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Water Hazard Detection Based on Color and Texture Features

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Abstract

In this paper, we focus on the need for water hazard detection based on the characteristics of the static water body in off-road environment, which includes three main sections: extraction of color and texture features, building SVM model and practical detection of water bodies. Based on the features of high intensity, low saturation and low texture of the water bodies existed in off-road environment. Saturation-value ratio feature extracted from hsv color space of water body region, combined with other four texture features conducted by gray level co-occurrence matrix constitute the five-feature vector. Training set is established from sample images after the images are well preprocessed. Then build the svm model based on the training set. Our task is to separate practical samples into two classes: water region and land region according to the predict result calculate by svm model. Experimental results demonstrate significant progress on detection of water body hazard in off-road environment, which effectively reduce the influence of illumination variation exert on detection when only using color feature to detect.

Keywords: Computer Image Processing; HSV Color Space; Texture; Gray Level Co-Occurrence Matrix; SVM Support Vector Machine.

1. Introduction

Water hazard is one of the most challenging obstacles in off-road environments. The failure detection of the water hazard by UGV (Unmanned Ground Vehicle) could cause a deep trap in the hazard, which could damage the electronics of UGV [1]. Both passive sensors and active sensors have been explored for water detection. Active sensors often get no return value on free-still water, which has excellent effect on water detection. Furthermore, fusing information of active sensor and passive sensor could make water hazard more detectable [2,3]. But, it could be desirable for UGVs to work without emitting detectable electromagnetic signals when executing military operation [4,5]. Stereo range data use to analyze patterns consistent with range reflections. The stereo range data on terrain reflection dominated region below the ground surface (Rankin.A.L and Matthies.L in ground surface [6,7]. While, there may be little stereo range data on water hazard because the surface of water bodies lack texture generally, particularly when they are stationary [8]. Polarization cameras have been proved quite appropriate on water detection by several researchers [9]. However, the price of polarization cameras, the sane as SWIR, TIR and hyper spectral sensors, are relatively higher compared with visible sensors [10]. Consequently, passive perception solution, such as industrial color cameras, is more desirable for water hazard detection [11].

Water body hazard in outdoor environment tend to appears higher value, lower saturation and lower texture than terrain around comparatively. In this paper, we focus on the research of the characters listed above. Fusion of saturation-value ratio [7,8] color feature extracted from hsv model and four texture features: Asm, Ent, Con and Cor, conducted from GLCM are addressing in our experiments. Details of our multi-cue detector are discussed in the later section.

2. Water features analysis

2.1 Color Cue of Water

HSV model represent color with hue, saturation and value (also called brightness) in an attempt to be more intuitive and perceptually relevant than the RGB model described by Cartesian (cube) representation. Eq.1 used to achieve the transformation between RGB and HSV color space.

$$\begin{cases} V = \frac{1}{3}\left(R+G+B\right) \\ S = 1 - \frac{3}{R+G+B}\left[\min(R,G,B)\right] \\ H = \arccos\left\{\frac{\left[\left(R-G\right)+(R-B)\right]/2}{\sqrt{\left[(R-G)^2+(R-B)(G-B)\right]}}\right\} \end{cases} \tag{1}$$

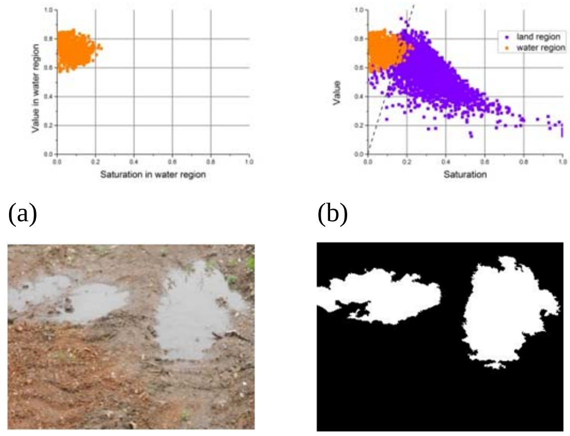
Water region with reflection of sky can be easily discriminated from terrain by value. Because water reflects colour of the sky, the average value of water where it reflects the sky is mid-way between that of the sky and the terrain. Nevertheless, water still possesses a relatively high brightness than terrain [10].

The other characteristic that water hazard presents usually is low saturation, while terrain around is saturated generally. We focus on this characteristic to detect water hazard, for it is more probable for a region with low saturation proved to be water hazard than a saturated region [11].

A.L. Rankin [7,8] recently performed a survey of saturation-value ratio. In this work, portion of the water regions with sky reflection was manually segmented. The hue, saturation, and value levels of these regions are plotted in Figure1. As illustrate in Fig.1(a), hue level of the water region with sky reflection covers full of hue spectrum, which means hue is of marginal use for water region detection. According to our sufficient statistic on saturation-value levels of water and terrain region respectively, as shown in Fig.1(b), water region cluster in the high value, low saturation region. Meanwhile, a ray from the origin, represents saturation-value ratio, separates the characteristic scatters of water region (orange scatters) and terrain region (purple scatters) practically. Fig.1(d) shows the segmentation using the saturation-value ratio on the image of Fig.1(c). Finally, saturation-value ratio could be selected to detect water region with reflection of sky

2.2 Texture cue of water

Although color cue performs satisfactorily in experiment above, formulating a single color cue capable for detect water region in different situation is still a big challenge. Color feature of water varies with ambient light condition. Low texture could be another cue for detection. R. M.Haralick proposed conception of gray level co-occurrence matrix (GLCM). This technology has been widely used in field of image texture analysis and become an important way to research texture characteristic from image [12].

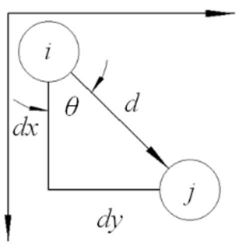


(a) (b)

(c) (d)

Fig.1: statistical analysis of saturation, value and hue of water and terrain region

(a)Saturation and Hue level of water region with sky reflection; (b) saturation and value in water region (orange) and terrain (purple) region respectively; (c)practical water hazard image with reflction of sky; (d)detect water region with s/v ratio.



$$\begin{bmatrix} P_d(0,0) & P_d(0,1) & \ldots & P_d(0,j) & \ldots & P_d(0,L-1) \\ P_d(1,0) & P_d(1,1) & \ldots & P_d(1,j) & \ldots & P_d(1,L-1) \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ P_d(i,0) & P_d(i,1) & \ldots & P_d(i,j) & \ldots & P_d(i,L-1) \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ P_d(L-1,0) & P_d(L-1,1) & \ldots & P_d(L-1,j) & \ldots & P_d(L-1,L-1) \end{bmatrix}$$

(a) pixel pair (b) gray-level co-occurrence matrix

Fig.2: representation of pixel pair in gray-level co-occurrence matrix

GLCM is defined to describe the relative frequencies with which a pair of pixels separated by a specified distance occurs on the image under a fixed angle. It presents as $P_d(i,j)(i,j=0,1,2,3,\ldots\ldots L-1)$, where L means image gray level; i, j are two pixels gray level; *d* means the fixed displacement vector. Generally, orientation θ are 0°, 45°, 90° and 135°. As shown in figure 2. Each element $P_d(i,j)$ in GLCM represents the relative frequency of which two pixels of gray level i, j appears under relative position (dx, dy).

Among fourteen textural statistical features extracted from GLCM, four of them are uncorrelated proved by Ulaby (Ulaby *et al* in 1986). Properties of these four features: ASM, Ent, Con and Cor are discussed below.

(1) ASM (angular second moment): also called energy. High energy means the gray level distribution form is constant or periodic.

$$\text{ASM} = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} P_d(i,j)^2 \tag{2}$$

(2) Ent (entropy): measures the disorder or complexity of an image. Low entropy means the image is texturally uniform or texturally simple.

$$\text{Ent} = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} P_d\left(i,j\right) logP_d\left(i,j\right) \tag{3}$$

(3) Con (contrast): measures the amount of local variations of the image. Low contrast image presents a low spatial frequency feature in an image.

$$\text{Con} = \sum_{\mathrm{i}=0}^{L-1}\sum_{\mathrm{j}=0}^{L-1}\left(\mathrm{i}-\mathrm{j}\right)^2 P_d(\mathrm{i},\mathrm{j}) \tag{4}$$

(4) Cor (correlation): measures linear dependencies of gray level. A higher correlation shows more homogeneous in the specified orientation.

$$\text{Cor} = \frac{\left(\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} ijP_d\left(i,j\right) - u_x u_y\right)}{\delta_x \delta_y} \tag{5}$$

Where:

$$u_x = \sum_{i=0}^{L-1} i \sum_{j=0}^{L-1} Pd\left(i,j\right)?\quad u_y = \sum_{j=0}^{L-1} j \sum_{i=0}^{L-1} Pd\left(i\ \ j\right)$$

$$\delta_x = \sum_{i=0}^{L-1}(i-u_x)\sum_{j=0}^{L-1} P_d\left(i,j\right),\quad \delta_y = ?\sum_{j=0}^{L-1} i-u_y \sum_{i=0}^{L-1} P_d\left(i\ \ j\right)$$

2.3 Color and Textures features extraction

We notice that textural feature of water and terrain region in off-road environment do not indicate strong cue of orientation. Thus, for each feature, we use the average of the feature under four orientations to reduce the computational complexity. In our work, we segment water region from the image and divide image into 8×8 sized sub blocks. After that we convert the image to HSV model to obtain saturation-value ratio color features from each sub block and extract texture features calculate from GLCM of each sub block after gray level compressed from 256 to 16, also for reducing computational complexity. Texture features and color feature are combined as a 5-D feature vector. Three image sample sets are analyzed. Statistical result of features extracted from water region and terrain region shown in Table 1.

We focus on the features distance between the two –class by analyze the Table.1. The ASM and the Cor of water region higher than that of terrain region, while Ent and Con is lower. What's more the s/v ratio feature of water is obviously under the relative feature of terrain. These analysis results consistent with the theory we introduced ahead.

Tab.1 five features extracted from sample image

`	Asm	Ent	Con	Cor	S/V
	0.3470	1.4892	0.2554	1.5171	0. 1402
water	0.1265	0.7940	0.8948	2.5243	0. 2815
	0.2484	1.0427	0.6755	3.0314	0. 1517
	0.0377	2.4564	1.2319	0.6116	0.5860
terrain	0.0868	3.3245	1.6472	0.2670	0.6524
	0.0499	1.9083	2.0469	0.4724	0.4727

3. SVM -Support Vector Machine

3.1 SVM fundamental

Support vector machines (SVM) are based on the principle of structural risk minimization (SRM), derived from statistical learning theory developed by Vapnik (Ivanciuc O *et al* in 2007). SVM appears more capable on generalization compared with existing machine learning algorithm especially when number of samples is quite infinite.

SVM method was originally designed for linearly separable classes of samples classification. Its' purpose is to finds the hyperplane with the maximum margin between two- class of samples. The hyperplane is defined by $w^T x + b = 0$, where **w** is normal to the hyperplane. The training data should satisfy the following constraints as Eq. (6):

$$y_i(w^T x_i + b) - 1 \geq 0,\ i = 1, 2, ..., n \tag{6}$$

Therefore the hyperplane which optimally separates the samples minimizes:

$$\Phi(w) = \min\ \frac{1}{2}\|w\|^2 \tag{7}$$

It is convenient to construct a Lagrangian function of the problem to solve constrained minimization problems defined by Eq. (6) and Eq. (7)

$$L(w,b,\alpha) = \frac{1}{2}w^T w - \sum_{i=1}^{n}\alpha_i[y_i(w^T x_i + b) - 1] \tag{8}$$

Where α are the Lagrange multipliers. The Lagrangian must be minimized with respect to w, b and maximized with respect to $\alpha \geq 0$.

3.2 SVM kernel function

When it is difficult for linear SVM classification algorithm to find an optimal hyperplane in a lower feature space, we use kernel functions to extend input features mapping into a higher dimension of feature space where SVM could perform a linear classification. Here are three widely used kernel mapping functions.

Polynomial kernel function：

$$K(x,x') = \left(\langle x, x' \rangle + 1\right)^d$$

RBF kernel function：

$$K(x,x') = \exp\left\{-\gamma\|x - x'\|^2\right\}, \gamma > 0$$

Sigmoid kernel function：

$$K(x,x') = \tanh(v\langle x, x' \rangle + c)$$

Among the three kernel function, RBF kernel converge on a wide range and compute fast with fewer parameter. We also use RBF kernel in our work,

4. Result

In our work, a platform based on our own UGV is operated to collect image with water hazard, with resolution of 320×240. Image process platform constructed by computer containing an AMD 2.0GHz processor. Libsvm package developed by Chih-Jen Lin in Taiwan University applied to build SVM model with default parameters and separate water from sample images. In our work, we extract features from several sets of preprocessed images and train the normalized feature matrix to form a satisfied SVM model. Large amount of images a test in our work, the accuracy of this method achieves 96.2% (accuracy defined by the ratio between tested region and the practical region). As shown in Fig.3, the method we applied in this paper achieves a satisfied result

Fig.3: Performance of the method to detect water body hazard

5. Conclusions

In this paper, we have summarized an approach of water hazard detection in off-road environment using passive sensors. A multi-cue water detector fuses the feature from water color and texture. Compared with the previous water detector using single feature, this method is robust to variation of ambient lightness.

Because the water hazard in wide-open environment often appears with reflection from terrain around, it is still hard for our method to identify terrain reflection from the water region. In future work, we will focus on another features of water that are more robust performing in out-door environment water detection and improve the autonomous environment perception and obstacle avoiding ability.

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