Engineering, **2013, 5, 553-560**
http://dx.doi.org/10.4236/eng.2013.510B114 Published Online October 2013 (http://www.scirp.org/journal/eng)

Noninvasive Blood Glucose Monitoring System Based on Distributed Multi-Sensors Information Fusion of Multi-Wavelength NIR*

Bo Zeng, Wei Wang#, Na Wang, Funing Li, Fulong Zhai, Lintao Hu
School of Information Science and Engineering, Lanzhou University, Lanzhou, China
Email: zengbo11@gmail.com, #wangw@lzu.edu.cn

Received 2013

ABSTRACT

In this research, a near infrared multi-wavelength noninvasive blood glucose monitoring system with distributed laser multi-sensors is applied to monitor human blood glucose concentration. In order to improve the monitoring accuracy, a multi-sensors information fusion model based on Back Propagation Artificial Neural Network is proposed. The Root-Mean-Square Error of Prediction for noninvasive blood glucose measurement is 0.088*mmol*/*L*, and the correlation coefficient is 0.94. The noninvasive blood glucose monitoring system based on distributed multi-sensors information fusion of multi-wavelength NIR is proved to be of great efficient. And the new proposed idea of measurement based on distributed multi-sensors, shows better prediction accuracy.

Keywords: Noninvasive Glucose Monitoring; NIR Arrays Signals Fusion; BP-Artificial Neural Network

1. Introduction

Diabetes has become a modern disease and more than 150 million people are suffering from it all around the world [1]. In order to prevent complication, the tight blood glucose level control is very essential. Currently, patients are recommended to monitor their blood glucose level via an invasive finger-tip stick method, this way will inevitably bring patients pain and infection [2]. In order to avoid the weakness of invasive method, a number of noninvasive measurements occurred, like middle-infrared emission spectroscopy [3,4], Near Infrared (*NIR*) spectroscopy [5,6]. The main drawback of infrared measurement is its accuracy and stability. In our past work, an infrared noninvasive blood glucose measurement system based on multi-sensors and Mixture of Experts (*ME*) [7] was designed. ME algorithm greatly improved the precision of noninvasive blood glucose measurement. In the noninvasive blood glucose monitoring system based on distributed multi-sensors information fusion of multi-wavelength *NIR*, this system was designed on the purpose of continuous blood glucose monitoring for patients at home and hospital [2]. Another advantage of this system was the introduction of distributed multi-sensors idea, this change has been proved to be better improvement for blood glucose prediction accuracy. In this distributed multi-sensors system, a multi-sensors information fusion model, Back Propagation Artificial Neural Network (*BP-ANN*), was applied.

2. Noninvasive Blood Glucose Monitoring Model

The experimental data for this research was obtained via NIR based on laser arrays as shown in **Figure 1**. The NIR light source consists of 3*3 laser diodes arrays operating at output powers of 5 mW [8].

2.1. Hardware Design

Wavelengths selection: According to the specialty of glucose molecular structure and absorption specialty, second order times frequency absorption exists between 1100 - 1300 nm, and first order times frequency absorption exists between 1500 - 1800 nm. Other components in blood, such as hemoglobin and water contain groups of hydrogen which can trigger NIR absorption as well. Water absorption peaks are mainly distributed between 1440 - 1460 nm and between 1940 - 1960 nm, those regions should be avoided in wavelength selection. Between 1400 - 1800 nm, water absorption only exists at 1787 nm, fat and protein exist no absorption peak in this region. Therefore, 1400 - 1800 nm region is suitable for measurement wavelength selection.

Measurement sites selection: In noninvasive blood

*The work is supported by National Nature Science Fund of China (No 30970876, 81141076).
*Corresponding author.

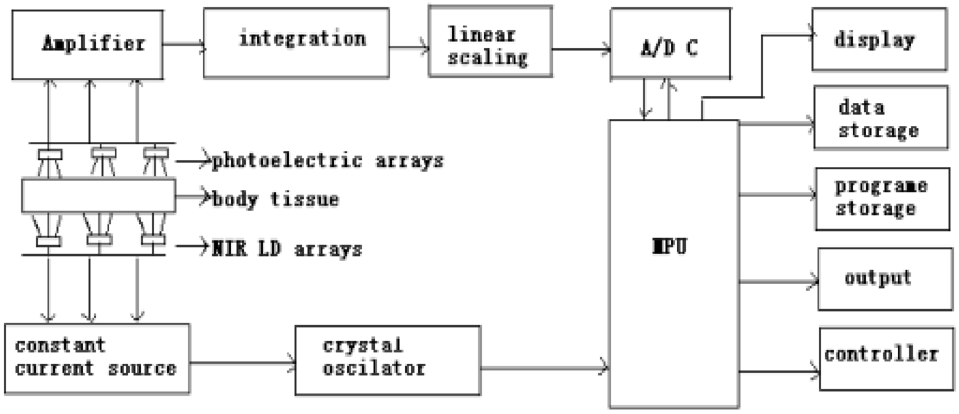

Figure 1. Framework of the multiwavelength arrays monitoring system.

glucose measurement, the selection of an ideal measurement site is essential. Four factors should be considered: First, for the convenience of measurement, the measurement site should be exposed outside; Second, in order to decrease the influence from outside factors, individual difference like gender, age and physical state should be low; Third, the measurement site should contain rich blood and the interference from other components is low; Last, NIR light can transmit measurement site easily. In the noninvasive blood glucose monitoring system based on distributed multi-sensors, left ear lobe, right ear lobe and the right hand part between thumb and index finger are selected as distributed measurement sites.

Circuit design: six channels of laser-driving and photoelectronic amplification circuit are designed in this system. **Figure 2** shows the laser-driving circuit, LD-driving and the part of photodiode feedback circuit help to maintain laser operate with output power of 5 mW and forward current of 30 mA. By adjusting POT1, forward current can be adjusted between 0 - 120 mA. **Figure 3** shows the photoelectrical signal amplification circuit. By applying an operational amplifier POT1 and some affiliated resisters and capacities, the obtained spectral signal can be amplified by 1000 to 3V, the amplified signal is transferred to plug seat JP2-1 which connected to AD converter.

2.2. Software Design

1) *Data acquisition and save*: Amplified spectral signal is first conveyed to AD converter, which supports Labview drive. So the converted data can be displayed on the screen programmed by Labview language. **Figure 4** shows the interface of acquired spectral data from six channels. At each channel, the average value of 10 successive acquired data is calculated as displaying information.

2) *Distributed multi-sensors information fusion based on BP-ANN*: BP-ANN is one kind of supervised learning network. There are two phases of positive transmitting processing and error reverse transmitting processing in the study processing of BP-ANN.

A three layers BP neural network (**Figure 5**) is applied to model fuse multi-sensors information and predict the blood glucose concentration in experiments. Least Square function is adopted as error function in the training of BP network, which writes as:

$$E_k = \frac{\sum_{r=1}^{m}\sum_{k=1}^{q}\left(y_{rk} - o_{rk}\right)^2}{2} \tag{2}$$

O_k is the output of note k; y_k is the corresponding desired output; q is the number of output notes, and m is the number of training samples. For the output weight, the revise value Δw_{jk} is:

$$\Delta w_{jk} = \eta \delta_k o_k \tag{3}$$

w_{jk} is the weight connecting the number k output note and the number j hidden note: η is the study speed, o_k is output value at the number k output note; δ_k is the gradient factor. For the hidden layer, revise value writes as:

$$\Delta w_{ij} = \delta_j o_j \tag{4}$$

w_{ij} is the weight connecting the number j hidden note and the number i input note; o_j is the output at the number j hidden note.

Figure 6 shows the training curve in the concentration prediction of blood glucose, after training of 10 times, the goal is reached and the performance can reach 0.088 mmol/L.

3) *Prediction result display based on Labview*: The acquired data displaying and predicted blood glucose concentration value interface is shown in **Figure 4**. On the interface, 8 measurement methods options are given. Corresponding blood glucose prediction program will be launched by clicking any switch, and the predicted value will be displayed as well.

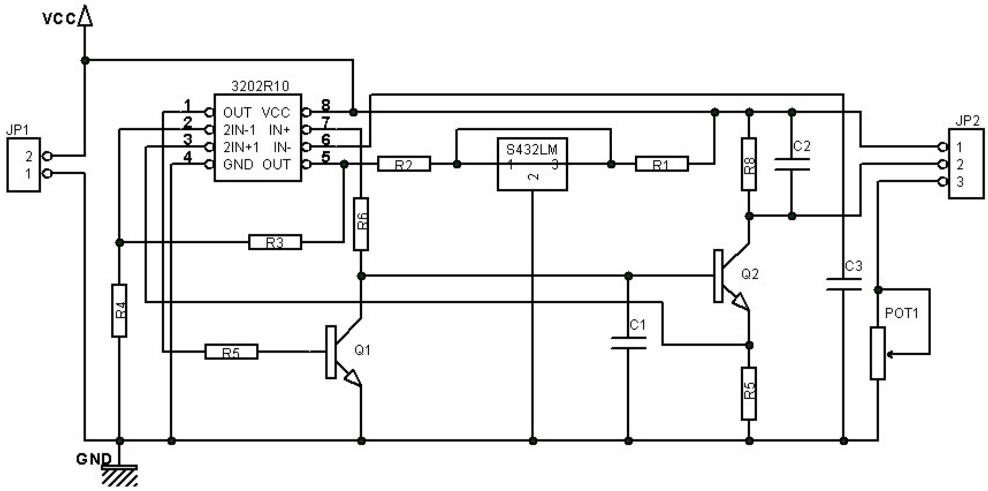

Figure 2. Laser-driving circuit.

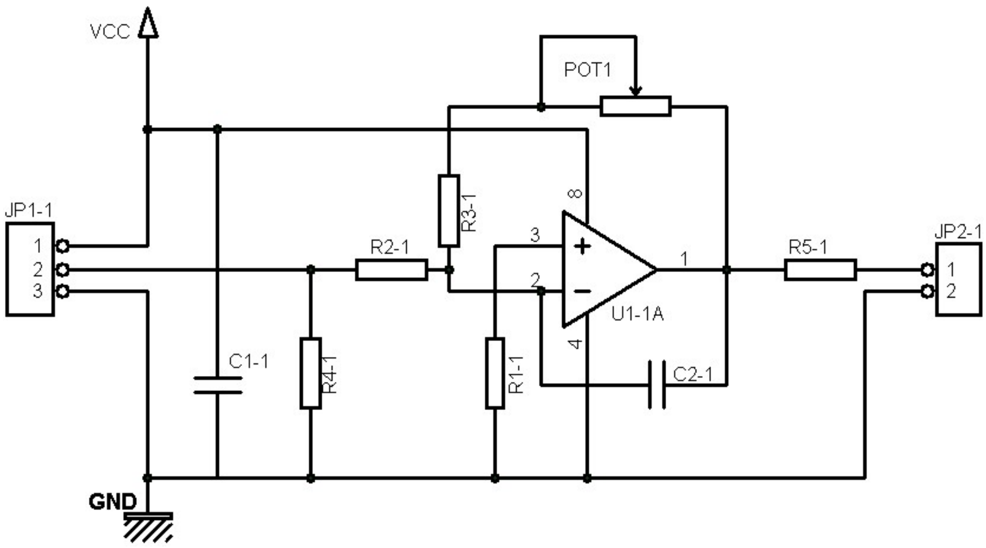

Figure 3. Photoelectrical signal amplification circuit.

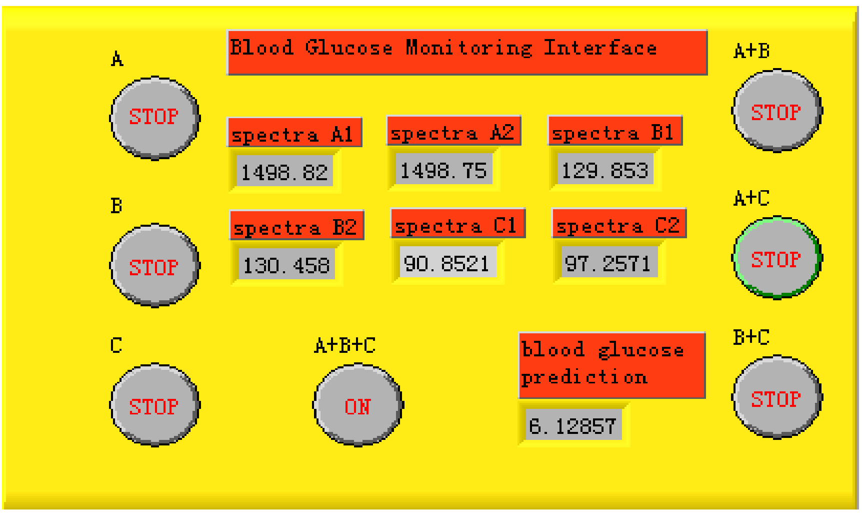

Figure 4. System interface of calculated blood glucose concentration.

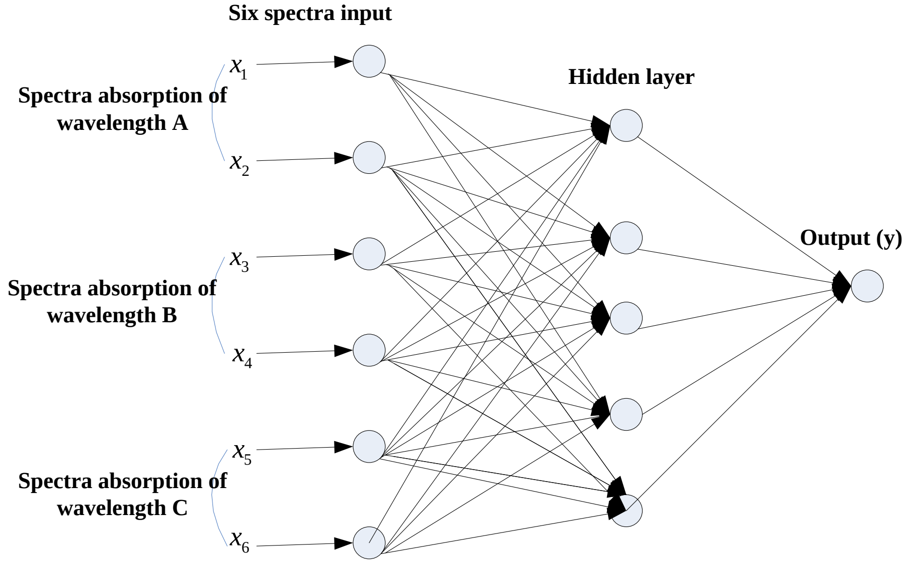

Figure 5. BP framework for multisensor information fusion.

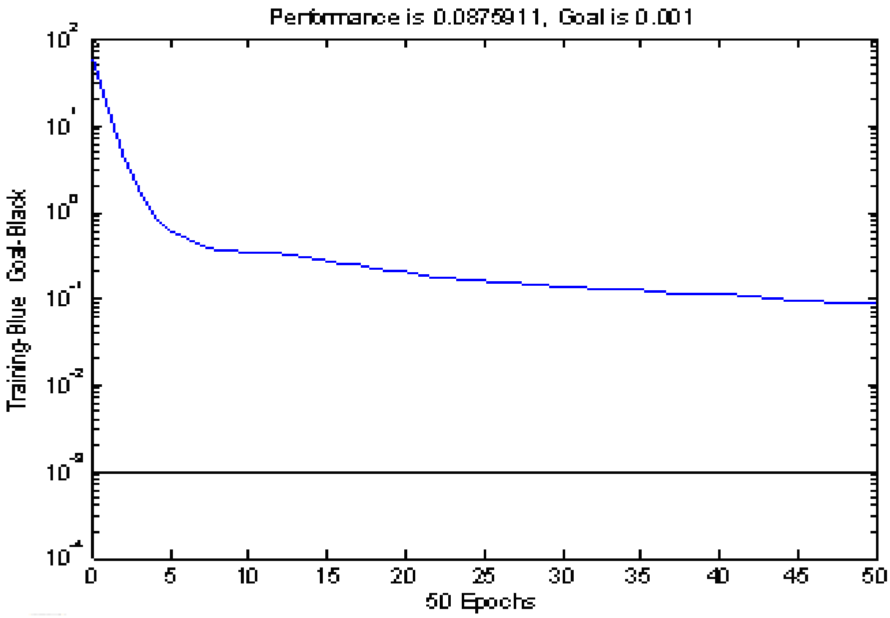

Figure 6. Training curve in human blood glucose concentration prediction.

3. Experiments

In both glucose samples experiment and noninvasive blood glucose measurement experiment, 7 measurement methods with single, two and three wavelengths were applied, which were named A, B, C, A + B, A + C, B + C and A + B + C method respectively.

3.1. Glucose Samples Experiment

Process of glucose experiment: All samples were measured in a 5 mm quartz cell and the temperature in the sample cell was controlled at about 37˚C. Two sets of 20 samples were prepared with varying concentrations, ranging from 10 to 200 mg/dL in 10 mg/dL steps. More than 500 original data sets were obtained, after eliminating some outlier samples, 200 samples with different concentrations were left for building calibration model. In the experiment, the spectrum of empty cell was measured firstly as a background [9].

Data preparation of calibration model: It is essential to figure out the significant difference between each group of spectral data sample. Statistic method of *T*-test was used to prove the validity of samples and to check out the outliers data. In **Table 1**, a total of 200 glucose

Table 1. Comparison of 20 glucose absorption spectra data.

Sample	10	20	30	40	50	60	70	80	90	100
$\bar{x} \pm s$	312.0 ± 0.005	311.8 ± 0.008	311.6 ± 0.003	311.4 ± 0.032	311.3 ± 0.020	311.1 ± 0.023	318.8 ± 0.003	310.6 ± 0.003	310.4 ± 0.003	310.1 ± 0.006
p	0.0001	0.0001	0.0001	0.0007	0.0001	0.0002	0.0001	0.0001	0.00005	0.00005
Sample	110	120	130	140	150	160	170	180	190	200
$\bar{x} \pm s$	309.9 ± 0.019	309.8 ± 0.020	309.5 ± 0.002	309.4 ± 0.005	309.2 ± 0.002	309.0 ± 0.019	308.7 ± 0.007	308.6 ± 0.018	308.3 ± 0.003	308.1 ± 0.019
p	0.0044	0.0001	0.00004	0.00003	0.0011	0.0004	0.0007	0.0001	0.0001	0.0001

absorption spectra were given out, the average and standard deviation of 10 measurement values for each glucose sample are calculated as well. Comparing with the differences between 20 groups of glucose NIR absorption spectra, their differences achieve significant level (*T-test*, $p < 0.05$).

3.2. Human Noninvasive Measurement Experiment

Process of Human noninvasive measurement experiment: In order to get training data covering wide variety scope of human blood glucose concentration, the blood glucose tests were made on volunteers at certain time before or after their meal with the interval time of half an hour. After measurement of blood glucose, multi-sensors were attached to measurement sites to get responding spectra information [10]. A total of 142 samples for each type of measurements were got in this experiment and the blood glucose concentration ranges from 3.2 mmol/L to 10.8 mmol/L.

Data preparation for BP-ANN training and testing: Similarly to the data preparation of calibration model, experimental data in noninvasive blood glucose measurement were given in **Table 2**. *T*-test is applied to test the spectra difference of different groups of blood glucose concentration, p of *T*-test is smaller than 0.05, which demonstrates that their differences reach significant levels.

4. Results

4.1. Building Calibration Model

In both the glucose samples experiment and noninvasive blood glucose measurement experiment, 7 kinds of calibration model were built to realize the function of continuous monitoring. In A + B + C method of glucose experiment, 20 spectra data samples were used to build the calibration model. **Figure 7** shows the relation between glucose concentration and glucose absorption spectra, from the figure we can see this validation owns a fine prediction ability for unknown received spectra information. In **Table 3**, the performances of different measurement methods were compared, in the A + B + C method, the RMSEP is 4.412 mg/dL and CC is 0.90, which shows a great improvement in prediction performance to other single or two wavelength methods. Compare with statistic values of three single wavelength and combination of two wavelength methods, single wavelength A shows best sensitivity

4.2. Results of Human Blood Glucose Noninvasive Measurement

4.2.1. BP-ANN Measurement Model

In the human noninvasive blood glucose measurement experiment, a total of 142 samples were obtained, 122 couples of blood glucose absorption spectra data and corresponding blood glucose reference values were used for the BP network training. As shown in **Figure 6**, the network can reach goal after 10 training, RMSEP of this model is 0.088 mmol/L and CC is 0.9315 in the method of A + B + C. Comparing with the other six methods, the BP-ANN greatly decreased the prediction error, which can be seen in **Table 4**.

4.2.2. Testing of Measurement Model

The left 20 samples were used as validation data sets to test performance of the measurement model. 20 spectra information data were inputted to the BP-ANN multi-sensors information fusion model, 20 output values of predicted blood glucose concentration were received at the output layer, the result was given in **Table 5**. The RMSEP between NIR method and standard method is 0.3143 mg/dL. *T*-test is applied and p is 0.1728, bigger than 0.05, which demonstrate that the relation between those two values is well related.

5. Conclusion

In this noninvasive blood glucose monitoring system, two new measurement ideas were employed, which are continuous monitoring and distributed multi-wavelength measurements. The experimental result has proved that this system has an improved advantage in blood glucose prediction, and the multi-wavelength information fusion model has also contributed greatly to the monitoring

Table 2. Difference comparison of 28 groups of blood glucose absorption spectra data.

Sample	10.8	10.5	10.1	10.0	9.8	9.6
$\bar{x} \pm s$	567.95 ± 0.03	568.42 ± 0.15	568.93 ± 0.49	569.01 ± 0.33	568.98 ± 0.47	569.91 ± 0. 22
p	0.0125	0.0332	0.0318	0.0412	0.0215	0.0358
Sample	9.4	9.1	8.9	8.6	8.3	8.2
$\bar{x} \pm s$	570.24 ± 0.10	570.67 ± 0.32	571.29 ± 0.41	571.44 ± 0.6071	572.06 ± 0.22	572.87 ± 0.49
p	0.0215	0.3025	0.0217	0.0160	0.0321	0.0245
Sample	7.8	7.6	7.4	6.9	6.7	6.5
$\bar{x} \pm s$	573.52 ± 0.25	573.63 ± 0.21	574.03 ± 0.72	575.18 ± 0.43	575.36 ± 0.37	575.57 ± 0.39
p	0.0418	0.044	0.0360	0.0214	0.0124	0.0173
Sample	6.3	5.9	5.7	5.3	4.9	4.7
$\bar{x} \pm s$	576.745 ± 0.36	577.15 ± 0.63	577.89 ± 0.26	578.13 ± 0.31	579.16 ± 0.11	579.58 ± 0.34
p	0.0368	0.0123	0.0451	0.0358	0.0201	0.0426
sample	4.4	4.2	3.9	3.7	3.5	3.1
$\bar{x} \pm s$	579.80 ± 0.25	580.71 ± 0.23	581.07 ± 0.32	581.13 ± 0.21	581.21 ± 0.03	572.15 ± 0.16
p	0.0103	0.29	0.0412	0.0328	0.01	0.0257

Table 3. Performance comparison with different measurement methods in calibration model.

Statistics value	A	B	C	A + B	A + C	B + C	A + B + C
RMSEP (mg/dL)	4.92	8.36	11.41	6.25	8.02	9.75	4.41
CC	0.89	0. 79	0.67	0.82	0.77	0.74	0.90

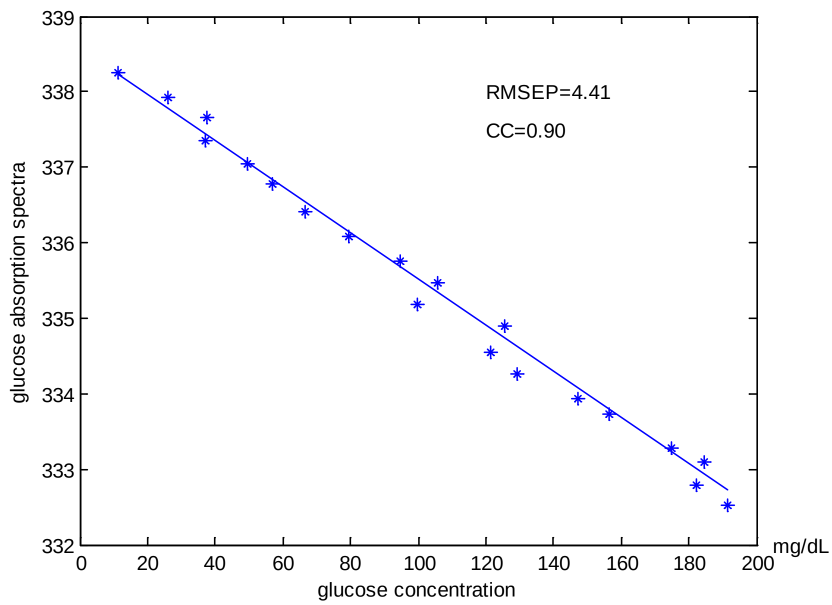

Figure 7. Relation between glucose concentration and spectra absorption.

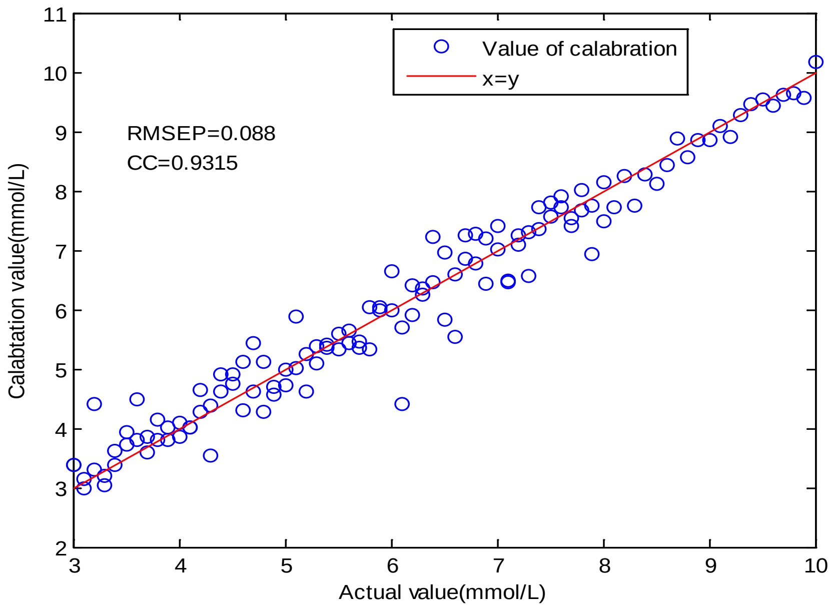

Figure 8. Relation of blood glucose concentration between measurement method and NIR arrays information fusion method.

Table 4. Performance comparison of different measurement methods in measurement model.

Statistics value	A	B	C	A + B
RMSEP(mmol/L)	0.175	0.362	0.423	0.2651
CC	0.8522	0.7325	0.6355	0.79342
Statistics value	A + C	B + C	A + B + C	A + B + C based on BP
RMSEP(mmol/L)	0.31288	0.39528	0.115	0.088
CC	0.76392	0.6821	0.8938	0.94713

Table 5. Analysis result of blood glucose concentration between comparison method and NIR method.

Numerical order	NIR method (mmol/L)	Standard method (mmol/L)	difference
1	3.3888	3	−0.3888
2	3.9451	3.5	−0.4451
3	3.8019	3.8	−0.0019
4	4.0913	4.0	−0.0913
5	4.7504	4.5	−0.2504
6	4.2858	4.8	0.5142
7	4.7266	5.0	0.2734
8	5.3335	5.5	0.1665
9	6.0472	65.8	−0.2472
10	6.6496	6.0	−0.6496
11	6.9600	6.5	−0.4600
12	7.2690	6.8	−0.4690
13	7.0227	7.0	−0.0227
14	7.5781	7.5	−0.0781
15	8.0006	7.8	−0.2006
16	8.1452	8.0	−0.1452
17	8.1090	8.5	0.3910
18	8.8642	9.0	0.1358
19	9.4608	9.5	0.0392
20	10.1804	10	−0.1804
RMSEP	0.3143		
p		0.1728 (T-test, $p > 0.05$)	

property. In the later work, we hope that new multi-wavelength strategy can be used to further improve the prediction accuracy.

REFERENCES

[1] A. A. Mbaideen and M. Benaissa, "Determination of Glucose Concentration from NIR Spectra Using Independent Component Regression," *Chemometrics and Intelligent Laboratory Systems*, Vol. 105, No. 1, 2010, pp. 131-135. http://dx.doi.org/10.1016/j.chemolab.2010.11.008

[2] M. Rohrscheib, R. Robinson and R. P. Eaton, "Non-Invasive Glucose Sensors and Improved Informatics—The Future of Diabetes Management," *Diabetes*, *Obesity and Metabolism*, Vol. 5, No. 5, 2003, pp. 280-284. http://dx.doi.org/10.1046/j.1463-1326.2003.00275.x

[3] H. V. L. Toal, M. Weidenmuller, A. Xhelaj and W. Mantele, "A Novel Approach to Non-Invasive Glucose Measurement by Mid-Infrared Spectroscopy: The Combination of Quantum Cascade Lasers (QCL) and Photoacoustic Detection," *Vibrational Spectroscopy*, Vol. 38, No. 1-2, 2005, pp. 209-215. http://dx.doi.org/10.1016/j.vibspec.2005.02.025

[4] M. Mueller, M. Grunze, E. H. Leiter, P. C. Reifsnyder, U. Klueh and D. Kreutzer, "Non-Invasive Glucose Measurements in Mice Using Mid-Infrared Emission Spectroscopy," *Sensors and Actuators B*: *Chemical*, Vol. 142, No. 2, 2009, pp. 502-508. http://dx.doi.org/10.1016/j.snb.2009.08.048

[5] K. Maruo, M. Tsurugi, J. Chin, T. Ota, H. Arimoto and Y. Yamada, "Noninvasive Blood Glucose Assay Using a Newly Developed Near-Infrared System," *IEEE Journal of Selected Topics in Quantum Electronics*, Vol. 9, No. 2, 2003, pp. 322-399. http://dx.doi.org/10.1109/JSTQE.2003.811283

[6] K. X. Xu, Q. J. Qiu, J. Y. Jiang and X. Y. Yang, "Non-Invasive Glucose Sensing with Near-Infrared Spectroscopy Enhanced by Optical Measurement Conditions Reproduction Technique," *Optics and Lasers in Engineering*, Vol. 43, No. 10, 2004, pp. 1096-1106. http://dx.doi.org/10.1016/j.optlaseng.2004.06.018

[7] W. Wang, L. F. Yan, B. W. Liu and H. Zhang, "Multi-sensors Information Fusion With Neural Networks for Noninvasive Blood Glucose Detection," *Lecture Notes in Computer Science*, Vol. 3498, 2005, pp. 760-766. http://dx.doi.org/10.1007/11427469_121

[8] Y. L. Yeh, "Real-Time Measurement of Glucose Concentration and Average Refractive Index Using a Laser Interferometer," *Optics and Lasers in Engineering*, Vol. 46, No. 9, 2008, pp. 666-670. http://dx.doi.org/10.1016/j.optlaseng.2008.04.008

[9] Q. B. Li, L. N. Li and G. J. Zhang, "A Nonlinear Model for Calibration of Blood Glucose Noninvasive Measurement Using Near Infrared Spectroscopy," *Infrared Physics & Technology*, Vol. 53, No. 5, 2010, pp. 410-417. http://dx.doi.org/10.1016/j.infrared.2010.07.012

[10] A. Caduff, M. S. Talary, M. Mueller, F. Dewarrat, J. Klisic, M. Donath, L. Heinemann and W. A. Stahel, "Non-Invasive Glucose Monitoring in Patients with Type 1 Diabetes: A Multisensor System Combining Sensors for Dielectric and Optical Characterisation of Skin," *Biosensors and Bioelectronics*, Vol. 24, No. 9, 2009, pp. 2778-2784. http://dx.doi.org/10.1016/j.bios.2009.02.001