ICIC Express Letters
Part B: Applications
Volume **7**, Number **2**, February **2016**

ICIC International ©2016 ISSN 2185-2766
pp. **461–468**

ROAD SURFACE CONDITION CLASSIFICATION METHOD BASED ON MULTI-FEATURE FUSION AND SVM CLASSIFIER

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Received July 2015; accepted September 2015

Abstract. *In order to detect the road surface condition such as dry, wet, snow or ice to keep vehicle running safe, a classification method for road surface condition using multi-feature and SVM (Support Vector Machine) classifier is proposed. Multi-feature is composed of luminance, color and texture feature that can be obtained by luminance extraction, intensity histogram, hue histogram and Gabor wavelet transform. Four kinds of data on road surface image samples are trained respectively by SVM classifier. The experiment results show that compared with the performance of BP neural network and Bayesian classifier, the classification result of various road surface condition with SVM classifier is achieved with high average accuracy, the maximal accuracy of classification is close to 81.5% in snow condition, and it also can provide the theoretical foundation to practical application for road state image discriminant.*
Keywords: Road surface condition, Image processing, Multi-feature, SVM, Classification

1. **Introduction.** Road surface condition plays an important role in traffic accident prevention system for reducing highway traffic accidents and improving the advancement of traffic management capabilities. Meanwhile, it also gives key information to driver when the road condition in front of vehicle is full of puddle of water because of a heavy rain, or other situations [1].

Currently, the road surface sensor is a major way for icy or wet condition information, but it has disadvantages such as extremely inconvenient maintenance and high initial installation costs, so the traffic image recognition technology based on road surveillance cameras, and combined with the slippery road, non-contact measurement and sensors which can determine road surface information quickly and automatically is becoming a hot spot of recent research [2,3]. Kuehnle and Burghout utilize road image gray statistical characteristic and neural network classifier to identify winter road condition [4]. Yamada et al. discuss the detection of wet-road conditions based on images captured by cameras on the rearview mirror of a vehicle [5]. Fukui et al. propose a road surface recognition method at fixed positions on the road combined with road gloss and spatial frequency spectra of the road surface [6]. Lars Forslöf collects road image containing dry, ice, snow and wet four kinds of condition, and extracts pixel gray statistical characteristic of original image, image edge and contour information, finally getting a neural network classifier for road slippery condition recognition [7].

Through the above analysis, the application of these methods in road surface condition detection has a certain effect; therefore, they still can be improved by new detection method. In our study, we select luminance feature, color feature and Gabor based texture feature such as multi-feature, and SVM classifier is applied to doing the dry, wet, snow or ice road images classification of learning and training.

2. Road Surface Multi-feature.

2.1. Luminance feature. In this section, supposing there is sufficient sunlight, we choose B components from RGB space as luminance instead of common grey level. The image features are calculated for the blocks identified as road area. Road surface luminance can be calculated by using the RGB color information space in Equation (1) [8].

$$L = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} B(i,j) \tag{1}$$

where L is mean of B components in the RGB color space; $M \times N$ is the block size; $B(i,j)$ is represented as the B components of coordinate (i,j). A luminance mean value comparison of road surface for different conditions is shown in Figure 1. The results show that luminance mean value of snow is larger than dry, wet, and ice situation.

2.2. Color feature. After converting HIS space for the image, the histogram of road surface image is extracted to be configured for each condition respectively as shown in Figure 2, and hue, intensity and saturation analysis of four kinds of typical road environment shows that the hue and intensity values of snow are obviously higher than the other three conditions. Contrary to the performance of snow, the hue and intensity values of wet are outstanding lower than the other three kinds of circumstances. Therefore, dry, wet and ice road surface have no differences in saturation value change [9].

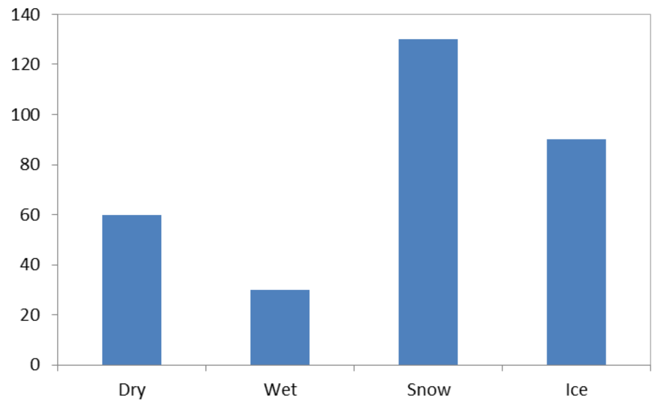


Figure 1. Luminance mean value comparison of road surface

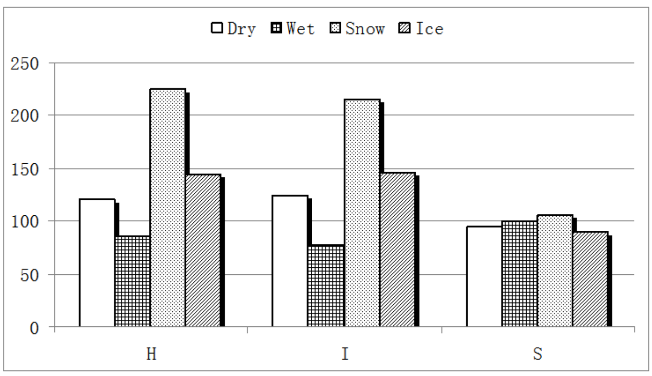
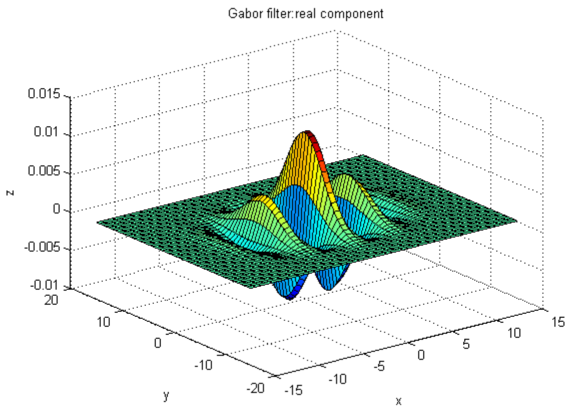
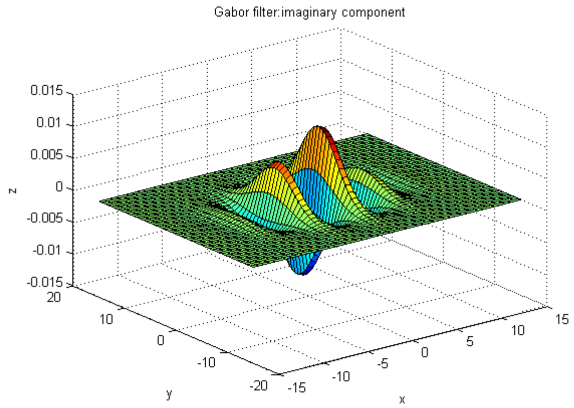


Figure 2. Comparison of road surface condition H, I, S color feature value

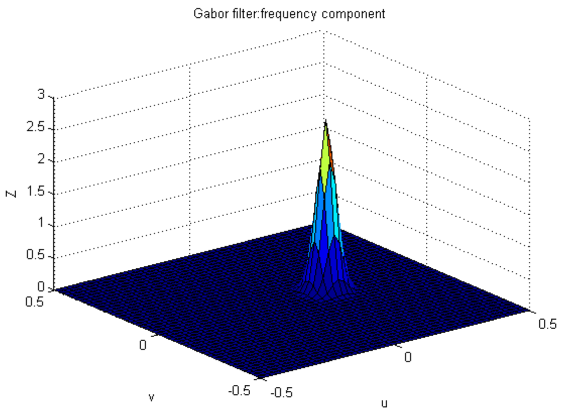
2.3. **Texture feature.** Gabor wavelet is applied to image texture feature extraction, it is the best description of signal space and frequency domain in the case of 2D uncertain condition. Figure 3 shows imaginary, real and frequency component of 2D Gabor wavelet transform [10].



(a) Real component



(b) Imaginary component



(c) Frequency component

FIGURE 3. 2D Gabor wavelet transform

The time domain form of 2D Gabor wavelet is calculated by using Equation (2).

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left\{-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right) + 2\pi j U_0\right\} \tag{2}$$

The frequency domain form of 2D Gabor wavelet is calculated by using Equation (3).

$$G(u,v) = \exp\left\{-\frac{1}{2}\left[\frac{(u-U_0)^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2}\right]\right\} \tag{3}$$

where $\sigma_u = \frac{1}{2\pi\sigma_x}$, $\sigma_v = \frac{1}{2\pi\sigma_y}$, σ_x and σ_y generally take constant 1.

In order to acquire a set of Gabor mother wavelet, we can use scale transformation and direction rotation, as shown in the following equations.

$$g(x,y) = a^{-m} g(x',y') \tag{4}$$

$$x' = a^{-m} g(x\cos\theta + y\sin\theta) \tag{5}$$

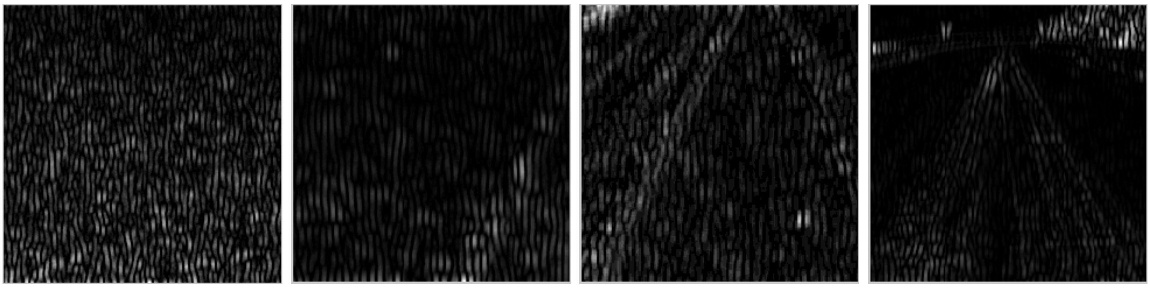
$$y' = a^{-m} g(-x\sin\theta + y\cos\theta) \tag{6}$$

where $\theta = n\pi/k$, $a > 1$, both of m and n are integers, k indicates the general direction numbers of Gabor wavelet, and a^{-m} is scale factor.

The input image is supposed to be $I(x, y)$, Gabor filter window size is $M \times N$, Gabor filter from m scale and n direction is expressed as $g(x, y)$, and then Gabor filter from m scale and n direction is calculated by using Equation (3). We can obtain texture feature from mean and variance calculation by $W(x, y)$ [11].

$$W(x, y) = \sum_{x=1}^{M} \sum_{y=1}^{N} I(x, y) g(x, y) \tag{7}$$

Figure 4 shows Gabor texture feature extraction results in case of various road conditions, which is achieved at $k = 8$, $\theta = \pi/4$, and $a^{-m} = \pi/2$.



(a) Dry (b) Wet (c) Snow (d) Ice

FIGURE 4. Various road surface Gabor wavelet texture features

3. **Support Vector Machine Classifier.** Support Vector Machine (SVM) classifier is proposed by machine learning method based on statistical learning theory [12]. Suppose there is a training sample set that contains l training sample points belonging to two different kinds of samples, and it is represented as $D = \{(x_1, y_1), (x_2, y_2), \cdots, (x_l, y_l)\}$, where $x_i \in R^N$, $y_i \in \{-1, 1\}$, $i = 1, 2, \cdots, l$. It can be divided into two categories by a separating hyperplane $w^{\mathrm{T}} \cdot x_i + b = 0$, and if the nearest hyperplane data and the maximum distance between the hyperplane, this classification hyperplane will be optimal classification hyperplane as shown in Figure 5.

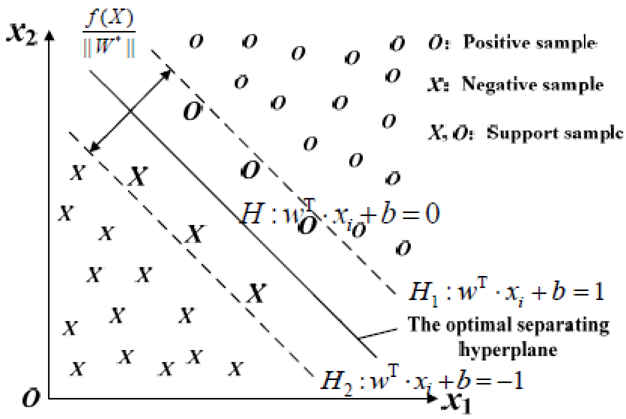


FIGURE 5. SVM linear classification

As shown in Figure 5, H plane indicates an optimal classification hyperplane, H_1 and H_2 are separately represented as hyperplane H on both sides of the closest point in hyperplane, and H, H_1 and H_2 are in Equation (8) to Equation (10).

$$H : w^{\mathrm{T}} \cdot x_i + b = 0 \tag{8}$$

$$H_1 : w^{\mathrm{T}} \cdot x_i + b = 1 \tag{9}$$

$$H_2 : w^{\mathrm{T}} \cdot x_i + b = -1 \tag{10}$$

All feature sample data are in form of $y_i(w^{\mathrm{T}} \cdot x_i + b) \geq 1$. Optimization solution is calculated by SVM classification in Equation (11).

$$\min_{w,b,\varepsilon} \frac{1}{2} w^{\mathrm{T}} w + C \sum_{i=1}^{l} \varepsilon_i, \quad C > 0 \tag{11}$$
$$y_i \left(w^{\mathrm{T}} \Phi(x_i) + b \right) \geq 1 - \varepsilon_i, \quad \varepsilon_i \geq 0$$

Gaussian radial basis function (RBF) is selected as the kernel function of SVM classifier in Equation (12).

$$k(X, Y) = \exp \left\{ \frac{|X - Y|^2}{2\sigma^2} \right\} \tag{12}$$

where $|X - Y|$ denotes the distance between two vectors, and σ is constant.

Determining the objective function, the optimal Lagrangian multiplier a^* is obtained by utilizing quadratic programming method.

$$\max H(a) = \sum_{i=1}^{l} a_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} y_i y_j a_i a_j k(X_i \cdot X_j), \quad 0 \leq a_i \leq C \tag{13}$$
$$\text{subject to} \quad \sum_{i=1}^{l} y_i a_i = 0, \quad a_i \geq 0, \quad i = 1, \cdots, N$$

The corresponding discriminant function is in Equation (14).

$$f(X) = \sum_{i=1}^{l} y_i a_i^* k(X_i \cdot X_j) + b^* \tag{14}$$

According to a support vector X of target samples library and target discriminant function, we can get deviation value b^*, and output target category can be calculated by the value of $\mathrm{sgn}(f(X))$.

4. **Classification Algorithm.** Proposed classification algorithm is composed of road image capture, preprocessing process, multi-feature extraction, feature samples configuration, SVM classifier training and classification process flowchart as shown in Figure 6. Three kinds of road surface image features from Section 2 are calculated for each training image samples as training data with 32×32 pixels unit, the images captured are 640×480 pixels format, yielding 1027 feature vectors per image, and finally four kinds of road surface conditions are distinguished by SVM classifier.

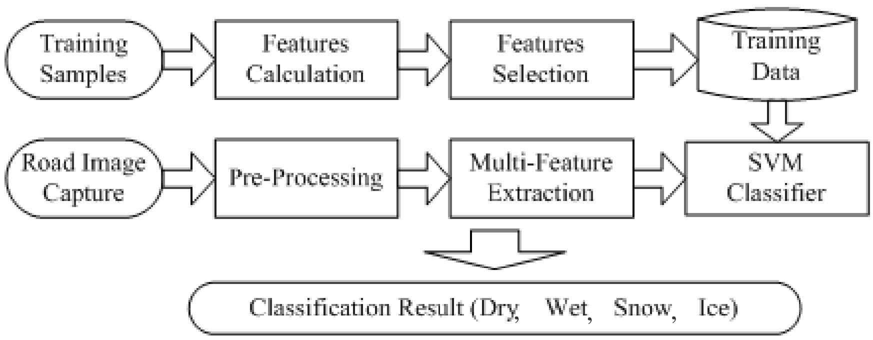


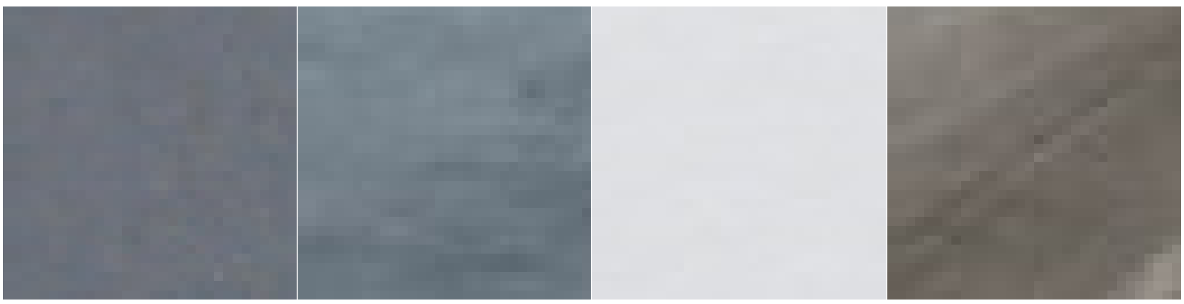
Figure 6. Flowchart of road surface condition classification algorithm

5. **Experiment Results.** In this section, we conduct an experiment to calculate the classification accuracy and verify the effectiveness of our method using MATLAB 7.0 with a Windows 7 operating system, road images captured by camera mounted on vehicle from difference environment consist of dry, wet, snow and ice conditions such typical examples of distinguishing the road surface conditions, as shown in Figure 7. Meanwhile, we suppose the whole road surface condition is the same, and use training image samples as total of 500 images (32×32 pixels format) for each road condition, as shown in Figure 8.

In case of different road surface, it is possible to distinguish road conditions stably. The classification accuracy for each road surface condition with different methods can be seen from Table 1. Compared with the performance of BP neural network and Bayesian classifier [13], SVM classifier is trained using the radial basis function with gamma term 10, the value of margin parameter C in soft margin is 0.5, and the neural nets have 15 hidden units in one layer, and weights are updated using conjugate gradient back-propagation, with the "tansig" activation function. The SVM classifier is possible to achieve a classification average accuracy of 75.8% in dry, 73.6% in wet, 81.5% in snow and 77.9% in ice condition. Table 2 shows the effectiveness of the proposed method comparing the classification average accuracy of SVM classifier using luminance feature and color feature only, texture feature only, and all three kinds of features.

(a) Dry (b) Wet (c) Snow (d) Ice

FIGURE 7. Typical road surface condition images



(a) Dry sample (b) Wet sample (c) Snow sample (d) Ice sample

FIGURE 8. Training image samples

TABLE 1. Comparison of classification performance

State \ Average accuracy	Classifier		
	BP neural network	Bayesian	SVM
Dry	74.7%	73.4%	75.8%
Wet	72.9%	70.2%	73.6%
Snow	78.3%	75.9%	81.5%
Ice	73.5%	71.3%	77.9%

Table 2. Comparison of classification accuracy of SVM with different features

State \ Average accuracy	Different methods		
	Luminance feature and color feature only	Texture feature only	All three kinds of features
Dry	53.5%	41.3%	75.8%
Wet	52.4%	40.2%	73.6%
Snow	56.1%	44.7%	81.5%
Ice	54.8%	42.6%	77.9%

6. **Conclusions.** In this paper, we have proposed a method to classify the condition of the road surface such as dry, wet, snow or ice using luminance, color, texture feature as multi-feature and SVM classifier. Four typical kinds of road surface image samples are trained respectively for SVM classification. The experiment results show that under various features, proposed method is possible to achieve a classification average accuracy of 75.8% in dry, 73.6% in wet, 81.5% in snow and 77.9% in ice condition, the maximal accuracy of classification is close to 81.5% in snow condition, and compared with the performance of BP neural network and Bayesian classifier, it is more suitable for road surface condition classification.

Acknowledgment. This work is partially supported by China National Natural Science Fund (ID: 51278062) and the Fundamental Research Funds for the Central Universities (ID: 310822161013). The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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