

Hyperspectral Image based on Deep Neural Network for Tumor Lesion Classification

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ABSTRACT

In this paper, we propose a method for wavelength bands reduction of near-infrared (NIR) hyperspectral imaging data to extract the cancer region with minimum input data. NIR hyperspectral imaging data has a spectrum data of each pixel and is suitable for distinguishing tumors region of the body rather than RGB imaging data. However, it is difficult to apply to the medical field because of processing time consumption and hardware size limitation. Therefore, it is necessary to remove the redundant wavelength bands which are not (or little) contributed to tumor region extraction. Although several previous studies for wavelength bands reduction have been conducted, these approaches focused on the characteristics of the wavelength itself. In this research, the proposed wavelength bands reduction method is focused on the node weights of the post-training deep neural network which is an indicator directly related to classification. The experimental results using GIST specimen demonstrated that four wavelength bands selected from all wavelengths bands by using the proposed method are effective for tumor distinguishing as well as all wavelength bands.

Keywords: Near-infrared; Hyperspectral imaging; Machine learning; Wavelength reduction

1 Introduction

Hyperspectral Imaging (HSI) is the parallel acquisition of spatial and their corresponding spectral information in image space and their combination thereof [1]. Each pixel of HSI data has spectral information (n wavelength bands). The spectral information is useful for material characterization. Accordingly, HSI can apply for object classification and detection based on the characterization [2-3]. The object classification and detection using HSI have been attracted attention in the medical field as non-invasive observation technology [4-7]. In particular, near-infrared (NIR) light with wavelengths of about 800 – 2500 nm has received attention as a 'biological window' because water and biological tissues have a few optical losses caused by scattering and absorption. NIR light can penetrate/see through deep tissues. NIR endoscope have a great potential as the surgery supporting system [8-10]. A few studies of extraction methods of cancer regions using NIR-HSI reported. Hamed et al. revealed that it is possible to classify gastric cancer and normal tissue region of ten extracted specimens using the NIR wavelength bands of 1226nm – 1251nm and 1288nm – 1370nm with HSI and support vector machine [11]. However, these methods are difficult to apply for real-time imaging processing because the hyperspectral data need too much processing time due to handling the multi-spectral images with many wavelength bands. To solve such problems, various method for extraction the important data

from the hyperspectral data and processing with minimum data were proposed [12-14]. In particular, Serranti et al. proposed the classification method of the oat and groat kernels using NIR-HSI [15]. In the method, the hyperspectral images of the oat and groat scattered in the same plane were analyzed applying Principal Component Analysis (PCA) for exploratory purposes and Partial Least Squares-Discriminant Analysis (PLS-DA) to build the classification models to discriminate the two kernel typologies. And the method demonstrated also that good classification results could be obtained using only three wavelengths, selected by means of a bootstrap-VIP (Variable Importance in Projection) procedure, allowing to speed up the classification processing for industrial applications. The method is assuming that the absorbance spectrum is a linear sum of the absorbance spectra as a material simple substance, the coefficients of selected wavelengths are calculated based on the linear problem. However, the medical images from different patients have various aspects of the feature as non-linear problems. And the PLS-DA is not suitable for large-scale datasets because of the method need to the optimized calculation of the parameters.

In this research, we propose that the wavelength bands reduction method focused on the node weights of the post-training deep neural network which is an indicator directly related to the identification. The proposed method is based on the artificial neural network which can apply hyper non-linear problems and large-scale datasets easily. In the experiments, Gastrointestinal Stromal Tumor (GIST) specimens were used for the evaluation of hyperspectral data. The proposed method evaluates by the validation accuracy of the GIST data, in comparison with PLS-DA.

2 Materials and Methods

2.1 Collection of Surgical Specimens and Definitive Diagnosis

Patients with clinically diagnosed GIST who underwent surgery were examined in this study. The inclusion criteria were: (i) clinical diagnosis of GIST; (ii) age of 20 years or older; and (iii) written informed consent for this study. The exclusion criteria were: (i) a history of prior chemotherapy; (ii) presence of hepatitis B virus surface antigen or hepatitis C virus antibody; and (iii) judged inappropriate for this study, such as improperly captured images. The indications for surgery were according to clinical practice guidelines for GIST in Japan. This study was approved by the Institutional Review Board of the National Cancer Center Japan (approval no. 2015-339) and conforms to the provisions of the Declaration of Helsinki and the Epidemiological Study Guideline issued by the Japan Ministry of Health, Labor, and Welfare. All patients provided written informed consent before inclusion.

2.2 Near-infrared Hyperspectral Image Capturing

An imaging system with a high-speed NIR hyperspectral camera (Compovision, CV-N800HS; Sumitomo Electric Industries, Ltd., Osaka, Japan) was used to obtain NIR-HSI images (wavelength: 1000–2350 nm; wavelength resolution: 6.3 nm) shown in Figure 1. The detector (NIR spectroscopic camera), captured data values for each wavelength band, on each pixel per line of the image, in one scan. By scanning multiple lines (by sliding the sample stage), three-dimensional HSI images (x-y- λ axes) were obtained, producing a virtual “data cube” for processing and analysis. The HSI image has three-dimensional hyperspectral data characterized by two spatial dimensions and one spectral dimension. The value of the pixel is 320×640 , the wavelength bands are 1000nm - 2350nm in the step of approximately 6.3 nm and the size of one spectral data is a 16-bit integer (the maximum value is 65535). Each of the fresh specimens which are resected from stomach were placed on the sliding stage without trimming,

and NIR-HSI images were acquired from the mucosal side under illumination from a halogen lamp (0.96 W/cm²). Visible light images of the fresh specimens were also captured by a digital camera for make the teaching datasets. The acquired raw images were calibrated using white and dark reference images as the following equation:

$$f = \frac{V_n - D}{W - D} \times 65535 \quad (1)$$

where V_n is the value of spectral data, D is the value of dark data, W is the value of white data at that pixel. If $W - D$ was negative, the value of f was considered zero.

2.3 Preprocessing and Labeling

The normalization was operated to convert the hyperspectral data to reflectivity, and then the absorbance was got from reflectivity as the preprocessing.

$$Reflectivity = \frac{raw\ value}{65535} \quad (2)$$

$$Absorbance = -\log_{10}(Reflectivity) \quad (3)$$

Through the preprocessing of all GIST hyperspectral data, the longer than 2150 nm wavelength of all GIST specimens captured hyperspectral data had a big noise and an irregular difference. The data at longer than 2150 nm was deleted from the datasets. Therefore, the wavelength bands in the datasets are 196 bands from 900 nm to 2150 nm. In addition, reflectance rates of over 70% and below 10% were defined as highlights and shadows, respectively, and these pixels were removed from the datasets.

To create two regions showing pixels of normal mucosa and of the GIST lesion, a boundary line was drawn by a pathologist. In this study, the boundary line drawn by the pathologist is considered correct, however, humans cannot mark a region correctly up to a pixel in fact. Therefore, the edge of the boundary region and the GIST lesion was also removed from the datasets. Figure 2 shows the example of the NIR-HSI GIST image, the boundary line of the GIST lesion, and the classification image of GIST.

2.4 Wavelength bands reduction method based on weights of post-trained deep neural network

Artificial Neural Network (ANN) is a mathematical model imitating the neuron structure, which is used for pattern analysis, classification, and so on by learning a huge amount of non-linear data. Each of the data in the input array is connecting to all of the output through the abstract intermediate layer on ANN, it is possible to compute the contribution of one of the inputs to the output layer [16-19]. ANN has the potential to reduce the number of inputs (wavelength bands) based on the contribution of each weight of nodes to find the correct classification.

Figure 3 shows the network structure used in the proposed method. Dropout is applied to each output other than the last layer to suppress overfitting and Adam is selected for optimization. The calculation of the contribution of each input data to select the important wavelength bands to distinguish the GIST lesion (Tumor) and normal mucosa region (Normal) in the proposed method as following steps:

Step 1: To build the classification models by using the Deep Neural Network composed only of the entire fully-connected layer without bias and using the rectified linear activation function (ReLU) with all wavelength bands (196 bands) and the created datasets.

Step 2: To conduct a forward calculation by each one pixel of the datasets using the building classification model, and record all output of the node of all layer in the neural network.

Step 3: To conduct a pseudo forward calculation by each one pixel of the datasets same as Step 2, but at this time, only i th wavelength band is used and the other wavelength bands data are zero. Then the final output of the building classification model without ReLU is the “contribution degree” of the i th wavelength band of the one pixel. And during the calculation, the minus value of the output of all nodes of all layer recorded by Step 2 is set to zero, because the minus contribution is not affected to select the important wavelength bands of binary problem.

Step 4: To continue to calculate the “contribution degree” of all wavelength bands (196 bands) and the wavelength bands of the top three “contribution degree” are selected as a candidate.

Step 5: To continue to calculate the “contribution degree” of all wavelength bands (196 bands) of all pixels of the datasets as Step 2-4. The important wavelength bands are selected in descending order of the number of times selected as the candidate in the validation datasets.

In this research, after the building classification model through the DNN with the datasets, the validation test was carried out using 1000 pixels data (196 wavelength bands of one pixel, 100 tumor pixels data and 100 normal pixels data extracted from each specimen) as the test datasets. The “contribution degree” of each test data are calculated and sum when the validation is correct.

3 Results

Figure 4 shows the loss and accuracy of running machine learning to build the classification model by using the DNN shown in Figure 3 with the GIST specimens’ datasets. The validation accuracy of the final epoch was 94.2%, which was a very good accuracy taking the incompleteness of the boundary line into consideration. In addition, the possibility of over-fitting was denied because of the similarity between training and validation curve. And the classification model by using PLS-DA was built with all wavelength bands of the datasets. The maximum validation accuracy was 93.1% in case of eight latent variables retained.

The wavelength bands reductions were carried out by using both methods. The results of the wavelength bands reduction are shown in Table 1. In the PLS-DA method, the top five wavelength bands coefficient selected by means of a bootstrap-VIP procedure. In the proposed methods, the top five important wavelength bands selected in descending order of the number of times selected as the candidate in the 1000 pixels validation datasets. To verify the appropriateness of the wavelength bands reduction, the classification models of both methods were built by using only the top four/five selected important wavelength bands, and the validation accuracy of each models were calculated. The results of the validation accuracy are shown in Table 2.

Figure 5 shows the NIR image of the specimens with the boundary line and the visualized classification image by using all and selected wavelength bands. Left images indicate correct boundary of lesions marked by a pathologist. Middle images are classified by using all wavelength bands. Right images are classified by using four selected wavelength bands by using the proposed method. The accuracy of leave-one-out cross validation of each GIST specimen carried out with (a) the all wavelength bands and (b) the four selected important wavelength bands by using the proposed method (Table 3).

4 Discussion

The four out of five wavelength bands selected by using the proposed method were similar to the wavelength bands selected by using the conventional method (PLS-DA). Although both selected methods had significant accuracy for the wavelength bands reduction, the validation accuracy of the

proposed method using all and selected wavelength bands surpassed the validation accuracy of the conventional method (PLS-DA) (see Table 2). Additionally, considering that the work of data processing, the proposed method had the advantage of the simplicity about the building classification model and the important wavelength bands selection. The validation results of each GIST specimen carried out by the classification model with DNN using the four wavelength bands selected by the proposed method was similar to the all wavelength bands classification model (see Table 3). The most important advantage of the proposed method is that the proposed method can apply for non-linear problem because the proposed method based on DNN with ReLU. Therefore, the proposed method was considered more reliable than the conventional method (PLS-DA).

The leave-one-out cross-validation using the proposed method was carried out to evaluate the possibility of the application for the unknown specimens. The first step of Leave-one-out cross-validation is the selection of one specimen for test data from the entire specimen. Then, training and validation are carried out to build the classification model using all of the data of specimens expecting the selected one. Finally, the classification accuracy is calculated using the previous classification model and the test data. After the wavelength bands reduction, the accuracy of training data was decreased, on the other hand, the accuracy of the validation and the normal tissue identification were increased (see Table 3). The increase of the validation accuracy means that the classification model using all wavelengths were over-fitting to the training data because of the excessive amount of the data. In addition, the bias for the tumor (normal in the case of specimen No.3) identification was solved by the increase of the normal tissue identification accuracy. Thus, it is considered that the wavelength bands reduction by the proposed method is efficient for the classification of the unknown specimens.

5 Conclusion

In this research, we proposed that the method for wavelength bands reduction of near-infrared (NIR) hyperspectral imaging data to classified the GIST lesion with minimum input wavelength bands for medical applications. The proposed method can build the classification model simply by applying the conventional Deep Neural Network learning techniques and select the important wavelength bands based on the built classification model. The proposed method can apply non-linear problem because of the proposed method based on DNN with the rectified linear activation function (ReLU). In the experiment, the four important wavelength bands are selected by the proposed method. And the validation accuracy of only using four selected wavelength bands is the almost same as using all wavelength bands. The wavelength bands reduction and the evaluation of classification accuracy were carried out by the conventional method and the proposed method. The results showed that the reliability and operability of the proposed method are higher than the conventional method. The experimental results using GIST specimens clearly demonstrated that four wavelength bands selected from all wavelengths bands by using the proposed method are effective for the distinguishing as well as all wavelength bands.

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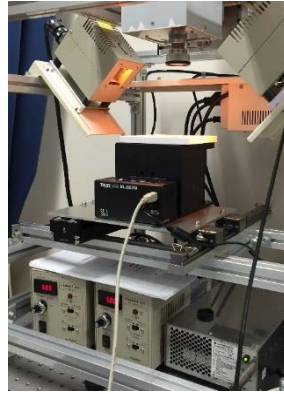


Figure 1. Setup of NIR-HSI system (Compovision®, Sumitomo Electric Industries, Ltd., CV-N800HS).

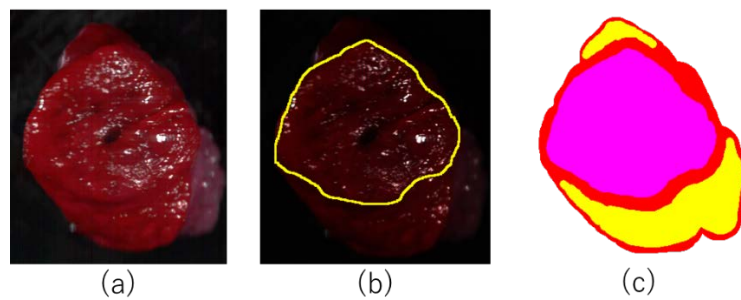


Figure 2. The sample of the datasets of NIR-HSI from the imaging system of Compovision. (a) NIR pseudo image of extracted GIST. (b) the boundary line of the GIST lesion in the image of specimen. Inside of yellow circle is expected GIST lesion. (c) A label image of specimen, which is inputted to datasets as purple is GIST lesion, yellow is normal mucosa region and red is removed from the datasets.

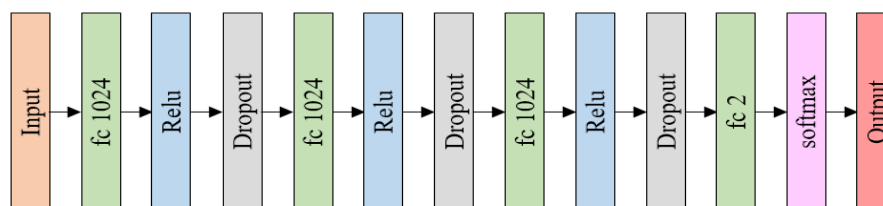


Figure 3. Deep Neural Network structure.

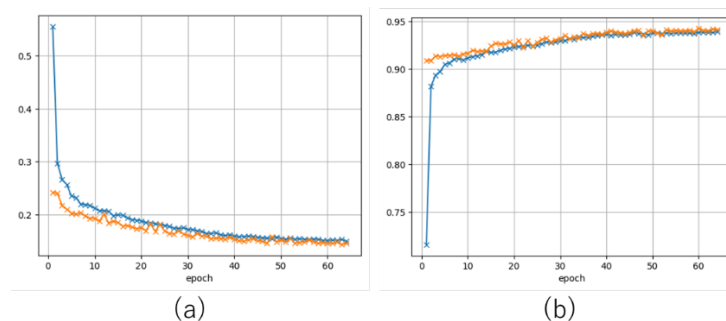


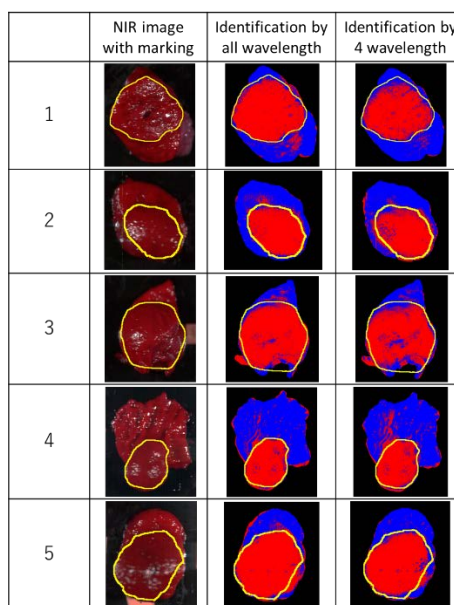
Figure 4. (a) Loss and (b) accuracy when the classification model is building by DNN with the GIST specimens' datasets. Blue line is a training curve. Orange line a variolation curve.

Table 1. The top five selected importance wavelength bands for the GIST classification model by using (a)PLS-DA and (b) the proposed method.

(a)			(b)		
Wavelength number	Wavelength [nm]	Coefficient [-]	Wavelength number	Wavelength [nm]	Count used for 1000 classification [-]
14	996.12	1.218 (Tumor)	28	1084.75	294 (Normal)
27	1078.42	1.239 (Normal)	41	1167.02	216 (Tumor)
38	1148.03	0.708 (Tumor)	55	1255.57	237 (Tumor)
55	1255.57	0.701 (Tumor)	74	1375.69	317 (Normal)
75	1382.01	0.434 (Normal)	89	1483.09	343 (Tumor)

Table 2. The average classification accuracy of the GIST specimens. In the proposed method, only four wavelength bands used for the classification because the accuracy of the four and five wavelength bands are not big different.

	Proposed method	PLS-DA
All wavelength bands	97.6%	93.1%
Selected wavelength bands	95.9% (4 bands)	91.4% (5 bands)

**Figure 5. The result of GIST calcification by using the proposed method. The yellow line indicates the boundary line. Red region is the estimated GIST lesion. Blue region is the normal mucosa region. Left images are correct image by a pathologist. Middle images are classified by using all wavelength bands. Right images are classified by using four selected wavelength bands by using the proposed method.****Table 3 The accuracy of leave-one-out cross validation of the GIST specimens carried out with (a) the all wavelength bands and (b) the four selected important wavelength bands by using the proposed method.**

(a)					(b)				
	Training	Validation	Cancer	Normal		Training	Validation	Cancer	Normal
1	98.3%	71.1%	96.5%	45.6%	1	94.4%	92.1%	90.1%	94.0%
2	98.2%	82.8%	96.3%	69.2%	2	95.2%	86.3%	97.0%	75.6%
3	98.7%	84.6%	77.1%	92.2%	3	96.2%	83.8%	83.6%	84.0%
4	96.9%	89.8%	97.0%	82.6%	4	95.7%	90.5%	98.4%	82.5%
5	98.3%	91.8%	98.7%	84.8%	5	94.8%	96.7%	94.9%	98.4%
Average	98.1%	84.0%	93.1%	74.9%	Average	95.3%	89.9%	92.8%	86.9%