Development and Testing of a Portable Soil Nitrogen Detector Based on Near-infrared Spectroscopy

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Abstract—**Access to soil information is accompanied by the entire agricultural production process. The conventional method (Physicochemical analysis) for detection of nitrogen in soil is complex and time-consuming. In this work, we present a portable soil nitrogen detector by using a chip-scale Fourier transform infrared spectroscopy sensor to enable rapid detection of soil nitrogen, and a supporting software with functions such as spectral acquisition, background subtraction, and data storage was also program. The detector was used to detect the spectral data in the actual farmland environment. 120 randomly selected soil samples were used to calibrate soil nitrogen to soil reflectance using partial least squares. 76 randomly selected samples were withheld for validation. Results of the experiments indicated values for the coefficient of determination as high as 0.934, and root mean square error was 1.923. After the model was embedded in detector, 10 soil samples were tested for verification. The relative error between the predicted value and the real value was less than 13%, and the minimum relative error was 5.56%. The results verified that detector can initially realize the rapid prediction of soil nitrogen and provide a certain technical reference for miniaturization of portable detecting instruments.**

Keywords—Soil nitrogen; Detector; NIR spectroscopy; Diffuse reflection

I. INTRODUCTION

In the process of agricultural production, nitrogen is one of the most important nutrients in soil, and one of the large number of elements required for the healthy growth of crops[1]. Detection of soil nitrogen content is great significance for understanding soil fertility, studying crop fertilization dosage, and increasing crop yield. Although the standard chemical analysis methods (Kjeldahl method, spectrophotometry, etc.) are accurate, the analysis and testing process is complicated, time-consuming, and use large amounts of alkali which is easy to cause environmental pollution.

Near-infrared (NIR) spectroscopy has the characteristics of fast, non-contact and pollution-free analysis, which is widely applied in petroleum[2], agriculture[3, 4], food[5] and other fields[6, 7]. This method is suitable for the detection of nitrogen in soil. With the development of NIR spectroscopy, Ehsani[8], Xiu[9], Shi[10] et al. had used NIR spectroscopy to predict the nitrogen content in uniform soil, and established a model with higher precision, which verified the feasibility of using NIR spectroscopy to detect soil nitrogen. Li[11], An[12], Gao[13] etc. proposed the scheme for soil nitrogen rapid measurement instrument based on spectral technology, but most of studies took soil with configured in the laboratory,

which was divorced from the actual complex farmland environment and cannot be applied to actual detection.

Based on the research of near-infrared diffuse reflection technology, this paper proposes a rapid detection device for soil nitrogen. The instrument is applied to the actual farmland environment for calibration and testing, and a suitable model is established. This paper provides technical support for the rapid acquisition of soil nitrogen.

II. INSTRUMENT DESIGN

Combined with the actual need of farmland, our purpose is to develop a portable instrument for measuring nitrogen content of farmland soil. The instrument should have the characteristics of simple structure, small size, high signal-to-noise ratio and stable performance.

A. Hardware Design

Previous studies have confirmed the feasibility that use NIR spectrum in 1300 -2400 nm to detect the nitrogen content in soil[14, 15]. A si - ware's NeoSpectra Micro that a chip - level Fourier transform infrared spectrum module was selected as the signal detector. This chip - scale spectral module consists of a Monolithic single-chip Michelson interferometer and a single element uncooled InGaAs photodetector. It is only 18*18*4 mm in size, which gives full play to the high resolution of the Fourier transform spectrometer and greatly reduces the size of the instrument. The module has a spectral range 1350-2500 nm, optical resolution 16 nm, signal-to-noise ratio 2000:1, wavelength accuracy ±1.5 nm.

We used two tungsten halogen lamps as the light source, 5V, 0.15A power supply, maximum color temperature is 2450 K, illumination ranges 350-2500 nm. The optical path structure is shown in Fig. 1., the detector and the light source are at an angle of 45°. The light emitted by the light source is diffusely reflected on the sample and is detected by the photodetector after Michelson interference. The instrument is controlled by a Raspberry Pi computer board via serial peripheral interface (SPI). The use of raspberry PI computer board makes the stoichiometric calculation faster and the overall power consumption smaller[16]. This detector is powered by 5V and 2A power supply, which can realize the demand of portability and field real-time detection.
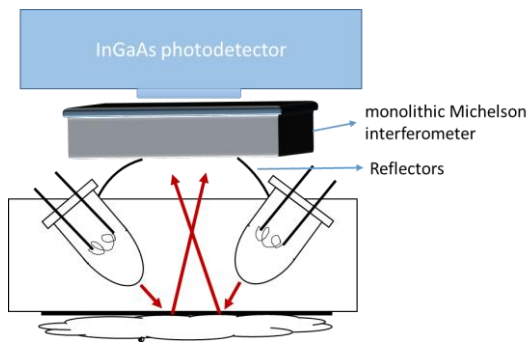
Fig. 1. Schematic diagram of the light path.

B. Software Design

The raspberry PI computer board is very convenient for the operation, data transmission and storage of the instrument. Based on this instrument, we designed a set of interface software running on raspberry PI computer, which is used to realize data collection, display, storage, calculation of absorbance and reflectance, and spectral data processing. The software was written by Eclipse Jee development tool and includes six main functions: resolution selection, sampling time, absorbance reflectance conversion, background acquisition, spectral acquisition and display. When in use, the interface operation can be realized by adding a touch screen on the raspberry PI computer board. The software flow chart and function diagram is shown in Fig. 2.
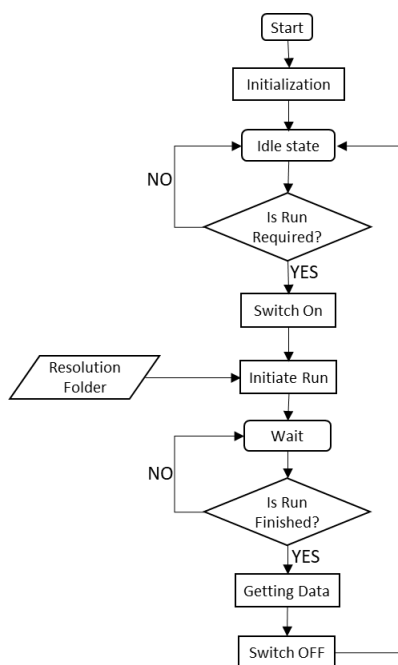

Fig. 2. Software flow pattern.

For ease of use, reduce the size of the instrument caused by the touch screen, we developed a mobile phone Android application(APP). The APP is connected to the Raspberry Pi computer through Bluetooth. After the device is connected, the user can also operation the performed through the APP, which is convenient for measurement. Software features including background subtraction, detection, data storage, etc. as shown in Fig. 3.

When the detector is used, first connect the platform through the mobile phone Bluetooth, and then to eliminate the fluctuation of the light source and the noise of the electronic system, measure the standard whiteboard storage as the background before each test, then test the sample, and finally you can choose to store the spectral data and detection results on the mobile phone.
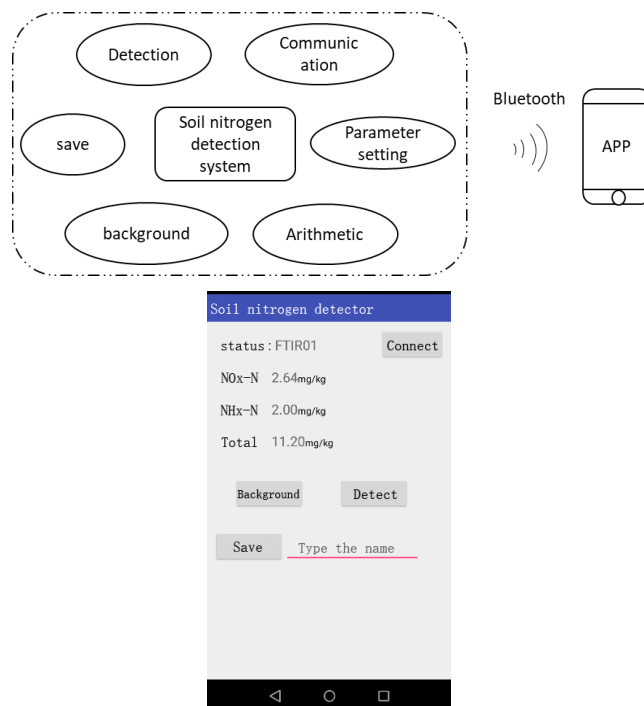

Fig. 3. Software function diagram and software interface.

III. MODEL ESTABLISHMENT

A. Materials and Methods of Spectral Acquisition

The establishment of the detector model fully considers the complex environment in the actual farmland testing process. The site was selected in Xiaotangshan modern agricultural science and technology demonstration park (Beijing). In the park, there are plantations, experimental fields and various complex farmland environments with different nitrogen content gradients. We selected 40 areas with different farmland environment and different nitrogen content in the park (Contains bushes, woods, corn fields, riversides, polders, etc.).

During the experiment, soil was taken out and removed weeds in surface. Then, the soil was screened with an 8-mesh sieve and placed on a plastic board. Before testing the soil, press the instrument probe on the standard white board to test the background, and then press the probe on the soil sample to test the soil infrared spectrum. Each sample was collected at a different location for 5 times. The photos taken on site are shown in Fig. 4(a). After the spectral collection was completed, the soil was sealed and preserved with plastic bags, and then sent to the Institute of Agricultural Resources and Regional

Planning of CAAS for physical and chemical analysis to obtain the standard nitrogen content. Soil spectral data are shown in Fig. 4(b).
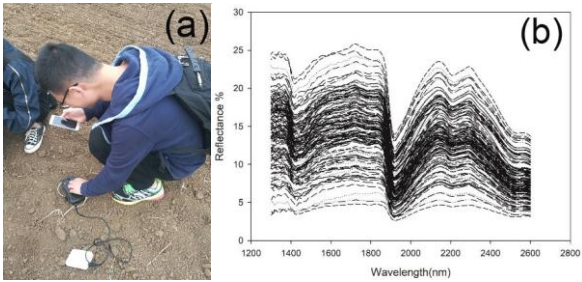

Fig. 4.   (a) the site photos, (b) soil spectra.

Standard physical and chemical analysis showed that the nitrate nitrogen content ranged 0.05-32.93 mg/kg, and the total nitrogen content ranged 0.530-1.661 g/kg. The gradient of total nitrogen content was not obvious, so nitrate nitrogen was selected as the object to test the instrument in this study, and the nitrate nitrogen content of samples was shown in Table 1.

As shown in the Fig. 4(b), the spectral curves have significant peaks at 1400 nm,1900 nm, 2200 nm, which are mainly caused by the absorption of water. The spectral wavelengths related to soil nitrogen are mainly at 1500~1850 nm (double frequency) and 2000~2400 nm (combined frequency)[17] of nitrogen-containing groups, so it is reasonable to choose multiple spectral bands for modeling.

TABLE I.   THE CONTENT OF NO₃⁻-N OF 40 SOILS

sample	NO₃⁻-N (mg/kg)	sample	NO₃⁻-N (mg/kg)	sample	NO₃⁻-N (mg/kg)	sample	NO₃⁻-N (mg/kg)
1	7.024561404	11	6.5610608	21	14.193988	31	7.7812319
2	3.440583333	12	5.5036771	22	7.3136234	32	17.103188
3	8.095891648	13	7.310544	23	0.0487758	33	8.293913
4	3.89730725	14	8.7132952	24	6.9111502	34	32.931618
5	2.64147619	15	0.9940023	25	12.631721	35	19.266574
6	4.469827784	16	3.1786952	26	13.56774	36	2.8286621
7	2.009200463	17	12.555051	27	5.8044097	37	3.6053812
8	1.445537383	18	26.075785	28	4.4061758	38	7.9060244
9	6.336670391	19	27.330495	29	5.1754491	39	8.2878511
10	10.79954595	20	27.347273	30	10.813603	40	3.9086667

B.   Spectral Pretreatment

In order to obtain better results, it is necessary to remove the abnormal spectrum before modeling. Therefore, we used robust principal component analysis (PCA) algorithm to analyze the data and use Mahalanobis extract abnormal samples. As shown in Fig. 5, among the 200 spectral samples, 79,65,69,172 have large scoring distance and orthogonal distance, which can be judged as abnormal samples and be removed.
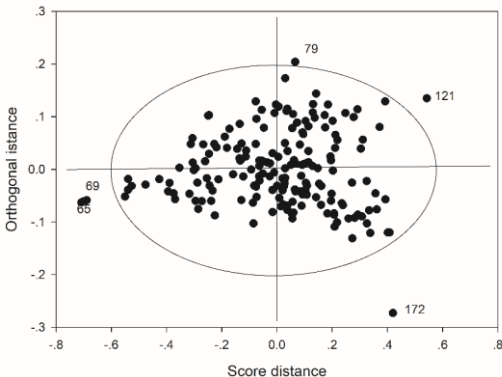

Fig. 5.   Mahalanobis distance orthogonal scoring plot.

For the NIR spectrum, in order to establish a robust quantitative model, it is necessary to preprocess the spectral data. As can be seen from the original spectrum in Fig. 4(b), although the spectra are similar in overall, there is a serious drift. Hence, the spectra were subjected to Sacitzky - Golay (SG) smoothing, Standard Normal Variate (SNV), Multiplicative Scatter Correction (MSC) and first derivative (1St derivative) respectively. The purpose of different spectral pretreatment is to compare and analyze the different influence for the results of the model. By comparison, the better pretreatment method is selected. This paper uses The Unscambler 9.7 (Camo) to preprocess and model the raw data spectrum.

C.   Modeling Evaluation Method

The mathematical model was evaluated by complete interactive verification and external verification[18]. Correlation coefficient (R^2), verification root mean square error (RMSECV) and prediction root mean square error (RMSEP) were used as evaluation criteria. R^2 is a statistical indicator indicating the linear correlation between two variables. The closer the R^2 value is to 1, the greater the correlation. The RMSE reflects the deviation between the real value and the predicted value, and the smaller the value, the better.

D.   PLS Regression Modeling

Partial least square (PLS) was used to analysis the spectrum after performing different preprocessing methods. PLS can find the best function matching with the data by minimum sum of squares errors. This algorithm is robust and reduces the interference caused by light scattering[19, 20]. In

this study, 3 of the 5 spectra of each sample were selected as a calibration set, the rest of 2 as a test set. Remove 1300-1350 nm and 2450-2500 nm band to eliminate the original spectral band noise, and remove 1400 nm, 1900 nm, and the near of 2200 nm band in order to reduce the interference of water. Then the PLS algorithm was used to model and analyze the selected 120 spectra. The results of PLS are shown in Table 2.

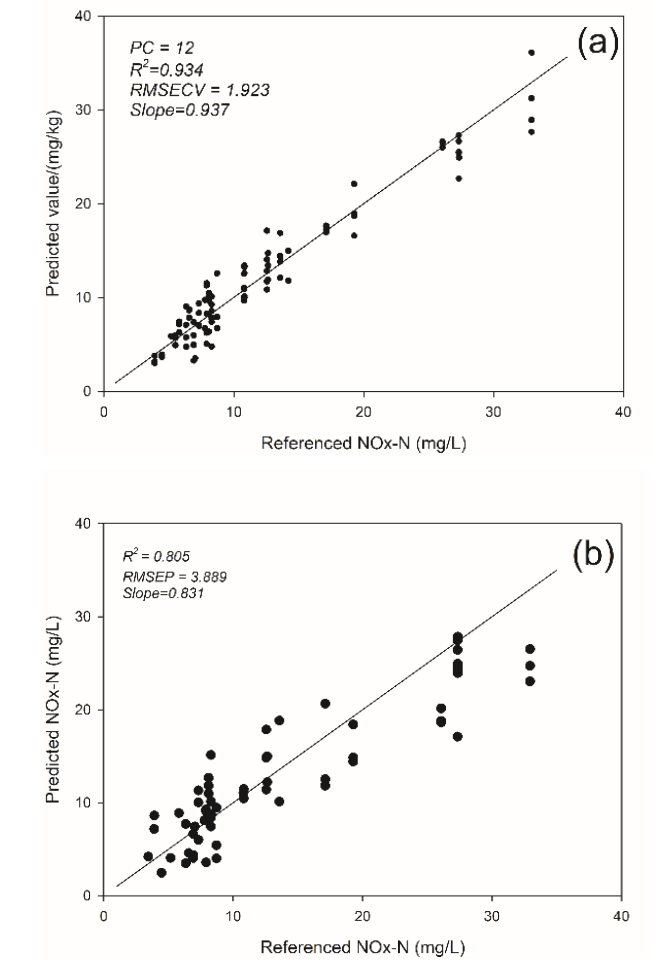| Pretreatment method	Principal components	R^2	RMSECV
No pretreatment	13	0.65	4.944
Smoothing	9	0.658	3.753
MSC	11	0.702	3.506
SNV	13	0.642	5.053
1St derivative	12	0.934	1.923

Fig. 6. Scatterplot comparison of actual and predicted values of soil attributes for the hold-out validation data set. Calibration models were developed with partial least squares (PLS).

Table2 shows the results of different pretreatment methods after PLS modeling. The results show that the model that use first derivative is better than other pretreatment methods. Fig.6(a) shows the correspondence between the predicted values and the referenced values in the PLS mode after pre-processing with first derivative. The horizontal axis is the referenced value of soil nitrate nitrogen, and the ordinate is the predicted value. The coordinate points are all around the fitted line, the slope is 0.937, which is approximately equal to 1, PC = 12, R^2=0.934, RMSECV = 1.923. The evaluation parameters are reasonable, so this study used this modeling results as the final result.

The remaining 76 prediction set samples was predicted by the above model, and the relationship between the predicted value and the referenced value is shown in Fig. 6(b). As can be seen from the Fig. 6(b), The coordinate point in the figure is around the fitted straight line, and the slope of the straight line is 0.83114, which is close to 1. The prediction results show that: PC = 10, R^2 = 0.805, RMSEP = 3.8895, and the prediction accuracy is average.

E.   Results Analysis

It can be seen from Fig. 6 that the deviation data from the line are mainly concentrated on the side with high nitrate content. Referring to Fig. 6 and Table 1, it can be seen that there are few soil samples with high content of nitrate nitrogen, and the soil is mainly concentrated between 2-15 mg/kg. Therefore, the reason for a poor prediction of the model prediction set may be that the soil sample has a small gradient of nitrate nitrogen content and is too concentrated in small concentrations.

IV.   VERIFICATION OF THE SOIL NITROGEN DETECTOR

After embed the above established model into the detector, 10 soil samples were randomly detected from different locations in the experimental base according to the method described above. The results were compared with the standard values, as shown in Table 3. It can be seen from the results that the detection error of the system is less than 13%, and the relative error minimum is 5.56%. The verification results of the detector show that the detector has high prediction ability and can be applied to the rapid detection of nitrate nitrogen in farmland soil.

TABLE III.   INSTRUMENT PERFORMANCE TEST

sample	Standard value(mg/L)	Predicted value(mg/L)	Absolute error	Relative Error(%)
1	3.441	3.647	0.206	5.986
2	12.555	11.47	1.085	8.641
3	6.337	7.065	0.728	11.488
4	10.8	9.586	1.214	11.240
5	26.076	23.971	2.105	8.072
6	27.33	23.845	3.485	12.751
7	5.504	6.202	0.698	12.681
8	14.194	15.212	1.018	7.172
9	7.311	6.507	0.804	10.997
10	17.103	18.055	0.952	5.566

V. CONCLUSION

Based on the research of near-infrared diffuse reflection technology, this paper proposes a set of design schemes for soil nitrogen detection. Since this scheme used NeoSpectra Micro as the signal detector, the size of the instrument was greatly reduced while the high resolution of the Fourier transform spectrometer was displayed. At the same time, the control software of the Raspberry Pi computer board and the mobile application is designed. Through the calibration and verification of the self-made instruments in the actual farmland environment, good experimental results were obtained. The relative error detected by the detector is less than 13% and the minimum relative error is 5.56%. The results show that the detector has the characteristics of small volume, high signal-to-noise ratio and stable performance, which can realize rapid detection of soil nitrogen. Research laid the foundation for further instrument miniaturization and industrial application.

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