Infrared Spectroscopy Technique for the Nondestructive Measurement of Fat Content in Milk Powder

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ABSTRACT

The aim of this study was to investigate the potential of the infrared spectroscopy technique for nondestructive measurement of fat content in milk powder. Fat is an important component of milk powder. It is very important to be able to detect the fat content in milk powder using a rapid and nondestructive method. Near and mid infrared spectroscopy techniques were used to achieve this purpose. Least-squares support vector machine (LS-SVM) was applied to developing the fat-content prediction model based on the infrared spectral transmission values. The results based on LS-SVM were better than those of back-propagation artificial neural networks. The determination coefficient for prediction of the results predicted by the LS-SVM model was 0.9796 and the root mean square error was 0.836708. It was concluded that infrared spectroscopy technique could quantify the fat content in milk powder rapidly and nondestructively. The process is simple and easy to operate. Moreover, the prediction results were compared between near infrared and mid infrared spectral data. The results showed that the performances of model with both mid infrared and near infrared spectral data were a little worse than that of the whole infrared spectral data. The results could be beneficial for designing a simple and nondestructive spectral sensor for the quantification of fat content in milk powder.

Key words: near- and mid-infrared spectroscopy, fat, milk powder, least-squares support vector machine

INTRODUCTION

Milk powder is a popular nutritional food; an increase of milk consumption has occurred in recent years. The proportion of every nutritional component in milk products is determined according to the needs of different people, and the nutrition components greatly affect the market price of the product. Inferior products that con-

tain poor or improper nutritional content may be produced to maximize profit, but have caused many cases of illness because of malnutrition. Improving the analytical methods for the determination of the qualities of milk powders could avoid these tragedies. Consumers commonly judge the quality of milk powder by using touch, color, smell, taste, rate of solubility, and so on. Although these methods of evaluation are simple and accepted by consumers, they are subjective and have low accuracy. Therefore, a rapid, accurate, and nondestructive quantification device or method is needed.

Fat is an important nutritional component in milk powder. Improper content of fat ingestion can cause obesity in humans, and consequently increase the incidence of hypertension, coronary heart disease, and diabetes. Currently, there are several methods widely applied for measuring the fat content in dairy products including the Röse-Gottlieb, Soxhlet extraction, Babcock, and Gerber methods (Rosenthal and Baruch, 1993), and gas chromatography (Deeth et al., 1983). However, there are several problems inherent in these methods—they are time consuming, complex, and they require sample destruction.

Infrared spectroscopy techniques, such as near infrared and mid infrared spectroscopy (**NIRS** and **MIRS**), offer quick analysis, minimal sample preparation requirements, and low cost. Infrared spectroscopy techniques have been widely applied as fast and nondestructive analytical methods. Although infrared spectroscopy techniques cannot always provide definitive compositional information about a food sample, they can often provide a means of screening food products for qualitative attributes without the involvement of time-consuming chemistry analyses in laboratories (Reid et al., 2005). Near infrared light (4,000 to 12,500 cm^{-1}) lies between the visible and mid infrared regions and has been widely applied for the detection of protein, fat, and total solids in cheese and milk (Rodriguez-Otero et al., 1995; Laporte and Paquin, 1999). Hermida et al. (2001) applied NIRS to analyze moisture, SNF, and fat in butter. Sorensen and Jepsen (1998) assessed the sensory properties of cheese by using NIRS. The NIRS bands mainly correspond to C–H, O–H, and N–

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H vibrations, which originate from fundamental bands in the mid infrared region. Mid infrared light scanned in the region of 400 to 4,000 cm^{-1} is applied to the detection of compositional differences between samples based on vibrations of various chemical groups at specific wavelengths in the mid infrared region of the spectrum (Reid et al., 2005). The frequencies and intensities of specific fundamental absorption bands can provide MIRS information related to the relevant functional groups.

However, because of the characteristics of overtone and combination, the molar absorptivity of NIRS is low (i.e., low sensitivity). In contrast, the MIRS bands are fundamental; thus, the peaks of MIRS are specific, sharp, and sensitive (i.e., high molar absorptivity). The spectral reproducibility of MIRS including signal-to-noise ratio is poor compared with NIRS (Chung et al., 1999). Thus, 2 techniques have independent advantages and disadvantages and need to be considered and applied according to different requirements. In recent years, several articles have compared the performance of MIRS and NIRS. Reid et al. (2005) applied MIRS and NIRS techniques, respectively, to differentiate the basis of heat treatment and variety of apple juice samples. Bras et al. (2005) compared and combined NIRS and MIRS spectra in calibrations of soybean flour. Chung et al. (1999) compared NIRS and MIRS for the determination of distillation properties of kerosene. Takeuchi et al. (2006) investigated the states of H_2O adsorbed on oxides by NIRS and MIRS.

Because milk powder is a highly complex matrix, the corresponding infrared spectral data contain highly overlapped peaks regardless of bandwidth. It is necessary to use chemometric methods to extract the relevant quantitative information. Although the establishment of a chemometric model is time consuming, analysis can be performed quickly once the model is established (Bras et al., 2005). In this study, a support vector machine (SVM) was developed using both NIRS and MIRS.

Support vector machine is a universal learning method proposed by Vapnik (1998). It uses a function called kernel to map the data input space to a high-dimensional feature space with fewer training data. In this space, the problem becomes linearly separable (Burges, 1999). Support vector machine applies the structural risk minimization principle, which is superior to the traditional empirical risk minimization principle used by conventional neural networks, to avoid overfitting and multidimensional problems. Least-squares support vector machine (LS-SVM; Suykens et al., 2002) is a modified version of SVM that applies least squares error in the training error function. Least-squares support vector machine has the capability for linear and nonlinear multivariate calibration and

solves the multivariate calibration problems in a relatively rapid way (Suykens and Vanderwalle, 1999). The learning problem is formulated and represented as a convex quadratic programming problem (Lu et al., 2003) to obtain the support vectors. It adopts a least-squares linear system as the loss function and is applied in the pattern recognition and nonlinear evaluation. Due to its attractive advantages and excellent performance, LS-SVM has attracted attention and gained extensive application in spectral analysis (Chauchard et al., 2004; Borin et al., 2006).

The aim of this study was to investigate the potential of the infrared spectroscopy technique for nondestructive measurement of fat content in milk powder. The LS-SVM model was compared with a back-propagation artificial neural network (BP-ANN) model based on statistical parameters of prediction results. Moreover, to determine the optimum spectral range, this study evaluated the detection of fat content based on NIRS and MIRS.

MATERIALS AND METHODS

System Setup and Data Measurement

In this study, 7 brands of milk powder produced by the Inner Mongolia Yili Industrial Group Co. Ltd. (a major corporation in China milk powder market) were bought in a local supermarket. The 7 brands were 0 to 6 mo infant milk powder, 6 to 12 mo infant milk powder, 1 to 3 yr toddler milk powder, 3 to 6 yr infant milk powder, student milk powder with zincum, women's nutrition milk powder, and whole milk powder. A Jasco model FT/IR-4000 Fourier transform infrared spectrometer (Jasco, Tokyo, Japan) was used in this study. The valid range of this spectrometer was 7,800 to 350 cm^{-1} , and the auto scan speed was 2.0 mm/s. The experiment was carried out at $\sim 25^\circ\text{C}$. Each milk powder sample was mixed with potassium bromide at a ratio of 1:49 to enhance the transmission rate. The mixture was compressed into a uniform tablet with a diameter of 5 mm and a thickness of 2 mm and then scanned by the spectrometer. Each sample was scanned 40 times; these 40 data points were averaged as the transmission value (%) of the sample. The spectral data of approximately 60 samples were measured for each brand, and finally the spectral data of 409 samples were obtained. Spectra Manager CFR software (Jasco) was used for spectral measurement and analysis. Due to system imperfections, obvious scattering noise was observed at the beginning and end of the spectral curve. Thus, the first 52 and last 1,175 transmission data points were eliminated to improve the measurement accuracy. The NIRS analysis was based on 4,000 to 6,666 cm^{-1} and the MIRS analysis from 400 to 4,000 cm^{-1} . The fat content of each

sample was measured by the Röse-Gottlieb method following GB/T 5413.3-1997 (National Standard of China; AOAC, 1990). The fat content value was expressed as grams of fat per one hundred grams of milk powder.

LS-SVM

Assume a set of training samples is given as $\{x_k, y_k\}_{k=1}^N$, with the input $x_k \in R^N$ and the output $y_k \in R$. The LS-SVM model is given as $y(x) = w^T \phi(x) + b$ at the beginning, where $w \in R^n$ is the weight vector and b is the bias. A nonlinear mapping function, $\phi(\cdot)$, is applied to transform the low dimensional nonlinear input data space into a higher dimensional feature space. The regularized least-squares cost function is given as follows:

$$\min J(w, e) = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{k=1}^N e_k^2.$$

The constraint is given as follows:

$$y_k = w^T \phi(x_k) + b + e_k, k = 1, \dots, N,$$

where γ is the regularization parameter that balances the model's complexity and the training errors, and e_k is the random error. Then, the Lagrange function was adopted to solve this optimization problem:

$$L(w, b, e, \alpha) = J(w, e) - \sum_{k=1}^N \alpha_k \{w^T \phi(x_k) + b + e_k - y_k\}$$

where α_k is a Lagrange multiplier called support value. The equation is optimized by partially differentiating with respect to each variable:

$$\begin{cases} \frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{k=1}^N \alpha_k \phi(x_k) \\ \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{k=1}^N \alpha_k = 0 \\ \frac{\partial L}{\partial e_k} = 0 \rightarrow \alpha_k = \gamma e_k, k = 1, \dots, N \\ \frac{\partial L}{\partial \alpha_k} = 0 \rightarrow w^T \phi(x_k) + b + e_k - y_k = 0, k = 1, \dots, N \end{cases}.$$

When the variables w and e are removed, the equation can be rewritten as a linear function group:

$$\begin{bmatrix} 0 & \vec{1}^T \\ \vec{1} & \Omega + \gamma^{-1}I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}$$

with

$$\begin{cases} y = [y_1, \dots, y_N] \\ \vec{1} = [1, \dots, 1] \\ \alpha = [\alpha_1, \dots, \alpha_N] \\ \Omega = \{\Omega_{kl} \mid k, l = 1, \dots, N\} \end{cases}.$$

According to Mercer's theory (Vapnik, 1995), there is a relationship between the mapping function, $\phi(\cdot)$, and the kernel function, $K(x_i, x_j)$, as

$$\Omega_{kl} = \phi(x_k)^T \phi(x_l) = K(x_k, x_l), k, l = 1, \dots, N.$$

There are several common kernel functions such as linear, polynomial, radial basis function (**RBF**) kernel, and multilayer perceptron (**MLP**). In our work, RBF kernel was selected as the kernel function:

$$K(x, x_k) = \exp(-\|x - x_k\|^2 / \sigma^2).$$

The LS-SVM regression model can be obtained thus:

$$y(x) = \sum_{k=1}^N \alpha_k K(x, x_k) + b.$$

In the SVM or LS-SVM process, the determinations of the proper kernel function and the best kernel parameters need to be solved. The RBF kernel is a nonlinear function and a more compacted supported kernel. The RBF kernel can reduce the computational complexity of the training procedure while giving good performance under general smoothness assumptions. Proper parameter setting plays a crucial role in building a good LS-SVM regression model with high prediction accuracy and stability. We used a grid-search technique to determine the optimal parameter values such as regularization parameter γ and the RBF kernel function parameter σ^2 , which is the bandwidth in the common case of the RBF kernel. Parameter γ determines the trade-off between structural risk minimization and empirical risk minimization and is important to improve the generalization performance of LS-SVM model. Parameter σ^2 controls the value of function regression error, and influences the number of initial eigenvalues or eigenvectors directly. Small values of σ^2 yield a large number of regressors and eventually can lead to overfitting. On the contrary, a large value of σ^2 can lead to a reduced number of regressors, making the model simpler, but ultimately less accurate. Moreover, σ^2 reflects the sensitivity of LS-SVM model to the noise from input variables. All the aforementioned calculations were performed using Matlab 7.0 (Math Works, Natick, MA). The freely available LS-SVM toolbox (LS-SVM v. 1.5, J. A. K. Suykens, K. U. Leuven, Leuven,

Belgium) was applied with Matlab to derive all of the LS-SVM models.

RESULTS AND DISCUSSION

Reflectance Spectral Investigation

Figure 1 shows the spectral transmission curves based on different brands at the mid- and near-infrared regions. The trend of different curves in the NIR region is similar. The NIR spectral curves are relatively parallel. In the NIRS region, there are 3 obvious absorptions. The one around $4,329\text{ cm}^{-1}$ arises from fat. The one nearby ($4,312\text{ cm}^{-1}$) represents vibration of protein. The vibration of H_2O appeared around $5,155\text{ cm}^{-1}$ (Yan, 2005). Compared with the NIRS region, the curves are complex in the MIRS region. The obvious areas around $1,747$, $2,854$, and $2,925\text{ cm}^{-1}$ embody characteristic troughs of fat (Zhou et al., 2006). The troughs around $1,160$ and $1,250\text{ cm}^{-1}$, which present the vibration of fat and C–O, are overlapped.

LS-SVM Regression Model

The number of transmission values obtained from 400 to $6,666\text{ cm}^{-1}$ was $6,500$, which is too many to establish a fast and accurate model; therefore, principal component analysis (PCA) was applied in the spectral analysis. Principal components (PC) obtained by PCA were set as the optimal input variables of LS-SVM instead of the original $6,500$ variables. The LS-SVM models were established based on different numbers of PC from 6 to 12 . The optimal number of PC was determined as 8 after comparing the final prediction results of LS-SVM models. The PCA process was carried out by using Matlab 7.0 (Math Works).

A total of 409 samples was split into 2 groups randomly, 339 of which were used for calibration, and the remaining 70 samples (10 for each brand) were for prediction. Least-squares support vector machine was performed with RBF kernel. Parameters γ and σ^2 were optimized in the range of 2^{-1} to 2^{10} for γ and 2 to 2^{15} for σ^2 . For each combination of γ and σ^2 parameters, the root mean square error of cross-validation (RMSECV) was calculated and the optimum parameters were selected when the minimum RMSECV was obtained. The optimizing process is shown in Figure 2. The grid indicated by the diamond symbols in the first step is 10×10 , and the searching step in the first step is large. The optimal search area was determined by error contour line. The grid indicated by the “ $\times$ ” symbols in the second step is 10×10 , and the searching step in the second step is smaller. The optimal search area was determined based on the first step. Finally, the optimal pair of (γ, σ^2) was determined as 55.168 and 19.5531 , respec-

tively. To assess the relative robustness of LS-SVM regression method for the fat content, the determination coefficient for prediction (R_p^2), and root mean square error for prediction (RMSEP) were calculated. The high R_p^2 of 0.9796 with low RMSEP of 0.836708 showed that LS-SVM had a strong ability for regression analysis (Figure 3).

As a commonly used chemometric method, BP-ANN was used to establish the model with the same sample set in LS-SVM, which was split into 2 groups: a calibration set of 339 samples and a prediction set of 70 samples. The BP-ANN models were established based on different numbers of PC from 6 to 12 . The optimal number of PC was determined as 8 after comparing the final prediction results of BP-ANN models. Thus, 8 PC were set as the optimal input variables of BP-ANN. Sigmoid function was applied as the transfer function, the number of nodes in input layer was 8 , the number of nodes in the hidden layer was 9 , the number of hidden layers was 1 , and function trainlm (Levenberg-Marquardt) was used as the learning rule. The performance of LS-SVM was found to be better than BP-ANN based on the spectral region from 400 to $6,667\text{ cm}^{-1}$ (Table 1). The LS-SVM model greatly improved the prediction accuracy compared with BP-ANN, with higher R_p^2 and lower RMSEP values. The LS-SVM model succeeded in predicting the fat content in milk powder, and was superior to the conventional BP-ANN regression. These results indicate that LS-SVM is a powerful tool for spectral analysis. The process of BP-ANN was carried out in Matlab 7.0 (Math Works).

Comparing Predicted Results of MIRS and NIRS Models

The LS-SVM model was established based on MIRS and NIRS transmission values. The sample sets for calibration and prediction were the same as the set for LS-SVM based on the entire spectral range. The prediction results based on different spectral range are shown in Table 1.

From Table 1, it was concluded that the LS-SVM model performed better in the MIRS region than in the NIRS region. By analyzing the original spectral transmission plots, it was seen that the curves in MIRS region were more complex than those in the NIRS region. The main difference of each curve in the NIRS plot was offset, and there was a lot of high-frequency noise in the NIRS region. These characteristics are useless for the model establishment. In the MIRS region, the curves are smoother, and there are great differences among each brand of milk powder. Because the bands in the MIRS are fundamental bands of NIRS bands, it provides more information about frequencies and inten-

Figure 1. Near infrared spectroscopy (NIRS) and mid infrared spectroscopy (MIRS) transmission rate of 7 brands of milk powder. At the NIRS region, $4,329 \text{ cm}^{-1}$ represents fat, $4,312 \text{ cm}^{-1}$ represents protein, and $5,155 \text{ cm}^{-1}$ represents H_2O . At the MIRS region, $1,747$, $2,854$, and $2,925 \text{ cm}^{-1}$ represent fat.

Figure 2. Optimizing process of gam (γ) and $sig2$ (σ^2) parameters by grid search in a least-squares support vector machine model.

sities (Chung et al., 1999). Although it is hard to distinguish each brand by visual examination, the prediction results of 2 LS-SVM models showed that these complex curves contain more useful information than parallel curves and demonstrated that the LS-SVM model could extract the useful information successfully. Moreover, results based on the entire infrared region are more accurate than results from MIRS and NIRS; in particular, the RMSEP of prediction results in both MIRS and NIRS region are larger than that in the whole infrared region. However, the prediction results of fat content detection in either the MIRS or the NIRS region could satisfy the demand of consumers. Moreover, data processing based on the entire infrared spectral region is more complex, and the instrument based on the whole infrared spectral region is expensive. Thus, the determination of infrared spectral region should be chosen according to the required application.

Figure 3. Reference vs. predicted values of fat content in milk powder based on a least-squares support vector machine model established with the spectral range from 400 to 6,667 cm^{-1} .

CONCLUSIONS

The results of this study show the potential for the application of infrared spectroscopy technique with LS-SVM for the determination of the fat content in milk powder. The infrared spectroscopy technique allows for an accurate, fast, and nondestructive measurement of fat content in milk powder. The operation spectra measurement is simple and more convenient than chemistry methods. It can be concluded that LS-SVM is a promising alternative for regression analysis but that the model needs to be improved in its rigorousness and robustness before its online application. Further work should be done to expand the number, variety, and brand of samples and optimal wavebands need to be selected for designing a spectral measurement device.

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Table 1. Performance of the least-squares support vector machine (LS-SVM) model and back propagation artificial neural network (BP-ANN) model for fat content prediction based on different spectral ranges

Algorithm	Spectral range	Parameter ¹			
		γ	σ^2	R_p^2	RMSEP
BP-ANN	Mid and near infrared (400 to 6,667 cm^{-1})	—	—	0.9605	1.693944
LS-SVM	Mid and near infrared (400 to 6,667 cm^{-1})	55.168	19.5531	0.9796	0.836708
LS-SVM	Mid infrared (400 to 4,000 cm^{-1})	82.2551	11.8963	0.9556	1.666778
LS-SVM	Near infrared (4,000 to 6,667 cm^{-1})	119.377	9.5405	0.9466	2.434585

¹Parameters: γ = regularization parameter, gam ; σ^2 = radial basis function kernel parameter, $sig2$; R_p^2 = determination coefficient for prediction; RMSEP = root mean square error for prediction.

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REFERENCES

- AOAC. 1990. Official Methods of Analysis. 15th ed. Assoc. Off. Anal. Chem., Arlington, VA.
- Borin, A., M. F. Ferrao, C. Mello, D. A. Maretto, and R. J. Poppi. 2006. Least-squares support vector machines and near infrared spectroscopy for quantification of common adulterants in powdered milk. *Anal. Chim. Acta* 579:25–32.
- Bras, L. P., S. A. Bernardino, J. A. Lopes, and J. C. Menezes. 2005. Multiblock PLS as an approach to compare and combine NIR and MIR spectra in calibrations of soybean flour. *Chemometrics Intell. Lab. Syst.* 75:91–99.
- Burges, C. J. C. 1999. Geometry and invariance in kernel based methods. Pages 89–116 in *Advance in Kernel Methods-Support Vector Learning*. MIT Press, Cambridge, MA.
- Chauchard, F., R. Cogdill, S. Roussel, J. M. Roger, and V. Bellon-Maurel. 2004. Application of LS-SVM to non-linear phenomena in NIR spectroscopy: Development of a robust and portable sensor for acidity prediction in grapes. *Chemometrics Intell. Lab. Syst.* 71:141–150.
- Chung, H., M. S. Ku, and J. S. Lee. 1999. Comparison of near-infrared and mid-infrared spectroscopy for the determination of distillation property of kerosene. *Vib. Spectrosc.* 20:155–163.
- Deeth, H. C., C. H. Fitz-Gerald, and A. J. Snow. 1983. A gas chromatographic method for the quantitative determination of free fatty acids in milk and milk products. *N.Z. J. Dairy Sci. Technol.* 18:13–20.
- Hermida, M., J. M. Gonzalez, M. Sanchez, and J. L. Rodriguez-Otero. 2001. Moisture, solids-non-fat and fat analysis in butter by near infrared spectroscopy. *Int. Dairy J.* 11:93–98.
- Karoui, R., A. M. Mouazen, H. Ramon, R. Schoonheydtm, and J. De Baerdemaeker. 2006. Feasibility study of discriminating the manufacturing process and sampling zone in ripened soft cheeses using attenuated total reflectance MIR and fiber optic diffuse reflectance VIS-NIR spectroscopy. *Food Res. Int.* 39:588–597.
- Laporte, M. F., and P. Paquin. 1999. Near-infrared analysis of fat, protein and casein in cow's milk. *J. Agric. Food Chem.* 47:2600–2605.
- Lu, C., T. Van Gestel, J. A. K. Suykens, S. Van Huffel, I. Vergote, and D. Timmerman. 2003. Preoperative prediction of malignancy of ovarian tumors using least squares support vector machines. *Artif. Intell. Med.* 28:281–306.
- Reid, L. M., T. Woodcock, C. P. O. Donnell, J. D. Kelly, and G. Downey. 2005. Differentiation of apple juice samples on the basis of heat treatment and variety using chemometric analysis of MIR and NIR data. *Food Res. Int.* 38:1109–1115.
- Rodriguez-Otero, J. L., M. Hermida, and A. Cepeda. 1995. Determination of fat, protein, and total solids in cheese by near-infrared reflectance spectroscopy. *J. AOAC Int.* 78:802–806.
- Rosenthal, I., and R. Baruch. 1993. 100 years of measuring the fat content of milk. *J. Chem. Educ.* 70:480–482.
- Sorensen, L. K., and R. Jepsen. 1998. Assessment of sensory properties of cheese by near-infrared spectroscopy. *Int. Dairy J.* 8:863–871.
- Suykens, J. A. K., T. Van Gestel, J. De Brabanter, B. De Moor, and J. Vandewalle. 2002. Least squares support vector machines. World Scientific Publishing, Singapore.
- Suykens, J. A. K., and J. Vanderwalle. 1999. Least squares support vector machine classifiers. *Neural Process. Lett.* 9:293–300.
- Takeuchi, M., L. Bertinetti, G. Martra, S. Coluccia, and M. Anpo. 2006. States of H₂O adsorbed on oxides: An investigation by near and mid infrared spectroscopy. *Appl. Catal. A-Gen.* 307:13–20.
- Vapnik, V. 1998. *Statistical Learning Theory*. John Wiley and Sons Inc., New York, NY.
- Vapnik, V. N. 1995. *Statistical Learning Theory*. Springer, New York, NY.
- Yan, Y. L. 2005. *Basic and Application of Near Infrared Spectroscopy Analysis*. China Light Industry Press, Beijing, China.
- Zhou, Q., S. Q. Sun, L. Yu, C. H. Xu, I. Noda, and X. R. Zhang. 2006. Sequential changes of main components in different kinds of milk powders using two-dimensional infrared correlation analysis. *J. Mol. Struct.* 799:77–84.