Near-IR Material Discrimination Method by Using Multidimensional Response Variables PLS Regression Analysis

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***Abstract*—In this paper, we propose a method to discriminate human skin, plants, and asphalt based on the spectral reflectance properties of each material in near-infrared ray (NIR) band. A single material is detected by using only two or three wavelengths corresponding to the absorption bands and the other wavelength based on the spectral reflectance properties of the target material. However, with more than two materials, materials are not always discriminated by using only the absorption wavelengths of each material. In this paper, we discriminated three materials using multiple NIR wavelengths. In this proposed method, a multiclass classifier for the materials is generated by using Partial Least Squares (PLS) regression analysis, and three materials are discriminated by multiple predicted values obtained by the classifier. Also, optimum wavelengths to discriminate are selected by using VIP. As a result of an experiment, three materials were discriminated with high accuracy.**

Keywords*—*material discrimination; PLS regression analysis; PLS2; Multi-spectral image processing; VIP

I. INTRODUCTION

In recent years, research on Intelligent Transport Systems (ITS) has been actively carried out. Human skin detection methods based on the spectral reflectance properties of the skin in NIR band to detect the pedestrian or the driver have been proposed. Suzuki et al. proposed a skin detection method based on the spectral reflectance properties[1]. In this method, two wavelengths in NIR band, 870nm and 970nm are used. Morikawa et al. proposed a more accurate skin detection method by using three wavelengths, 870nm, 970nm and 1050nm[2]. In these cases, 970nm is selected because it is in the absorption band of the skin. Also, 870nm and 1050nm are selected because their reflectance ratios are higher than 970nm.

In order to develop auto cruise and a safe driving support system, it is necessary to discriminate multiple materials which are often in the driving environment (e.g. human skin, clothes, plants, asphalt and concrete). In this paper, we propose a material discrimination method of human skin, plants and asphalt based on the spectral reflectance properties of the materials in NIR band.

In this paper, we propose a method to discriminate three materials by using PLS regression analysis for NIR multi-spectral images. PLS regression analysis finds hyperplanes of minimum variance between predictor variables and response variables[3][4]. Therefore, it avoids the multicollinearity problem, and a reliable regression model is generated.

Hattori et al. proposed a three materials discrimination method using PLS1[5]. PLS1 is one of the PLS regression analysis algorithms. It outputs one-dimensional response variables, and it generates a binary classifier. This method discriminates three materials by using multiple binary classifiers generated by PLS1.

We discriminated three materials by using PLS2 which outputs multidimensional response variables, and it generates a multiclass classifier[6]. We generated a classifier by using PLS2 for NIR multi-spectral images from 650nm to 1050nm, and discriminated three materials by using the classifier.

II. NEAR-INFRARED IMAGE

A. Spectral reflectance properties

We focused on the spectral reflectance properties of materials. The spectral reflectance properties depend on the component of materials, and especially they have discriminative properties in the NIR band. The spectral reflectance properties of the human skin, the plant and the asphalt are shown in Fig. 1.

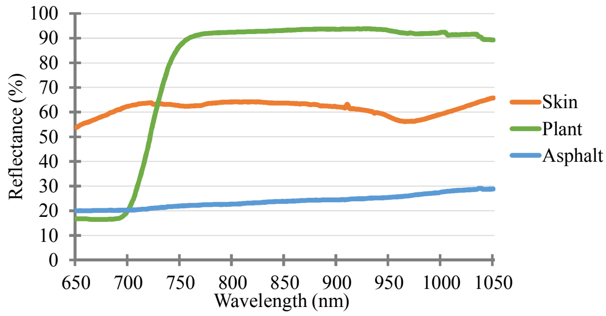

Fig. 1. Spectral reflectance properties of skin, plant and asphalt

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B. NIR image

201 NIR images acquired in 2nm steps between 650nm and 1050nm are used. In this paper, the term "all wavelengths" refers to these 201 wavelengths. NIR images were taken in a dark room, and a halogen lamp is used as a light source. NIR images were taken by a 16bit CCD camera with a NIR tunable filter as shown in Fig. 2.

NIR images of the skin, the plant and the asphalt captured by this camera system are shown in Fig. 3. Here, the NIR image of w nm is defined as I_w, and $I_w(x, y)$ is the pixel value at the point of (x, y).

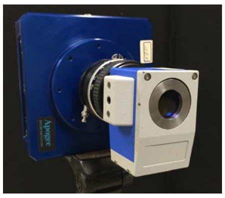

Fig. 2. 16bit CCD camera and NIR tunable filter

(a) 600nm (b) 850nm (c) 1050nm

Fig. 3. NIR images of skin, plant and asphalt

III. Material Discrimination Method

The material discrimination method has a training process and a discrimination process. In the training process, a multiclass classifier of materials is generated by PLS regression analysis. In the discrimination process, materials are discriminated by multiple predicted values obtained by the classifier.

A. PLS regression analysis

Partial Least Squares (PLS) regression analysis was first developed by Herman Wold in the 1960s and 1970s to address problems in economic path-modeling, and it was subsequently adapted to other modeling problems. PLS generates a reliable regression model even if the number of training data is small. We present a brief introduction to PLS. For more details, see [3].

PLS is based on latent component decomposition. Dimension reduction is performed for the predictor variables and the response variables. The compression axis is called "loading", and values projected onto the loading are called "score". In addition, the latent component is called "factor".

In PLS, the loading is set to maximize the correlation between scores of the predictor variables and scores of the response variables. Thus, the regression equation generated by PLS sufficiently represents the relationship between the predictor variables and the response variables. Fig. 4 shows a schematic of the dimension reduction of PLS. Where P and Q represent loadings of the predictor variable and the response variables, and T and U represent scores of the predictor variable and the response variables.

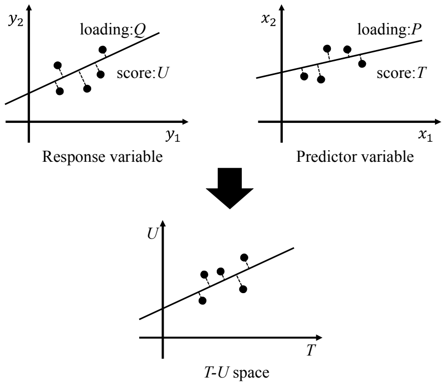

Fig. 4. Dimension reduction of PLS

PLS is based on the following regression equation:

$$y = \boldsymbol{XB}$$
$$y = x_1 b_1 + x_2 b_2 + \cdots + x_n b_n \tag{1}$$

where $\boldsymbol{X}$ is a predictor variable, y is the corresponding response variable, and $\boldsymbol{B}$ is the regression coefficient.

NIPALS is a popular algorithm of PLS. It is one of many methods that find eigenvectors of matrices. It was originally developed for Principal Components Analysis (PCA), but it was subsequently used to iteratively extract factors for PLS. Algorithm 1 provides an outline of the NIPALS algorithm in the case of multidimensional response variables of PLS (PLS2). For more details, see [4].

Algorithm 1. NIPALS algorithm

Define

A	: Number of factors
$\boldsymbol{X}$	: Predictor variable
$\boldsymbol{Y}$	: Response variable
$\boldsymbol{W}$	: Weight matrix for the $\boldsymbol{X}$ block
$\boldsymbol{C}$	: Weight matrix for the $\boldsymbol{Y}$ block
$\boldsymbol{T}$	: $\boldsymbol{X}$ score
$\boldsymbol{U}$	: $\boldsymbol{Y}$ score
$\boldsymbol{P}$	: $\boldsymbol{X}$ loading
$\boldsymbol{Q}$	: $\boldsymbol{Y}$ loading
$\boldsymbol{B}$	: Regression coefficient

```
for a=1 to A do
    U_a = a column of Y_a
    while W_a is not convergence do
        W_a = X_a^T U_a / U_a^T U_a
        W_a = W_a / ||W_a||
        T_a = X_a W_a / W_a^T W_a
        C_a = Y_a^T T_a / T_a^T T_a
        C_a = C_a / ||C_a||
        U_a = Y_a C_a / C_a^T C_a
    end while
    P_a = X_a^T T_a / T_a^T T_a
    Q_a = Y_a^T T_a / T_a^T T_a
    X_{a+1} = X_a - T_a P_a^T
    Y_{a+1} = Y_a - T_a Q_a^T
end for
B = W(P^T W)^{-1} Q^T
```

PLS allows us to set any number of factors, but an optimum value exists. Generally, the best number of factors is determined using cross-validation. In this research, we use leave-one-out cross-validation.

B. Training process

In this process, a multiclass classifier for skin, plants and asphalt is generated by PLS regression analysis.

To generate the classifier for the three materials, skin, plants, asphalt, and other materials (e.g. background) are set to class labels 1, 2, 3 and 4, respectively. Pixel values extracted from regions corresponding to each class in NIR images of each wavelength are stored to x_c^w as expressed in (2), where $c=\{1, 2, 3, 4\}$ and $w=\{650, 652, \cdots, 1050\}$. Then, a pixel value set extracted from all wavelengths is stored to $\boldsymbol{x}_c$ as expressed in (3). In this research, pixel value sets of 375 points were extracted from each material region.

$$x_c^w = I_w(x, y) \tag{2}$$

$$\boldsymbol{x}_c = (x_c^{650} \quad x_c^{652} \quad \cdots \quad x_c^{1050})^T \tag{3}$$

x^1, x^2, x^3 and x^4 extracted each 375 points are used as predictor variables $\boldsymbol{X}$ in PLS regression analysis.

$$\boldsymbol{X} = (\boldsymbol{x}_1 \quad \cdots \quad \boldsymbol{x}_2 \quad \cdots \quad \boldsymbol{x}_3 \quad \cdots \quad \boldsymbol{x}_4)^T \tag{4}$$

Furthermore, response variables corresponding to each predictor variable are necessary to apply PLS. In the case of PLS2, the number of dimensions of the response variables is set to the number of class labels, and these dimensions are corresponded to each class. The value of response variable's dimension corresponding to predictor variable's class is set to 1, and the values of response variable's other dimensions are set to 0.

$$\boldsymbol{Y} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ & \vdots & & \\ 0 & 1 & 0 & 0 \\ & \vdots & & \\ 0 & 0 & 1 & 0 \\ & \vdots & & \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{5}$$

The regression coefficient $\boldsymbol{B}$ is calculated from the predictor variables $\boldsymbol{X}$ and the response variables $\boldsymbol{Y}$ by using PLS regression analysis, and the multiclass classifier for skin, plants and asphalt is generated. Generated regression model is a multiclass classifier to separate the classes by the multiple predicted values calculated from $\boldsymbol{X}$ and $\boldsymbol{B}$.

C. Discrimination process

In this process, the three materials are discriminated by using multiple predicted values obtained by the multiclass classifier generated in the training process.

Discrimination process is applied for each pixel in NIR image. Firstly, pixel values of the pixel of interest from all wavelengths are extracted. In the next step, multiple predicted values (y_1, y_2, y_3, y_4) in the response variable $\boldsymbol{Y}$ are obtained by substituting the extracted pixel values for the predictor variable $\boldsymbol{X}$ of the classifier. Skin, plants and asphalt are discriminated by using these multiple predicted values.

In this paper, we propose two methods.

Method1: Materials are classified by maximum value of predicted values.

Method2: Materials are classified by maximum value of predicted values and thresholds.

1) Method1 : method of using dimension of the maximum value of predicted values

If the pixel is classified into a certain class, the predicted value in the response variable's dimension corresponding to the class is close to 1, and other predicted values are close to 0. Here, when the pixel value of interest is the skin, y_1 corresponding to skin is close to 1, and others y_2, y_3 and y_4 corresponding to plants, asphalt, and other materials are close to 0.

Therefore, the three materials are classified by using maximum value of predicted values as in Fig. 5. The material is classified for the material corresponded to the response variable's dimension whose value is the maximum of predicted values.

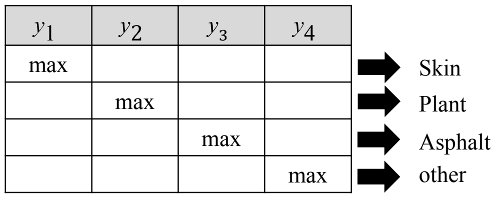

Fig. 5. Classify by using maximum value of predicted values

2) Method2 : method of using dimension of the maximum value of predicted values and thresholds

In this method, the three materials are classified by using thresholds in addition to the maximum value of predicted values in the case of Method1.

Thresholds (T_1, T_2, T_3) are corresponded to each predicted values (y_1, y_2, y_3) except y_4. If the maximum value of predicted value is smaller than threshold corresponded to the value, the material is classified to other materials as in Fig. 6.

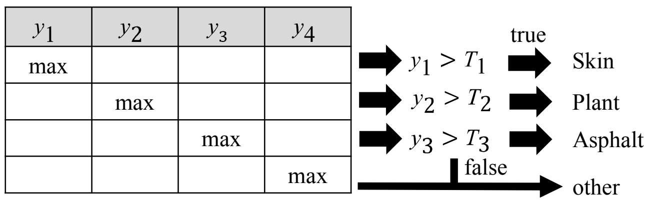

Fig. 6. Classify by using maximum value of predicted values and thresholds

Thresholds were determined so that the three materials were classified the most accurately between 0.00 and 0.99 in 0.01 steps.

IV. Optimum Wavelength Selection

Optimum wavelengths are selected by using Variable Influence on Projection (VIP).

VIP expresses the importance of each feature, and it is obtained by using parameters obtained by PLS regression analysis[7]. If the feature is important, VIP corresponded to the feature is higher.

Optimum wavelengths are selected by using VIP obtained by parameters which are generated by PLS regression analysis in training process. In this research, 4 wavelengths 650nm, 682nm, 706nm and 976nm were selected.

V. EXPERIMENT

We conducted a material discrimination experiment of human skin, plants and asphalt in a dark room. To evaluate the material discrimination result, Intersection over Union (IoU) was used.

Discrimination results of Method1 and Method2 by using all wavelengths are shown in Fig. 7. Results are colored in red, green and blue as skin, plants and asphalt, respectively. In Method2, optimum thresholds were determined to T_1=0.34, T_2=0.42, *and* T_3=0.75. (a) is a NIR 800nm image. (b) and (c) are discrimination results by Method1 and Method2, respectively. Also, IoU of each material and mean IoU are shown in TABLE I.

Discrimination results of Method1 and Method2 by using 4 wavelengths selected by VIP are shown in Fig. 8. In Method2, optimum thresholds were determined to T_1=0.37, T_2=0.49, *and* T_3=0.67. (a) is the same as in Fig. 7. (d) and (e) are discrimination results by Method1 and Method2, respectively. Also, IoU of each material and mean IoU are shown in TABLE II.

From TABLE I and TABLE II, the result of Method2 using all wavelengths was the highest in this experiment. However, discrimination accuracy of Method2 using 4 wavelengths was a result that did not differ much. From these results, we confirmed that our method can select efficient wavelengths.

(a) (b) (c)

Fig. 7. Discrimination result of Method1 and Method2 by using all wavelengths

(a) (d) (e)

Fig. 8. Discrimination result of Method1 and Method2 by using 4 wavelengths

TABLE I. DISCRIMINATION ACCURACY OF ALL WAVELENGTHS

Material of IoU	*Skin*	*Plant*	*Asphalt*	*other*	*mean*
Method1	0.951	0.961	0.881	0.972	0.942
Method2	0.951	0.961	0.933	0.963	0.952

TABLE II. DISCRIMINATION ACCURACY OF 4 WAVELENGTHS

Material of IoU	*Skin*	*Plant*	*Asphalt*	*other*	*mean*
Method1	0.901	0.943	0.820	0.966	0.907
Method2	0.902	0.942	0.892	0.949	0.921

VI. CONCLUSION

In this paper, we proposed a multiple materials discrimination method by PLS regression analysis based on the spectral reflectance properties of the materials.

Firstly 201 NIR images were acquired, and the multiclass classifier for the materials is generated by using PLS regression analysis. Then, the materials are discriminated by using multiple predicted values obtained by the classifier. We proposed two methods for discrimination by using the predicted values. Also, we selected optimum wavelengths by using VIP.

We conducted a discrimination experiment to compare these methods in the case of using all wavelengths or selected 4 wavelengths. From the result, we confirm that Method2 gives a better discrimination result than Method1, and the materials are discriminated with high accuracy even in the case of using 4 wavelengths.

Verification of the effectiveness in the outdoor environment is our future work to extend our proposed method for practical use.

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