe, 1987) , (D.A. Pomerleau, 1994).

However, this research isn't finished until now due to the many factors impeding a good result such as: shadow, illumination and great variations of the road surface. These problems, however, can be reduced, but not eliminated, when we use a road model in order to detect the driving region (B. Southall, 2001). There are tradeoffs between using a road model and pixel-based classification methods. If we use a road model, we need to solve a model selection and a model update problem. In addition it is very sensitive in illumination. In the other aspect, it has usage convenient and time cost advantage. If we use a pixel-based classification, it could be achieved in two domains like as frequency and time domains.

In frequency domain, wavelet-based (T.R.Reed, 1990), (C. Nikias, 1991), (O. Rioul, 1991), (G. Strang, 1989) and filter-bank-based classification (L. Wiskott, 1997), (R. O. Duda, 2001), (S. Krishnamachari, 1997) are used in order to extract the texture features from the image.

In time domain, the K-Mean family on the Gray scale image is used. The K-Mean family is K-Mean, Fuzzy-K-Mean, and Contiguity-K-Mean (J. Theiler, 1997). These methods have considerably reduced classification time as opposed to frequency-based classification. However the classification time is still not small enough for the method to be used in real-time applications.

In another approaches, (P. Jeong, 2003) used the K-Mean and the local adaptive threshold method in the combined feature vector space (P. Jeong, 2003), color/gray and texture, in order to classify the pixels as road or non-road. If we use pixel classification, we can solve the model selection problem, however, the high time cost and road cluster merging are required. In order to solve these problems, we propose a new real-time pixel-based classification method based on the Local Difference Probability (LDP).

In Section 2, we summarize the main characteristics of the proposed method in two

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phases: learning phase, and discriminator phase. In each phase, we explain the advantages over the generic classification method.

In Section 3, we describe the proposed method's theoretical background.

In Section 4, we present the results of the experiments.

In Section 5, the conclusion of this paper is presented.

2 NEW FEATURE OF THE PROPOSED METHOD

In this section, we will present the new features of the proposed method in the learning and discriminator points of view. These characteristics will be explained compared to the most used classification methods like as K-Mean, Fuzzy K-Mean, Contiguity K-Mean, and Bayesian rule.

2.1 Learning Phase

The most important thing for the unsupervised classification is initial cluster knowledge, and the most important thing for the supervised classification is prior information. The classification ability depends on these values.

In case of K-Mean, it starts from unknown prior information, and initial cluster center is selected randomly or is selected in certain fixed position.

In case of the Bayesian, it starts from known prior information. However, this information is obtained from the previous image.

In case of the proposed method, we combined advantages of both supervised and unsupervised classification; we use apriori knowledge to improve classification ability like as supervised classification, but we obtain it from the current image like as unsupervised classification. This helps eliminate inaccurate prior knowledge of the Bayesian rule, and reduces the classification time-cost by accurate cluster knowledge in the initial stage compared to K-Mean.

2.2 Discriminator Phase

In the case of K-Mean family and Bayesian rule, the discriminator represents Euclidean distance for K-Mean and Gaussian unit modal similarity for Bayesian rule are used as a discriminator. This makes the classification result noise sensitive. However, in the proposed method, the discriminator is established as a bimodal Gaussian. This makes a classification results less noise sensitive. The theoretical explanation of the LDP discriminator is presented in Section 3.1.

3 THE PROPOSED METHOD

The procedure of the proposed classification method consists of randomly selected region to obtain the discriminator and road pixel collection based on its value. The discriminator is described in the sub-Section 3.1, and the classification is described in the sub-Section 3.2.

3.1 LDP Prior Based Discriminator

The LPD prior inherits its characters from pure Gaussian property. In order to compute class convergence, minimum loss function based on the "non-additive" prior is used. In case of loss function with "non-additive" feature, the loss function can be expressed by the quadratic loss function form.

For $f \in \Re^m$: $L(f, \hat{f}) = (f - \hat{f})^T Q (f - \hat{f})$

where f is a prior function, $\hat{f}$ is a expected prior function, and Q is a symmetric positive-definite $(m \times m)$ matrix.

The formulation of minimizing expected loss function is rewritten according to the quadratic loss function.

A posteriori expected loss is

$$\begin{aligned}\delta_{PM}(g) &= \arg\min_f E[(f - \hat{f})^T Q (f - \hat{f})] \\ &= \arg\min_f \{E[f^T Qf \mid g] + \hat{f}^T Q\hat{f} - 2\hat{f}^T QE[f \mid g]\} \qquad (1)\end{aligned}$$

where, g is an observation.

Finally, a posteriori expected loss function with "non-additive" feature can be expressed as following way.

$$\delta_{PM}(g) = E[f \mid g] = \hat{f}_{PM} \qquad (2)$$

It still has "Posterior Mean (PM)" estimator character, even though quadratic loss function is used.

The LDP prior is obtained from the current random selected region. Lets denote its components as

$X_s^{(k)} = \{x_s^{(1)}, x_s^{(2)}, \cdots, x_s^{(k)}\}$, $X_s \in \Re \times \Re^+, k \in \{r, c\}$ (3)

where r is row, c is column in the random selected region. And s indicates "sampled region".

The LDP-based prior density at each pixel is

$$p(X_s^{(k)}) = \left| \frac{\partial p(X_s^{(k)} \mid \mu_k, \sigma_k^2)}{\partial x_s} \right| = (X_s^{(k)} - \mu_k)^2 \exp\{\frac{-(X_s^{(k)} - \mu_k)^2}{\sigma_k^2}\} \quad (4)$$

where μ_k and σ_k are mean and standard deviation obtained by 4N at each pixel position.

To achieve absolute form, power of 2 is applied on the coefficient of exponential.

This prior density is computed only inside the randomly selected region.

This proposed LDP-based model selection method doesn't need to update model in each time stamp. It allows independent density model in each pixel position. The model convergence is performed in ***Minimum Probability Distance*** (**MPD**) like as "Minimum loss function". This is also proposed method. MPD procedure is summarized as following steps.

Step 1) Local probability distance is computed using LDP-based prior density inside randomly selected region. Let's it denote as

$$\{p_d^{(k)}\}_{k=1}^{M} = \Big\{ \left|p(x_s^{(k)}) - p(x_s^{i})\right| + \left|p(x_s^{(k)}) - p(x_s^{j})\right| + \left|p(x_s^{(k)}) - p(x_s^{l})\right| + \left|p(x_s^{(k)}) - p(x_s^{m})\right| \Big\}_{k=1}^{M} \quad (5)$$

where, i (east), j (west), l (south), and m (north) are four direction neighbours (4N) of each point, i.e., $\{(k),(k-1),\cdots,(1)\}$. And M is a number of used pixels inside randomly selected region.

Step 2) Mean Distance is obtained by applying an average on all distances obtained from current random selected region as described below.

$$p_D(D \mid \mu, \sigma^2) = \{p^{(1)}_d, p^{(2)}_d, \cdots, p^{(k)}_d\}, \quad p_D = \frac{1}{M}\sum_{i=1}^{M} p_d^{(i)} \quad (6)$$

Step 3) New models are computed in image space.

Let's denote image space as

$X_i^{(k)} = \{x_i^{(1)}, x_i^{(2)}, \cdots, x_i^{(k)}\}$, $X_i \in \Re \times \Re^+, k \in \{r, c\}$ (7)

where r is row, c is column. And i indicates "image region".

The LDP-based density at each image pixel is

$$p(X_i^{(k)}) = \left| \frac{\partial p(X_i^{(k)} \mid \mu_k, \sigma_k^2)}{\partial x_i} \right| \cong (X_i^{(k)} - \mu_k)^2 \exp\{\frac{-(X_i^{(k)} - \mu_k)^2}{\sigma_k^2}\} \quad (8)$$

As we can see, a prior density and new model density are same. Following earlier mention, this is derived from concept of individual density model.

Step 4) Local probability distance is computed in each image pixel using LDP-based density.

Lets it denote as

$$\{p_d^{(k)}\}_{k=1}^{N} = \Big\{ \left|p(x_i^{(k)}) - p(x_i^{i})\right|, \left|p(x_i^{(k)}) - p(x_i^{j})\right|, \left|p(x_i^{(k)}) - p(x_i^{l})\right|, \left|p(x_i^{(k)}) - p(x_i^{m})\right| \Big\}_{k=1}^{N} \quad (9)$$

where, i, j, l, and m are four direction neighbourhood (4N) of each point, i.e., $\{(k),(k-1),\cdots,(1)\}$. And N is a number of used pixels in the image space.

Step 5) MPD-based minimum loss function is achieved by using Eq. (1).

In Eq. (1), $\hat{f} \equiv f_s = p_D(X_s)$: prior function obtained from the randomly selected region. $f \equiv f_i = p_d^{(k)}(X_i)$: prior function of each pixel in the image space. In the practical phase, $Q = 1$, $\varepsilon = 0$, and loss function are scalar like as $\sqrt{(f_i - f_s)^2} < 0$. Therefore the computation complexity is simple, and the classification condition is $f_i < f_s$. If the pixel satisfies this condition, it belongs to the road class. Otherwise, it is certain that it doesn't belong to the road class because the proposed method only uses one class.

3.2 Implementation of the LDP Prior Based Discriminator

The proposed LDP-based classification is a sort of supervised classification. The differences between the LDP-based classification and the most used supervised classification, namely Bayesian classification, are that the LDP-based classification uses current state visual information for the prior knowledge, and that the pixels aren't classified by the Gaussian similarity of the pixel values, but by the distance between the Gaussian similarities among the pixels converted to LDP. To achieve this, we have to solve two problems.

We have to select a well-established road sample region in order to extract prior information in current image frame. We assume that this area is placed in front of the ego vehicle.

We have to determine the size of road sample area. We adopt 25% of height and 25% of width of the image roughly because its size does not influence much classification

Once the position and the size of the sampled road area are determined, we have to compute the discriminator inside it. The procedure of obtaining discriminator starts from the noise filtering by applying 9N averaging. Then the computation of LDP is performed by applying 4N on the noise-filtered pixel in sequence.

The 9N averaging and the LDP are computed at the entire pixels of the sampled road area excepting border of the area. This procedure is finished when all pixels of the well-established road area are used for calculation of the 9N averaging and the LDP computation. Then, the distances among the LDPs are computed. We discard the smallest and largest distance values in the sets of distances corresponding to the well-established sample road area. Because we consider that it is affected by the noise.

The average of distances is:

$$\overline{P_d}(x) = \frac{\sum_{i=1}^{M}\sum_{k=1}^{4} d_i(k) - \sum_{j=1}^{r}\sum_{k=1}^{4} d_j(k)}{4*(M-r)} \tag{10}$$

where r is the number of discarded distances.

"$\overline{P_d}(x)$" will be used as the discriminator for classification. It is equivalent to f_s in step 5.

3.3 Road Pixel Classification

Sometimes the pixels classified as road don't cover the entire road region because the discriminator is computed by randomly sampling the road area (well-established sample road region).

It means that the discriminator doesn't satisfy all variance of the distance between two local pixel probabilities in the selected sample area. Therefore we need randomly selected road area acceptance/rejection procedures. It is achieved by the following constraint condition.

The number of classified points has to be greater than the number of pixels of the selected sample area. The randomly selected road area that satisfies equation (16) becomes the selected area for computing discriminator.

$$^{\forall}i, {^{\forall}j} \in R, \quad \sum_{i=1}^{M} i \geq \sum_{j=1}^{r_s \times c_s} j \tag{11}$$

where M is a number of set of classified pixels, and r_s is a row of the selected sample area and c_s is a column of the selected sample area.

The initial road cluster center, one cluster center is required, is chosen inside road area, randomly. The classification procedure is performed in radial direction from initial cluster center. In each radial direction, if the distance is smaller than the distance obtained from Equation (10), that pixel is belonging to road class. The classification is terminated when no pixel position moves.

Finally, road area is constructed by the contour of the last extended pixel positions.

4 EXPERIMENTS

In this section, we will present the experiment results in 3 different aspects.

In the 1st aspect, ***the feature vector space of LDP*** are presented. This new feature vector space is a core part of the proposed method, and it gives many advantages in the classification phase. It is presented in Figure 1.

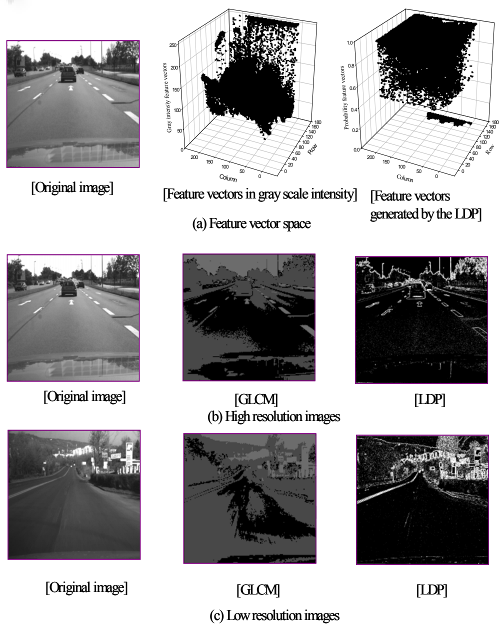
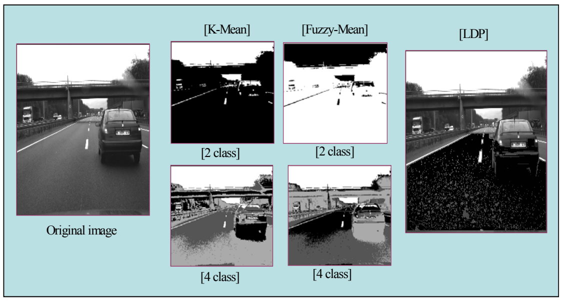


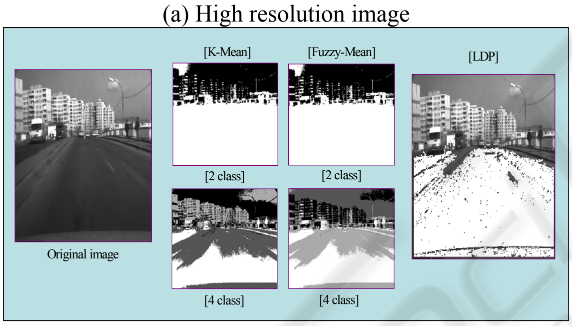
Figure 1: The proposed new feature vector space and its characteristic.

In Figure 1 (a), we can notice that the LDP's feature vectors are concentrated from 0.8 to 1, and the raw feature vectors of Gray image are scattered from 0 to 200. It means that the LDP's feature vectors are more efficient and more robust than in the Gray intensity feature vectors in the feature vector grouping (road pixel classification).

Figure 1 (b) shows that how the proposed feature vector space provides easer separation of the border and non-border region then the generic feature vector space. It also gives us accurate border of road and only road class on the image.



(a) High resolution image



(b) Low resolution image

Figure 2: The comparison results of the classification accuracy and the classification efficiency.

In the 2nd aspect, we present ***the time elapsed during classification***. This elapsed time is obtained from relative time. It is obtained in the same testing environment. We use a Pentium-IV 2.1Ghz CPU, 256 Mbyte memory, and 4 Mbyte graphic memory. The results are presented in Table 1.

The proposed method 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. K-mean family takes $O(n_c \times n_r \times c)$, where c is the classifier classes' number. The quantity of the saved classification time is $O(n_c \times n_r \times c) - O(n_p)$.

In addition we present the quantitative analysis of the classification. The proposed method uses one class classifier. The K-Mean family uses two classes classifier and four classes classifier. The K-Mean family has lots of false negative/positive error (about 43%) in two classes and (about 25%) in four classes comparing with LDP (about 10 %). In addition the manual road class selection is required in the K-Mean family case. It is very difficult or it is almost impossible to be achieved automatically. But the proposed LDP based classification solves this problem. The comparison results of classification accuracy and time cost are presented in Figure 2 and Table 1.

In the 3rd aspect, ***the segmentation ability*** is presented compared to Level set (N.K. Paragios 2000) that is the representative of region growing method in real-time condition. It is presented in Figure 3. In case of Level Set, the segmentation ability strongly depends on the edge detection method. Once the coefficient of the edge detection filter is determined at the first image frame, it cannot be changed until the image-processing task is finished in the image sequence. It is shown in Level Set module in Figure 3. The segmentation ability is changed according to different coefficient values even if the same image is used. The used coefficient values are 0.1 (①), 0.2

Table 1: The quantitative analysis of the classification ability and the relative time cost of the classification. (3,000 images are used, and its size is 256x256).

Items	Used classes	K-Mean	Fuzzy K-mean	Contiguous K-Mean	LDP
Error (%) (average)	2 classes	44.82	43.51	43.3	13.6
	4 classes	27.96	25.21	23.5	No need
Time cost (average)	2 classes	55.7 ms	500 ms	125 ms	31 ms
	4 classes	125 ms	2104 ms	250 ms	No need

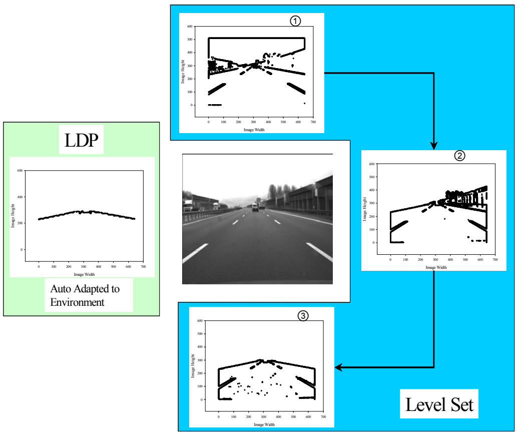


Figure 3: Comparison results of the segmentation between Level Set and LDP.

(②), and 0.3 (③). However, the proposed LDP-based segmentation automatically determines classification classifier according to the feature vector of the images at each image frame, and it gives a key rules to keep same segmentation result in the variant environment. In order to achieve quantitative results, 1000 sequence images are tested. The extension error rates are presented in Table 2.

Table 2: The comparison of the over/under extension ratios.

Coef. Of Kernel / Method	0.7	0.1
Level Set	≅ 69.4 %	≅ 70.6 %
	Automatic selection	
LDP	≅ 8.6 %	

In summary of Experiments, the proposed LDP-based classification is a more powerful method for the road following application in the classification cost, the classification ability, and the feature vector space points of view.

5 CONCLUSION

We proposed the real-time classification method based on the robust LDP-density discriminator, i.e., LDP prior, for the road following application of the Unmanned Ground Vehicle (UGV). We solved the pixel classes merging and only road class selection problem that appeared on the road region when the number of classes increased, and reduced the classification cost. In addition we improved the classification ability by using the probability feature vector space, i.e., LDP's feature vector space, from Gray intensity feature vector space.

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