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Full Length Research Paper

Detection of crack eggs based on near infrared reflectance spectrum and discriminant analysis

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This paper analyzes the detection of crack eggs based on near infrared reflectance (NIR) spectrum and discriminant analysis (DA). In order to choose the proper detecting conditions, this paper designs several experiments according to different factors, such as different wave band, all kind of spectrum processing methods and the number of principal components. The experiments results reveal that, when we choose DA method within the spectrum region between 3800 and 11386 cm^{-1}, the number of principal components is 13, MSC or SNV are selected to pre-process the original spectrum, the recognition rate for calibration set is 97.5%, and the rate for validation set can reach up to 90%.

Key words: Crack eggs, detection, NIR, spectrum, DA.

INTRODUCTION

Eggs are staple agricultural products in China, which play an important role in agriculture and national economy. According to statistics, China's egg industry's output value has reached 1600 to 2000 million Yuan. Since 1985, China's egg production was highest in the world for 26 years. Now china has become an egg-producing country. Eggs, as an important supplier of protein, fat and various vitamins to human body, play an essential role in our daily life. However, bacteria will result in faster modification of an egg, especially when the eggshell is damaged, so the detection of crack eggs must be an important process in the whole egg industry. Traditional crack detection methods (Ma, 2007) rely mainly on manual detection, which are labor-costing and time-costing. How to work out automatic detection methods with higher efficiency evokes the attention of the researchers, such as detection methods based on image characteristic difference (Wang et al., 2004) and acoustical characteristic difference (Peng et al., 2009). Their Shortcomings are: (1) only visible cracks by eyes can be detected based on image. If the cracks are invisible, the method can not be used; (2) For the very small crack, only when the percussion point falls near the crack, the method of knocking signal detection can be used. Recent results on NIR push its application in agriculture (Rui et al., 2005), food industry (Yan et al., 2009), petrochemical industry (Yuan et al., 2005), pharmaceutical industry (Lee et al., 2010), textile industry (Yuan et al., 2010) and tobacco industry (Shi et al., 2008). This paper introduces NIR to the crack eggs detection system, which delivers a non-destructive detection to the crack eggs with high efficiency.

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MATERIALS AND METHODS

Experimental materials

We choose 50 Fresh eggs, of which 40 eggs are calibration set, 10 eggs are validation set. In the calibration set and validation set there are both half complete egg samples and another half are crack eggs with different crack extent by a universal tester. The eggs are marked and their spectrums are obtained within 24 h.

Spectrum data

Thermo Antaris NIR analyzer with fiber optic probe is applied in the experiment under constant temperature and humidity. The parameter setting of the spectrum detection is as follow: scanning wave velocity (3800 and 11386 cm^{-1}), scanning times (32), and spectrum resolution (8 cm^{-1}). Fiber optic probe is closely upon the

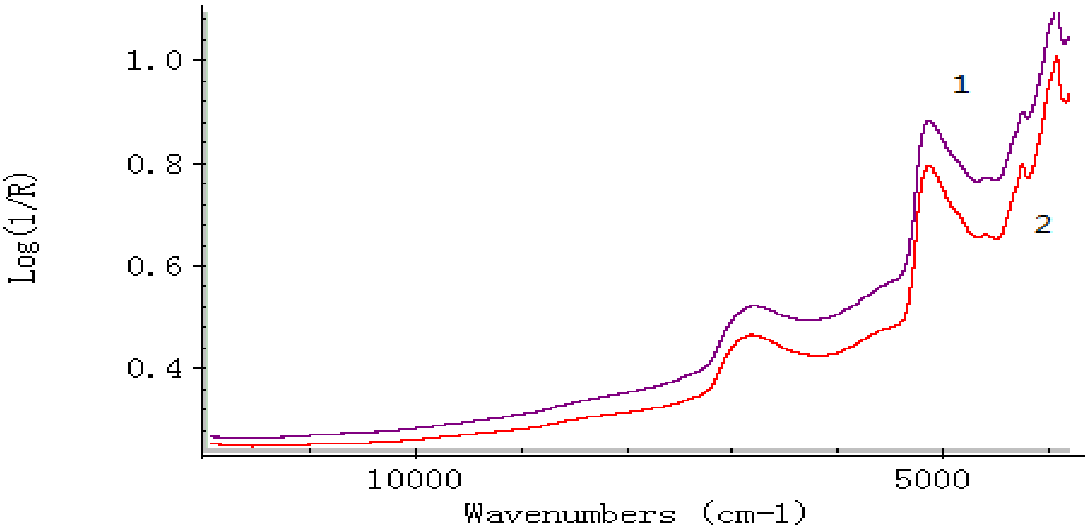

Figure 1. Spectrum of crack egg and good egg; 1: Crack egg; 2: Good egg.

Table 1. Result of different band regions using DA.

Wave band (cm $^{-1}$)	All samples	Error samples	The recognition rate (%)
3800-11836	50	2	96
4000-11836	50	18	64
5000-11836	50	15	70
9000-11836	50	20	60

eggshell. Separately the spectrums of three different positions of every egg are obtained, the average of the three spectrums is considered as the spectrum of the original egg. Figure 1 is the spectrums of a crack egg and a good egg.

Data processing

Before determining the calibration set and validation set, we have to delete the abnormal samples by using Chauvenet and residual test (Liu， 2008). The samples in this experiment have no abnormal samples. Due to noisy, environment factor, equipment feedback, operation errors and shape differences among eggs, there can be diffuse reflection. We compare the different influence of various pre-procession methods, such as multiplicative signal correction (MSC) and standard normal variation (SNV), one- order differentiation and two-order differentiation. Furthermore, the different spectrum bands influent heavily the model precision, so this paper compares the model precision within four different wave bands. We introduce discriminant analysis (DA) (Yu and Xiao, 2008) method into the qualitative analysis of the spectrum, so that the distinguish analysis of crack eggs is derived.

EXPERIMENT RESULTS

Wave bands and model precision

Table 1 gives out the result of 50 samples within different wave bands using DA without pre-procession .Obviously, compared with other three regions; the wave band of 3800～11836 cm $^{-1}$ is the best for the model precision. The recognition rate is 96%, so it’s reasonable to choose this wave band as spectrum analysis region.

Pre-procession methods and model precision

Within near infrared region (3800 and 11836 cm $^{-1}$), Table 2 compares the different calibration models with different pre-procession methods such as one-order different-tiation , two-order differentiation spectrum, MSC and SNV smoothing spectrum.

The results reveal that, the original spectrums are pre-processed by MSC or SNV, the recognition rate is the best.

The number of principal components and model precision

The number of principal components is important to the efficiency of DA method. Less principal components may result in lose of useful original data. However, too many

Table 2. Result of different pre-procession methods using DA.

Different preprocessing method	All samples	Error samples	The recognition rate/%
original spectrum	50	2	96
MSC smoothing spectrum	50	1	98
SNV smoothing spectrum	50	1	98
one- order differentiation	50	13	74
two-order differentiation	50	17	66
MSC and one-order differentiation	50	9	82
MSC and two-order differentiation	50	16	68
SNV and one- order differentiation	50	9	82
SNV and two-order differentiation	50	16	68

Table 3. Results of different number of principal components using DA.

The number of Principal components	The devotion rate of main component	All samples	Error samples	Recognition rate %
10	99.9	50	1	98
11	99.9	50	2	96
12	99.9	50	1	98
13	99.9	50	0	100
14	99.9	50	0	100
15	99.9	50	0	100
16	99.9	50	0	100
17	100	50	0	100

principal components can lead to over fitting because of the existence of too much noisy. Table 3 analyzes the distinguish precision with different numbers of principal components.

From table 3 we know, when we take only 13 principal components, the devotion rate of principal components can already cover 99.9% of the full spectrum; the model can fully detect the crack eggs. With more principal components, the increase of the devotion rate is slowed down, so we choose 13 principal components for DA.

The result of calibration set and validation set

According to the above analysis results, we choose another 50 samples, including 40 samples for calibration set and another 10 samples for validation set ,within the spectrum region between 3800 and 11386cm^{-1}, the number of principal components is 13, the pre-procession method is MSC or SNV. The result of detection using DA is shown in Figure 2.

Figure 2 shows that only one sample is error within the calibration set of 40 samples, and the correct recognition rate is 97.5% for the calibration set. Only one sample is error within the validation set of 10 samples, and the correct recognition rate is 90% for the validation set.

DISCUSSION

From recognition rate for the calibration set and prediction set, the method of near infrared reflectance is feasible. But it must be noted that, the whole wavelength range and 13 principal components factors will directly lead to a long-time identification, which is not appropriate with production requirements. Therefore, in the more follow-up study, we will select more samples and focus on effective band and minimal number of principal components to improve the identification efficiency.

Conclusion

Firstly, this paper analyzes the crack eggs by means of NIRS. It turns out that, when we choose DA method within the spectrum band between 3800 and 11386cm^{-1}, 13 principal components, the original spectrums are pre-processed via MSC or SNV, the recognition rate for calibration set is 97.5%, and for predictive set is 90%. Secondly, larger number of samples with different crack

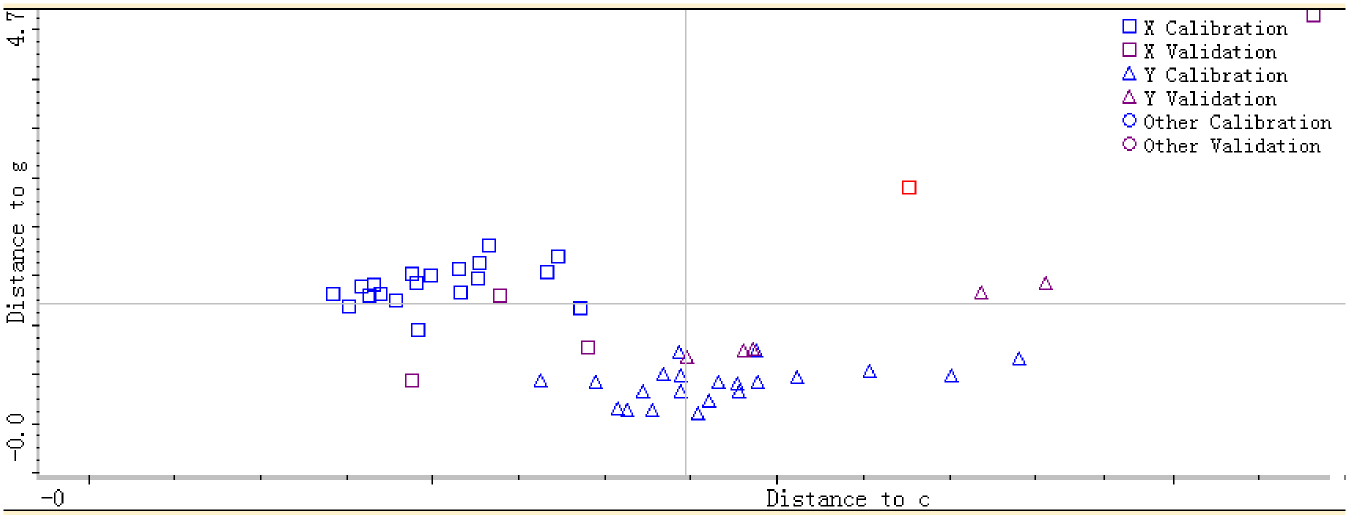

Figure 2. Classification results of crack eggs and good eggs.

types (such as point crack, linear crack and net crack and so on) can obtain more precise model. Thirdly, if we can parameterize the different crack degree of the crack eggs, a detective model related with different crack degree will be built.

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