Classification Algorithm for Road Surface Condition

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Summary
This study proposes a method to classify the state of the road surface condition using various features and SVM(Support Vector Machine) classifier. The Road surface conditions are classified into a set of pattern states such as dry, wet, snow, and ice. Each road condition has different polarization and frequency characteristics. Features obtained through wavelet transformation and histograms are classified by the SVM classifier.

Key words:
Texture classification Wavelet Packet Transform, Support Vector Machine.

1. Introduction

Road Surface Condition is important because it recognizes the dangerous road and conveys the information to the driver to prevent traffic accident. Especially, it gives information in advance to the driver when the roads are icy because of a heavy snow, or puddle of water due to a heavy rain in the summer time.

Currently, in order to know the status of the road, a person needs to personally use the visible camera to monitor the conditions, or check the conditions with the naked eyes or install the sensors on the surface of the road directly. But this way has disadvantage such as high initial installation costs or high maintenance cost. Therefore, installing the camera which can relatively detect a wide range of area, on the important road or installing the removable camera on transportation, can determine the status of the road quickly and automatically.

Road surface image can be classified as texture image and also the part that consists of the form called texture or the elements with similar properties. As for the conventional statistical methods to classify texture, such methods as GLCM(Grey Level Co-occurrence Matrix)[1], GMRF (Gauss Markov Random Fields)[2], and Local Linear Transform[3], have been proposed.

In the past, many classifiers have been used. Such as, nearest neighbor[4], fisher linear discriminant[5], neural network[6], baysian classifier[7]. But recently, SVM (Support Vector Machine)[8] has been developed and is widely used in pattern recognition field. Compared with other classifiers, the advantage of SVM is it minimizes the error by maximum margin. SVM introduced the concept of the margin so has outstanding performance even on high-dimensional data. The soft margin method allows mislabeled examples, and the kernel trick is used for nonlinear classification. In this paper, a wavelet based texture features and statistical features, histogram and color combination of the feature vectors to configure features and SVM classifier is applied to derive the optimal classification model.

2. Related works

2.1 Wavelet Packet Transform

Wavelet interpretation emerged by integrating the specialized technologies, such as technologies in the signal processing system developed individually to meet the special purpose. In recent years, many basic techniques were developed as a special application of wavelet theory, such as multi-resolution analysis method used in computer vision, sub-band coding technique used in image compression, deployment of wavelet series in applied mathematics.

Wavelet interpretation can be applied both in the case of continuous signal and discrete signal, and its potential applications are being recognized in various fields. Wavelet transform has advantageous features specifically in the analysis of non-stationary signal; therefore it is becoming a new alternative for the classic STFT (short time fourier transform) or gabor transform. The difference that distinguishes the classic STFT and wavelet transform is that STFT uses same size of filter window for all frequency bands, however wavelet transform uses a narrow window for the high frequency band, and wide window for low frequency band.

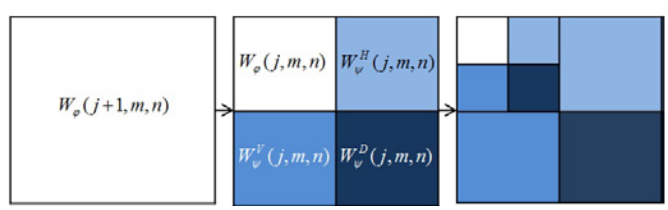

Figure 1 2D wavelet transform

Fig. 1 show the result of a two-dimensional image on the FWT performed repeatedly. Decomposition occurs at the

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wavelet packet transform not only the low-frequency but also at the entire frequency range[9].

2.2 Support Vector Machine

The existing pattern recognition methods, including the neural networks, have been designed with the aim of minimizing the error rate. On the other hand, SVM maximized the margin between the classes.

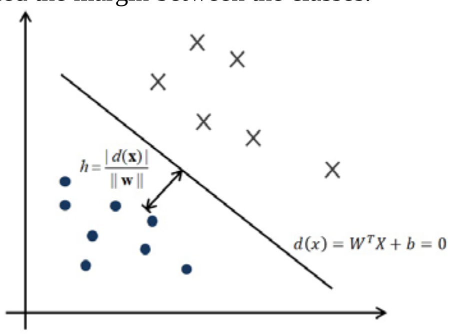


Figure 2 SVM linear classification

Linear SVM can express the decision hyperplane for binary classification decision as shown in equation (1). At this point, $\mathbf{x}$ is the feature vector which represents the sample, and is represented as $\mathbf{x} = (x_1, \cdots, x_d)^T$. $\mathbf{w}$ and b are parameter which define the crystal hyperplane.

$$d(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b = 0 \quad (1)$$

$d(\mathbf{x})$ divides the full feature space into two areas, $\mathbf{x}$ belongs to one side and is $d(\mathbf{x}) > 0$, the other side is $d(\mathbf{x}) < 0$. There are many ways to express the one hyperplane, can multiply c, any non-zero constant, in equation (1) will indicate the same hyperplane. $\mathbf{w}$ is the normal vector of the hyperplane, indicates the direction of the hyperplane and b indicates the position. The distance from the point to hyperplane is same as in equation (2).

$$h = \frac{|d(\mathbf{x})|}{\|\mathbf{w}\|} \quad (2)$$

Use kernel function to perform the nonlinear classification from the non-linear SVM, and typical kernel functions are in equation (3) to (5). Equation (3) means polynomial kernel, equation (4) is RBF(Radial Basis Function) kernel, equation (5) is hyperbolic tangent kernel[10].

$$K(\mathbf{x}, \mathbf{y}) = (\mathbf{x} \cdot \mathbf{y} + 1)^p \quad (3)$$

$$K(\mathbf{x}, \mathbf{y}) = e^{-\|x-y\|^2 / 2\sigma^2} \quad (4)$$

$$K(\mathbf{x}, \mathbf{y}) = \tanh(\alpha \mathbf{x} \cdot \mathbf{y} + \beta) \quad (5)$$

3. Proposed Algorithm

Proposed algorithm can be subdivided into DB configuration, preprocessing process, feature extraction, SVM training and classification process through the acquisition of road surface image. In the case of DB configuration, each road surface is classified as the four conditions that include dry, wet, snow and ice. At this point, DB is to be configured as acquiring polarized image by utilizing a polarization filter. It is to be classified as each surface state by SVM classifier by extracting the unique features of each surface state using the global feature and local feature from the image passed through the preprocessing process.

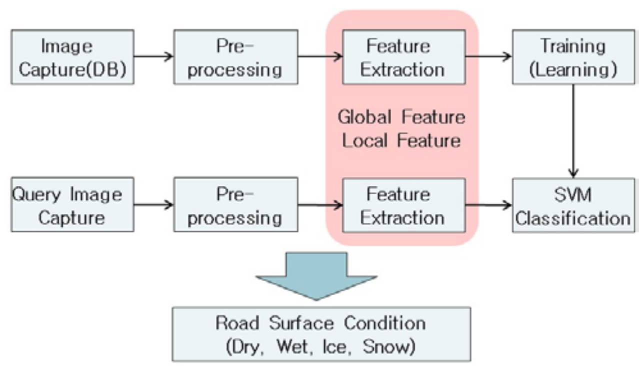


Figure 3 Classification Algorithm

3.1 Polarization

The polarization ratio of vertical polarized component and horizontal polarized component, which were acquired by passing the polarization filter through the image, is to be used. In general, the polarization ratio increases in the case of wet surface, whereas it appears small in the case of dry surface.

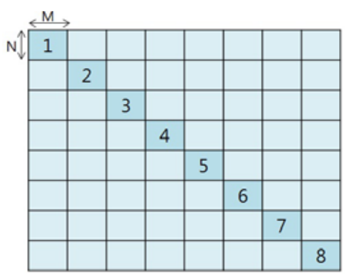
$$R_p = \frac{I_V}{I_H} \quad (6)$$

Equation (6) can classify the wet road conditions with other road conditions based on a certain threshold. According to the ratio of the polarizing ingredient in each status, typically 1.3 or more means wet road status. This can classify the wet status.

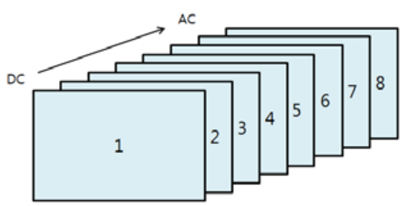
3.2 Wavelet Packet Transform Feature

When checking the feature of the image, no high frequency around the snow area, and the images are homogeneous, so low-frequency components are relatively strong. The dry road parts are the asphalt, so the texture component is strong containing the high-frequency components. Ice composition has the nature between the dry road and snow part.

In this study, 3-step wavelet packet transform and antonini filters are used. Fig. 4 (a) pictorially represents the images after the wavelet transform. The 3-step wavelet transforms are used. Therefore the images are divided into 8×8 blocks. To handle only the non-directional texture images, the only 8 diagonal blocks are used after the wavelet transform. Feature vectors from the 8 blocks are extracted by using each color and gray information.



(a)



(b)

Figure 4 Wavelet packet transform of image (a) 3 Level wavelet packet transform (b) Diagonal block Sorting

The diagonal block coefficients are used as the features. Fig. 4 (b) is the figure of extraction of only 8 diagonal blocks after the wavelet packet transform. Within the wavelet transform low-frequency is assembled on the upper-left corner of the image. In contrast, the high-frequency components are gathered in the bottom right portion. Therefore, generally snow part, which relatively has more low frequency, showed increasingly strong composition toward block 1, and dry road which relatively have more high-frequency showed strong composition toward the block 8. In this study, the gray information in the feature vector is extracted from each block, so it carries 8 characteristics. Therefore, can get $M \times N$ numbers of feature vector from one image.

3.3 Hue, Intensity Histogram

To extract the histogram of the image, a histogram of hue intensity is to be configured for each model respectively after converting HIS for the image as shown in Fig. 5. Each histogram is to be subdivided into 10 bins, which will subsequently be utilized as the features.

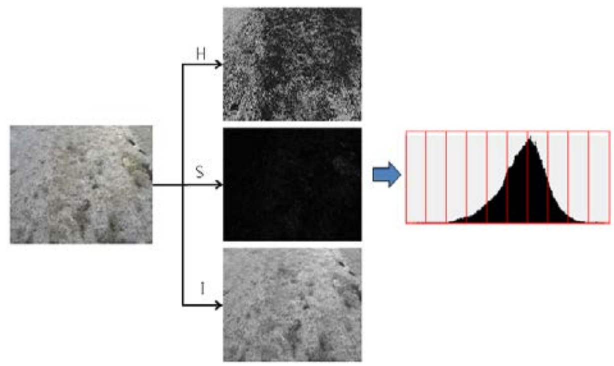


Figure 5 Hue, Intensity Histogram

3.4 WSF (Wavelet Statistical Feature)

To extract the overall features of the image, WSF (Wavelet Statistical Feature)[11] is to be used. The mean and standard deviation of each block configured are calculated in Fig. 4 as shown in the equation (7) and (8) in order to indicate the statistical features as to the quality characteristics of the image. WSF tend to indicate the statistical features of low frequency in the image as moving toward block 1 while indicating the statistical features of high frequency as moving toward block 8.

$$\text{mean} = \frac{1}{N^2} \sum_{i,j=1}^{N} p(i, j) \tag{7}$$

$$\text{Standard deviation} = \sqrt{\frac{1}{N^2} \sum_{i,j=1}^{N} [\, p(i,j) - m]^2} \tag{8}$$

4. Experimental Results

The road surface state DB is classified as the four states such as dry, wet, snow and ice. As for the DB that was used in the experiment, the two images of horizontal polarized image and vertical polarized image are to be configured for each surface image. The configured DB is as shown in Fig. 6.

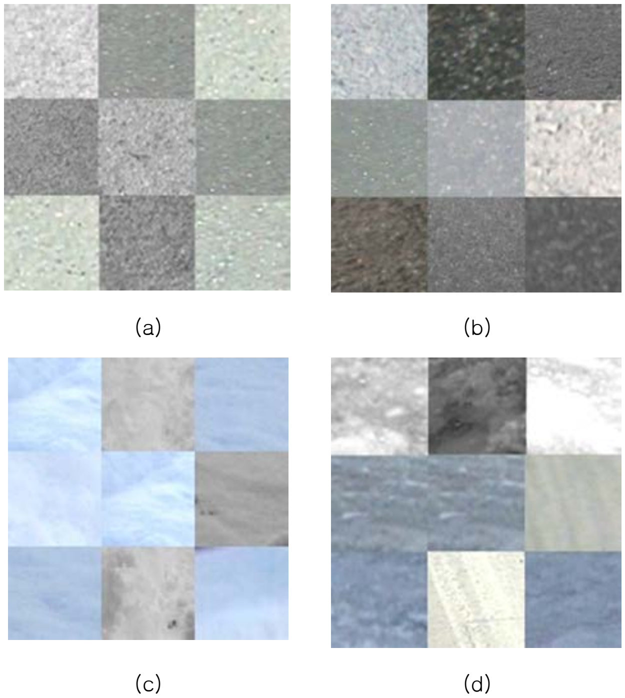


Figure 6 Image template of road surface condition
(a) Dry, (b) Wet, (c) Snow, (d) Ice

A model corresponding to each road surface state is to be created by training the image through SVM for each surface image and then the surface state to be classified will be classified by utilizing the created model. At this point, RBF kernel is applied to SVM. And the grid search is utilized in order to find the optimal SVM parameter. Fig. 7 indicates that the maximal accuracy of 89.1% is achieved at gamma=1 and c=0.5 when utilizing wavelet coefficient, hue intensity and WSF.

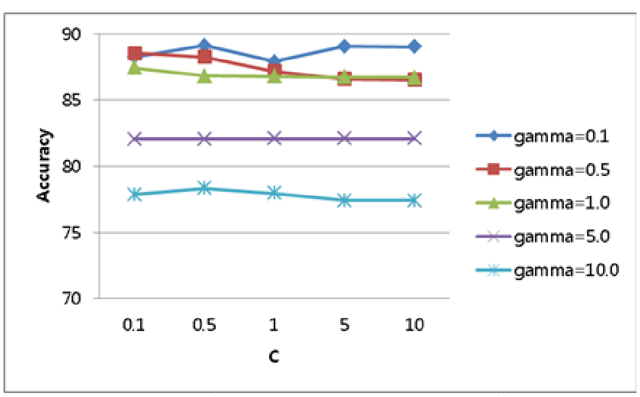


Figure 7 Classification Result using wavelet coefficient, hue intensity, and WSF.

The two methods were used. The first method was to use the cross validation to experiment repeatedly as subdividing DB into several units and the second method was to configure and test the training DB and the classification DB separately. Thus, the detection results of road surface state were determined by subdividing them into the block-accuracy method that determined the classified images for each 8×8 pixel unit and the ROI-accuracy that determined the entire ROI.

$$\text{Block-Accuracy} = \frac{\text{Number of True Positive Blocks}}{\text{Total number of Blocks}} \tag{9}$$

$$\text{ROI-Accuracy} = \frac{\text{Number of correctly identified ROI}}{\text{Total number of ROI}} \tag{10}$$

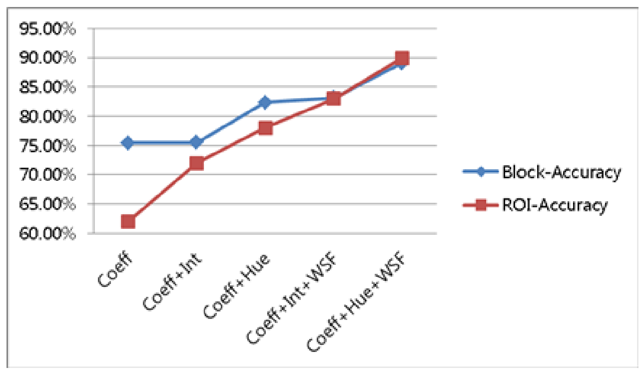


Figure 8 Road Surface Condition Classification Accuracy (Cross Validation)

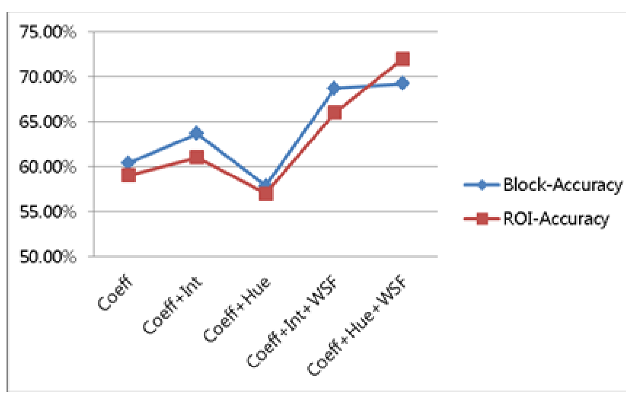


Figure 9 Road Surface Condition Classification Accuracy

As for the features that were used in the experiment, wavelet coefficient, intensity histogram, hue histogram and WSF were utilized. Block-Accuracy improved by 13.68% and ROI-Accuracy improved by 28% in terms of accuracy when adding hue intensity and WSF rather than when using wavelet coefficient in Fig. 8. And Block-Accuracy was found to have an accuracy improvement by 8.82%, whereas ROI-Accuracy had an accuracy improvement by 13% in Fig. 9.

5. Conclusion

In this study, we propose a method to classify the condition of the road surface such as dry, wet, snow and ice using various features and SVM. Each road condition has different polarization and frequency characteristics. Four kinds of data on road surface image template were trained respectively for SVM classification.

As a result of the experiment with various features, the accuracy was improved by 13.68% in Block-Accuracy and 28% in ROI-Accuracy when using wavelet coefficient, hue histogram and WSF as the features as compared with the case of using only coefficient as the feature.

Acknowledgments

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