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SIMULTANEOUS DETERMINATION OF L-ASCORBIC ACID AND GLUCOSE IN MIXTURE SOLUTION USING FTIR-ATR TERAHERTZ SPECTROSCOPY COMBINED WITH PLS2 REGRESSION

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ABSTRACT

This study deals with the simultaneous determination of L-ascorbic acid (L-AA) and glucose in mixture solution samples, by using terahertz (THz) spectroscopy and partial least squares regression technique. A calibration set consisting of 34 binary mixture solutions was applied for the construction of PLS model. The proposed procedure was successfully applied for the simultaneous determination of L-AA and glucose with acceptable result. The root mean square error of prediction (RMSEP) of 16 prediction samples was determined to be 2.55% and 1.92% for L-AA and glucose, respectively. SDR_{pred} of 2.880 and 4.730 could be obtained for L-AA and glucose, respectively.

Keywords : THz spectroscopy; PLS2 regression; L-ascorbic acid; glucose; mixture solution.

I. INTRODUCTION

L-ascorbic acid (L-AA), or vitamin C, is one of the water-soluble vitamins. It can be extracted widely in many biomaterials, such as fruit and vegetables. Recently, many food products, such as juices or sports drinks, are fortified with L-AA. During long storage and transportation, the quality of fruit juice is possible to change. Reference [1] reported that vitamin C concentration of orange, lemon, grapefruit and tangerine decreased after eight weeks of storage. It was also reported that at high temperature of storage (45°C), degree of vitamin C loss is higher than that at low temperature of storage (28°C). Reference [2] reported that content of ascorbic acid in orange juice from PET and glass bottles stored at 4°C and 25°C decreased after several days of storage. For this reason, it is very important to develop a new bio-sensing method which can be able to identify the concentration of vitamin C or L-ascorbic acid (L-AA) and other component of juices nondestructively without opening the packaging material of juice. This kind of sensor is important to establish a total quality management system for food quality and safety which can benefit both producers and customers. For this reason, it is highly desirable to be able to quantify L-AA in foods, especially in juices or sports drinks, for quality control purposes.

Many papers have established non-spectroscopic methods for L-AA determination. These conventional methods include titrimetry, chemiluminescence, fluorometric, chromatographic and electrochemical methods [3], [4]. Each method though has its limitations. For example, while the titrimetry method using dichlorophenolidophenol as the titrant is rapid, the titrant itself is unstable and must be standardized before use. In the case of the chromatographic method, while it is accurate, it is expensive and time consuming.

Of the spectroscopic methods, reference [5] reports using near infrared (NIR) spectroscopy coupled with stepwise multiple linear regression (SMLR) and partial least squares (PLS) regression to determine L-AA in pharmaceutical products at concentrations of 16.67%, 22.88% and 40%. In this analysis relative standard error (RSE) was used to assess the quality of the calibration and validation model, both for the SMLR and PLS regression. The RSE for the SML regression was 0.59-1.82% (calibration), and 0.72-2.34% (validation); and 0.69-2.46% (calibration), 0.89-2.85% (validation) for PLS regression. Spectroscopic methods using NIR, Mid Infrared (MIR) and Raman spectroscopy for determination of L-AA in powder and liquid samples has been reported [6]. In these measurements, coefficients of determination (R²) for L-AA were 0.966-0.999, 0.973-0.980, and 0.941 for MIR, NIR and Raman spectroscopy, respectively.

In the recent report, the possibility of using THz spectroscopy with ATR method for L-AA quantification in L-AA solution has been investigated [7]. The result was acceptable with the lowest root mean square error of prediction (RMSEP) = 2.791%. A ratio of standard deviation to prediction error (RPD) value of 4.48 was obtained

[7]. In recent report, the improvement of L-AA determination using THz spectroscopy by applying iPLS regression has been published [8]. This result may lead to a new application of THz spectroscopy for L-AA determination in juice samples especially for juice inside packing material in which THz waves have ability to penetrate the packing materials with low photon energy (safe for biological sensing). However, since that in real juice samples there are many kind of substances inside the juice solution, therefore to realize inspection system using THz spectroscopy for juice samples, it is desired to investigate the ability of measure L-AA in more complex solution (not only in pure L-AA solution). In the present study, first attempt to measure L-AA in mixture solution using THz spectroscopy was investigated by using binary mixture of L-AA and glucose solution. The present study highly contributed to open the development of using THz spectroscopy as new sensor in biological solution in more complex solution.

II. MATERIALS AND METHODS

A. Samples

Fifty samples of binary mixture solution of L-ascorbic acid (L-AA) and glucose were used as samples. The binary mixture solutions were prepared by dissolving appropriate amounts of L-AA powder (Wako Pure Chemical Industries, Ltd., Japan) and glucose powder (Grade: Guaranteed Reagent (GR); Nacalai Tesque, Inc., Kyoto, Japan) in distilled water. The ranges of concentrations were from 2.6446 to 26.4709% (mass percent, w/w) for L-AA and from 2.1660 to 33.3605% (mass percent, w/w) for glucose. For each sample, 300 μL of mixture solution were used for spectral acquisition.

B. Devices for FTIR-THz-ATR spectroscopy

THz spectra of mixture solutions were acquired using a Fourier-transform infrared (FTIR) based spectrometer (FARIS-1S, JASCO Corp., Japan). This system is based on a FTIR spectrometer (range of measurement: 20-450 cm⁻¹ or 0.6-13.5 THz) with a special light source made from a high pressure mercury lamp as a THz generating device. (See reference [7] for detail explanation of the system).

C. FTIR-THz-ATR spectroscopy

FTIR-ATR-THz spectra of the mixture solutions were acquired in the range 20-450 cm⁻¹, using a 16 cm⁻¹ of resolution. Each spectrum contains on average 200 scanning spectra. The reference for air was measured every 5 samples. The spectra intensity of samples and reference were obtained in single beam (SB) unit. During THz spectral measurement, the laboratory temperature and relative humidity were maintained at around 25°C and 65-70%, respectively. For each samples, the spectral measurement was conducted at constant temperatures of 24°C. To obtain this sample temperature, the temperature of silicon prism was controlled at 24°C. The absorbance value of the sample was calculated using equation 1 [7].

$$A(\nu) = -\log_{10} \frac{S(\nu)}{R(\nu)} \tag{1}$$

where:

 $A(\nu)$ is absorbance at wavenumber V $S(\nu)$ is intensity of sample at wavenumber? V

R(v) is intensity of air reference at wavenumber V

The calculated absorbance value was corrected using the ATR correction function provided in the software (JASCO Spectral Manager, JASCO Corp., Tokyo, Japan). The corrected values were used for further analysis.

D. Selection of the calibration sample set

Table 1. Characteristics of the L-AA and glucose in mixture solution		
L-AA concentration	Calibration set	Prediction set
Number of samples	34	16
Mean	13.886	13.879
Standard deviation	7.342	7.124
Glucose concentration	Calibration set	Prediction set
Number of samples	34	16
Mean	11.784	12.770
Standard deviation	7.931	9.090

L-AA and glucose are expressed as % (mass/mass or w/w).

The samples (50 samples) were divided in two different sets: (i) calibration, and (ii) prediction. The first sample set was used to develop calibration and performing full-cross validation test. The prediction sample set was used to evaluate the performance of the develop calibration model. The way to select the calibration and prediction sample set was as followed: first all samples were sorted based on L-AA values from the highest to the lowest. Then, from the highest L-AA we pick up 2 samples for calibration and 1 sample for prediction and repeat the process until the lowest L-AA. For this we selected 34 samples for calibration set and 16 samples for prediction sample set. Table 1 shows the composition of the different sets of the samples, including the maximum, minimum and average value of the L-AA and glucose.

E. Chemometric analysis

Chemometric analysis, including quantification analysis was carried out using The Unscrambler v. 9.2 software packages from Camo (Camo Process AS, Oslo, Norway). Quantification of L-AA and glucose in mixture solution were done simultaneously by partial least squares (PLS) regression analysis using the broad region (20-450 cm⁻¹).

F. Model evaluation

Performance of the calibration model and cross-validation was evaluated using the following statistical parameters; coefficient of determination between predicted and measured L-AA and glucose concentration (R²_{cal}), root mean square error of calibration (RMSEC), root mean square error of cross-validation (RMSECV) and the standard deviation ratio (SDR) of calibration (SDRcv) which can be calculated as follow [9]:

Low RMSECV and a high R²_{cal} and SDR_{cv} were desirable. SDR_{cv} above 3.0 is considered to be acceptable for practical spectroscopy applications [10].

To evaluate the prediction performance of the developed calibration model, the following parameters were used: the coefficient of determination in prediction (R^2_{pred}), the root mean square error of prediction (RMSEP), bias between the actual and predicted value, the bias-corrected standard error of prediction (SEP) and the standard deviation ratio (SDR) of prediction (SDR_{pred}). The RMSEP is an estimate of total prediction errors for an independent data set. The sources of error in the RMSEP value are including bias and SEP which can be mathematically expressed as follow [11]:

$$RMSEP^{2} \approx SEP^{2} + bias^{2}$$
⁽²⁾

Good prediction resulted in low RMSEP, bias and SEP and high SDR_{pred} value. The SDR_{pred} more than 3 was considered to be sufficient. The SDR_{pred} can be calculated as follow [9], [12], [13]:

$$SDR_{pred} = \frac{S.D_{predictionset}}{RMSECV}$$
(3)

III. RESULTS AND DISCUSSIONS

A. Typical spectra of L-AA and glucose in mixture solution

Fig. 1 shows the two typical spectra of L-AA and glucose in mixture solution with different concentration. We can see that the in the spectral shape, the spectra of mixture solution of L-AA and glucose is similar with the spectra of water. Mixture2 with higher concentration of L-AA and glucose in total has lower absorbance comparing to Mixture1. This is because the amount of free water in Mixture2 is lower than that of Mixture1.

B. Developing calibration model for L-AA and glucose determination

Calibration model for L-AA and glucose were developed simultaneously by using PLS2 regression using original and some pre-processing method. Savitzky-Golay (SG) smoothing was found to be the best pre-processing method for L-AA and glucose determination (result of pre-processing evaluation was not shown here). The optimum number of PLS factors was determined by the full-cross-validation procedure by plotting the root mean square error of cross-validation (RMSECV) against the number of factors and searching for the minimum error (results not shown).

Fig. 2 and 3 show the scatter plot of actual and predicted L-AA for the best calibration and validation using SG smoothing spectra, respectively. The calibration model has 5 PLS factors with $R_{cal}^2=0.963$ and the root mean square error of calibration (RMSEC) = 1.386558% (w/w). The validation of L-AA resulted in the root mean square error of cross-validation (RMSECV) = 1.660468% (w/w). It can be seen that the differences between the RMSEC and RMSECV of the developed model was small. It can be said that there is no potential for over fitting case of the L-AA determination using this model. Fig. 4 and 5 show the scatter plot of actual and predicted glucose for the best calibration and validation using SG smoothing spectra, respectively. The calibration model has 4 PLS factor (lower than L-AA model) with $R_{cal}^2=0.960$ and RMSEC = 1.567653% (w/w). The validation of glucose resulted in RMSECV = 1.880194% (w/w). It can be seen also that the differences between the RMSEC and RMSECV of the developed

model for glucose was small. It can be said that there is no potential for over fitting case of the glucose determination using this model.



Fig. 1. Typical spectra of mixture solution of L-AA and glucose in range 20-450 cm⁻¹.



Fig. 2. Scatter plot between actual and predicted L-AA for calibration using PLS2 regression method



Fig. 3. Scatter plot between actual and predicted L-AA for validation using PLS2 regression method



Fig. 4. Scatter plot between actual and predicted glucose for calibration using PLS2 regression method.



Fig. 5. Scatter plot between actual and predicted glucose for validation using PLS2 regression method

C. Prediction for L-AA and glucose in mixture solution

Using prediction sample set (n= 16), an evaluation on the performance of the developed calibration was investigated both for L-AA and glucose determination. Prediction for L-AA resulted in RMSEP= 2.473348% (w/w). With this RMSEP, SDR_{pred} of 2.880 could be obtained. Bias prediction was very close to 0.

As seen in Fig. 6, the regression between values found by the two-equation ATR-THz method (Y) and those obtained by the reference procedure (X) for L-AA provided a regression equation of Y = 0.8075X + 2.6711 (n = 16) which means that the developed ATR-THz method is not so accurate, it still requires a blank correction (the intercept is not almost zero) and presents constant relative errors (the slope is not very close to 1). However, the ATR-THz method shows possibility on L-AA determination in mixture solution and opens a practical application of using ATR-THz method for L-AA determination in more complex solution such as in juice samples.

For glucose, prediction resulted in RMSEP= 1.921876% (w/w). With this RMSEP, SDRpred of 4.730 could be obtained. This SDR_{pred} is higher comparing to SDR_{pred} for L-AA. Bias prediction was also close to 0.

As seen in Fig. 7, the regression between values found by the two-equation ATR-THz method (Y) and those obtained by the reference procedure (X) for L-AA provided a regression equation of Y = 1.0696X - 0.9742 (n = 16) which means that the developed ATR-THz method is better accuracy than L-AA with the intercept is closer to zero and the slope is also closer to 1.



Fig. 6. Scatter plot between actual and predicted L-AA for prediction using PLS2 regression method.



Fig. 7. Scatter plot between actual and predicted glucose for prediction using PLS2 regression method

D. Evaluation of structure of calibration model

In order to evaluate the structure of the calibration model for L-AA and glucose determination, a plot between regression coefficient and wavelength was constructed. As seen in Fig. 8, for L-AA determination there are several observed peaks. They are at 96 cm⁻¹, 173 cm⁻¹, 215 cm⁻¹, 273 cm⁻¹, and 358 cm⁻¹. These peaks may directly correspond with L-AA determination at mixture solution. It can be seen that the contribution of high frequency is higher comparing to that of lower frequency. It seems that L-AA determination of mixture solution was mainly determined by intramolecular vibration mode at higher frequency. For glucose the peaks of regression coefficient were much similar to the L-AA with different in magnitude sign. For example, the peak of L-AA at 358 cm⁻¹ has a magnitude of regression coefficient 7823 while for glucose at the peak of 358 cm⁻¹ the value of regression coefficient was -7823.



Fig. 8. Scatter plot between wavenumber and regression coefficient for L-AA and glucose determination using PLS2 regression method

IV. CONCLUSION

To summarize, we have measured simultaneously the L-AA and glucose spectral data in broad range of THz region in mixture L-AA and glucose solution. The validation of L-AA resulted in the root mean square error of cross-validation (RMSECV) = 1.660468% (w/w). The validation of glucose resulted in RMSECV = 1.880194% (w/w). The developed calibration model has high SDR_{cv} for both with SDR_{cv}= 4.421 and SDR_{cv}= 4.218 for L-AA and glucose, respectively. Prediction for L-AA resulted in RMSEP= 2.473348% (w/w). With this RMSEP, SDR_{pred} of 2.880 could be obtained. Bias prediction was very close to 0. This result showed a potential use of THz spectroscopy for L-AA determination in mixture solution.

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