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Near Infrared Spectroscopy for the Fruit Qualityanalysis

Mrs. ManishaVikasBhanuse
Research Scholar, Department of Electronics Engg.,
Shivaji University, Kolhapur, Maharashtra, India.

Prof. Dr. S. B. Patil
Dean III, JJMCOE, Jaysingpur,
Maharashtra, India

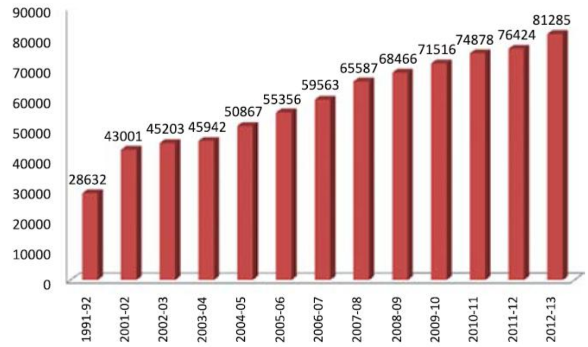
Abstract

Near infrared spectroscopy (NIR) is increasingly used during basic research performed to better understand complex materials encountered in agricultural, pharmaceuticals, combustion products, astronomy etc.This method is relatively inexpensive, rapid, non-invasive, non-destructive and is able to measure several constituents concurrently. Therefore interest in the application of near infrared spectroscopy to biological material Science has grown in recent times.Current manual methods of fruit quality analysis are dominated by near infrared analysis. This paper intends to review the basic theory of Near Infrared (NIR) Spectroscopy and itsapplications in the field of fruit quality analysis.
Keywords:NIR, wavelength, transmittance, reflectance,multivariate approach, PLS, MLR etc.

Introduction

India is an agricultural nation and stands prominent among all nations in the production of fruits & vegetables. National Horticulture Board (NHB) [12] estimated year wise fruit production in India in terms of Thousand Million Tones Graph 1). The fruit and vegetable sector has a vital role in farm income enhancement, poverty alleviation, food security, and sustainable agriculture in India. This sector, however, suffers greatly from postharvest losses. The estimates suggest that about 30–40% of fruits and vegetables are damaged after leaving the farm gate. These huge postharvest losses in India are mainly because of lack of improved technology and instrumentation for getting right information about storage life during ripening and transportation.

The increased awareness and sophistication of consumers have created the expectation for improving quality in fruits. Visual inspection of the fruits by human eyes is a primary method of quality inspection commercially. This method for fruit quality evaluation is time consuming, tedious, and inherently inconsistent and the results may not be reliable due to human errors or inexperienced technicians. Therefore a quick and more reliablefruit quality evaluation system is needed. In view of this, automated fruit quality analysis using machine vision is desirable to achieve fast and objective quality measurement.



Graph 1: Area & Production Growth Trends of fruits in Thousand Million Tones.(Source: Indian Horticulture Database)

Based on image processing and analysis, machine vision using NIR spectroscopy (NIRS) is a novel technology for recognizing objects and extracting quantitative information from digital images[1]. It provides multi-constituent analysis with a very high level of accuracy and precision as compared to conventional methods. Another important advantage of near-infrared analysisis that it doesn't require any sample preparation or manipulation with hazardous chemicals, solvents etc. Therecorded NIR spectra contain a variety of chemical and physical information of the sample to be analyzed. The biological constituents of fruits are often complex and therefore require special mathematical procedures for dataanalysis. This paper provides an overview of the critical factors that are useful and necessarywhen developing and implementing NIR spectroscopic methods for the assessment of various quality parameters of fruits.

Working Principle of NIRS

If matter is exposed to electromagnetic radiation, (Fig. 1) e.g. infrared light, the radiation can be absorbed, transmitted, reflected, scattered or undergo photoluminescence.

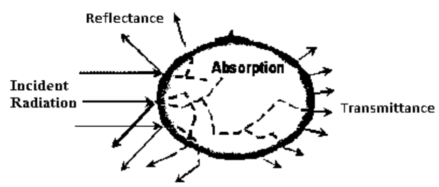


Fig.1 Interaction of organic material with EM Radiations.

The NIR spectrum consists of anumber of absorption bands that vary in intensity due to energy absorption by specificfunctional groups in a sample. NIRS can measure the concentration of components having different molecular structuressuch as protein, water, or starch in an organic material such as fruit. The NIR spectral region,from 700 to 2500 nm, lies between the visible and mid-infrared regions of theelectromagnetic spectrum. NIR spectra consist of overtonesand combination bands of the fundamental frequencies in the mid-IR region. NIR energy can easily pass through many organicsubstances due to its lowreflectivity and low absorptivity property.

NIRS technology transfers radiation energy to mechanical energy associated with the motion of atoms held together by chemical bonds in a molecule.

Methodology

NIRS is much advantageous over visible (Vis) or mid- infrared (MIR) spectroscopy. But NIR spectra are very complex. It consists of many overlapping peaks resulting broad bands. The chemical, physical, and structural properties of all species present in the fruit samplemay affect the spectral measurements. Also small sample-to-sample differences of a sample series can causevery small spectral differences i.e. the NIR spectral data obtained is depending on more than one variable simultaneously and thus this data is multivariate.This makes it difficult to interpret NIR spectra visually, assign specific features to specific chemicalcomponents or extract information contained in the spectraeasily.Therefore it is necessary to make use of multivariate approach for the data analysis to filterinformation that correlates to a certain property from a very big amount of data.

In qualitative andquantitative NIR analysis, the relevant part from the multivariate NIR spectral data is extractedwithout losing important information and to get rid of unwanted information. Multivariate analysis uses information derived frommultiple wavenumbers or wavelengths instead of single one. And thus the calibration is based on therelationship between the spectral variances at particular wavenumbers or wavelengthsand changes in the concentration. Fig. 2shows the NIR reflectance spectra of banana at different time intervals which will be useful in determining the firmness & moisture content in it.

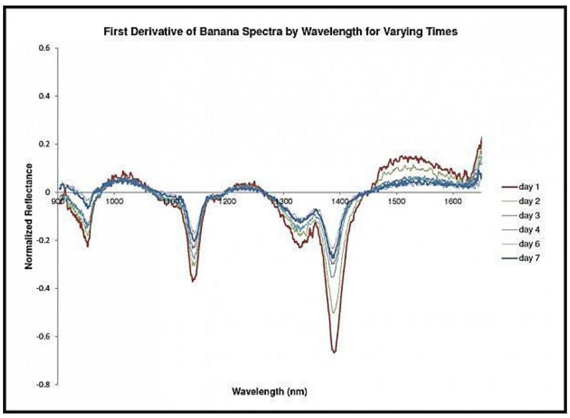


Fig.2: NIR spectral Variation of Banana.

The quality parameters of banana fruit such as moisture content and firmness were measured and the values were used for the development of prediction model using spectral data. Prediction model between the spectral reflectance and the quality parameters (Moisture content and firmness) of the bananas is developed by using partial least squares (PLS) analysis. The reflectance values at 1148 wavelengths of the fruits weretaken as predicting variables X matrix andthe quality attributes were taken as dependent variables Y matrix[2]. The PLS models are generally used to set up the multivariatemodel based on two data sets of the same object/sample namely spectral and biological values. The PLS can transform thelarge set of highly correlated experimental data into independentlatent variables or factors.

Using PLS algorithm, the predicted value of the attribute ofinterest is determined with the help of thewavelength scores, the number of PLS factors, and regression coefficient. The optimal number of latent variables forestablishing the calibration model is determined based on thepredicted residual error sum of squares. In fact, it's important to select the wavelengths, which contributeto the quality attribute of the sample. So, the highestabsolute value of the coefficients correspond to thewavelengths obtained from the PLS calibration model was selectedand used as the optimal wavelengths. Then these selected optimalwavelengths were used to establish multiple linear regressionmodels using MATLAB. MLR can be established with the help of following expression.

$$Y' = A_0 + [\sum_{n-1}^{n} An * Rn\boldsymbol{\lambda}$$

where, Y'is the predicted value of the quality attribute, n is thenumber of optimal wavelengths Ao and An are the regression coefficients,and $Rn\boldsymbol{\lambda}$is the reflectance at a wavelength k corresponding tothe Nth term in the model.

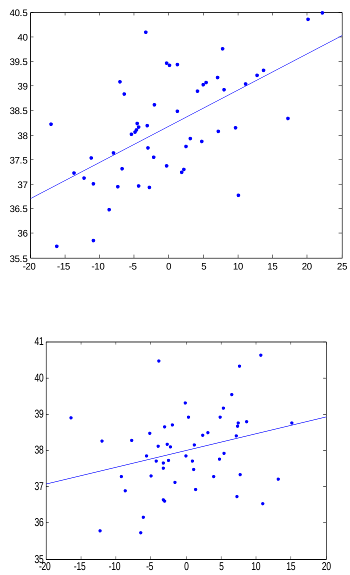


Fig.3 Multivariate analysis for Prediction of parameters

Principal component analysis (PCA) is conducted on the reflectance spectra data to determine the reliability of the selected wavelengths representingdifferent ripening/maturity stages [8]. The PCA transforms the acquired data set into a new coordinatesystem with the greatest variance of the data set projected in thefirst coordinate (also called the first principal component) andthe second greatest variance on the second coordinate and so on.The PCA is mainly used in dimensional reduction of the acquireddata set while retaining the important characteristic, which contributesmost of the variance.The average spectral reflectance in the range of 900–1600 nmcollected from the banana fruits at different maturity stages fromday one to day7. The banana fruits at day1, 2& 3 showed that themoisture content influenced the formation of characteristicabsorption bands. The reflectance values were comparatively lowerin matured fruits representing the days 4, 5, and 6 & 7 when comparedto the banana fruits representing at early stages.

Few of spectral bands showed the water contentof the fruit, which clearly defined the variation based on theamount of moisture available in the fruits. Since, the unripe fruitpeel had higher moisture and correspondingly the reflection isalso higher for the unripe fruit representing days 1 and 2. Thereflection was lower in the fruits representing the days 3, 4,5, and 6 due to lower moisture content in the fruit peel. The overall difference in reflection spectra of the banana fruitsmight be due to the noticeable changes that took place simultaneouslyduring ripening such as change in firmnessand moisture content.

The PLS calibration models were established for the bananafruits using the average spectra of the whole spectral range of1148 wave bands. The number of latent factors for PLS model forpredicting the maturity stages in terms of quality parameterswas determined by selecting the lowest value of predicted residualerrors sum of squares (PRESS).

Conclusion:

Banana fruit quality and maturity stages were studied at different times i.e. from day1 to day 7 by using NIR imaging technique. The quality parameters like moisture content, and firmness are determined and correlatedwith the spectral data. The spectral data are analyzed using the partial least square analysis. Theoptimal wavelengths are selected using predicted residual error sum of squares. The principal componentanalysis is also used to test the variability of the observed data. By using multiple linear regressions(MLR), models were established based on the optimal wave lengths to predict the quality attributes.

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