Estimation of egg quality parameters by acoustic measurements and multivariate analysis

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Abstract

150 eggs were examined by acoustic response method for quality parameters and crack detection through seven weeks, stored at room temperature. The samples were tested in an upright and horizontal position as well, and the received signal spectra and their wavelet transforms were analyzed, after preprocessing, the obtained coefficients were used as input variables for estimation of the measured physical parameters by partial least squares (PLS) regression. Goodness-of-fit (GOF) statistics were calculated to evaluate the applicability of the method. Spectral data was also used for classification by crack presence and age by linear discriminant analysis (LDA) with different preprocessing parameters. Every estimation was validated by 10-fold cross-validation. Best approximations were achieved with spectral coefficients (measured in the upright position of the egg) for mass, with every estimation errors under 10%. With optimum signal processing parameters a 100% correct classification was achieved for crack detection and age estimation also.

Keywords: nondestructive, egg, acoustic, wavelet

Introduction

Eggs are of high importance because of their nutritional value and their low ecological footprint among essential micro- and micronutrient sources. This expectedly will increase the demand for eggs in the future, therefore it is essential to develop reliable nondestructive testing (NDT) methods to estimate their physical properties and quality parameters. Such parameters can be the presence of cracks on the shell and the ratio of egg white vs the yolk for example. Several of these properties have industrial relevance, for instance the shell as a byproduct of egg powder manufacturing has economical value –and can be further processed forming consumer product with added value–, therefore calculation of the mass is desirable. Certain parameters corresponding with quality and processibility change throughout storage, such as the volume of the air chamber at the bottom, the viscosity and composition of the egg white due to decomposition, and so forth, therefore knowledge of the age of eggs are important. A hyperspectral imaging method was used by Zhang et al. (2015), and achieved a root mean squared error of prediction (RMSEP%) of 4.01% for freshness, internal bubbles and scattered yolk were identified by support vector machine (SVM) models with an accuracy of 90.0% and 96.3% respectively. The acoustic response method was found to be a useful tool to collect information about the internal properties of a sample non-destructively (Zsom-Muha el al., 2007). Pan et al. (2005) examined response frequencies of eggs after a mechanical impact at the equatorial zone, and achieved a crack detection rate of 87%. A similar accuracy rate of 87.5% was achieved by Zhu et al (2012) using an acoustic response method, their discrimination method was based on Bayes theory. Cho et al. (2000) also developed a crack detection algorithm based on an impulse response method and discriminant analysis. They achieved a 6% and 4% classification error for intact and cracked eggs respectively. An interesting experimental method was used for crack detection by Jin et al. (2015), who created a rolling plate with seven steps, creating seven acoustic signals, therefore no external excitation was necessary and the impact became uniform. This method also is more industry-focused and easy to implement. They managed to identify the optimal number of steps for the discrimination threshold, but only a 90% correct classification was achieved, based on the Mahalanobis distance, but this method could probably be refined algorithmically. A serious problem with these articles is that they do not report the validation results, therefore no solid conclusions can be drawn regarding actual applicability. A paper of industrial relevance by Bain et al. (2006) reported the probability of cracking based on the dynamic stiffness (K_{dyn}) and also find that the amount of cracked eggs was double of what was estimated by the producer. Attar and Fathi (2014) measured the resonance frequencies of the shell, albumin and yolk, and found a 0.97 and 0.91 correlation between the shell's resonant frequency and the strength and stiffness respectively. Wavelet transform based methods are becoming increasingly utilized lately because of the high calculation capacity increase witnessed in recent years. A crack detection method was used by Li et al. (2012) developed in MATLAB, and based on wavelet transformation and Bayesian discrimination, but the authors do not specify their accuracy rate, only stating they achieved a satisfactory result and up to 95% correct classification. Similarly, Deng et al. (2010) used a wavelet based crack detection method and SVM discrimination, and only reporting the maximum crack detection rate (98.9%).

The objective of the present study was to find out what quality parameters of eggs can be estimated reliably based on nondestructive acoustic testing combined with multivariate statistical methods.

Materials and methods

150 eggs with a mass between 53-63g were tested, 20 of these were subjected to destructive testing weekly, the samples were originally 1-2 weeks old. Samples were stored at 21-25 °C 50-70% relative humidity, in an upright, north-south (NS) position, and were tested for invisible micro cracks to separate the defected ones before beginning the experiments. Also the geometry of the eggs were measured by an image processing equipment, rotational symmetry was assumed for every sample. Every week all the remaining intact samples were examined with acoustic testing, also the 20 samples which were tested destructively for measurements of quality parameters were first cracked on purpose on the tip (opposite to the air chamber), and subjected to acoustic testing again. Acoustic excitation (a single knock) was carried out with a thin hollow steel rod in NS and a laid flat east-west (EW) positions separately, while samples were set upon a foam slab enclosing a microphone (figure 1). The microphone was connected to a Hewlett-Packard 53670A dynamic signal analyzer to support the microphone with a 200 VDC phantom power. The output signal was then forwarded to a PC and recorded at 96 kHz sample rate in lossless wav format, audio files were further processed with a program written in MATLAB R2012a.

The tested parameters and their units are listed in the header row of table 1.

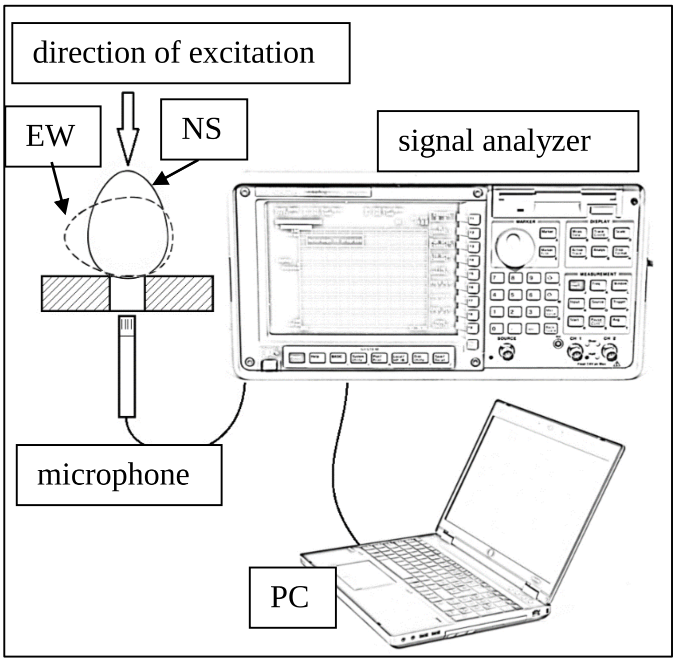

Figure 1.: Experimental setup, with the sample shown in both positions, with continuous line for the NS, and dashed line for the EW positions.

Ovality was calculated as the ratio of the length and width of the samples (m/m), and excentricity as the ratio of the distances into which the length is divided at the maximum width (m/m). Estimations for these two parameters were unsatisfying, therefore they were excluded from the table. Loss stands for the percentage of the weekly loss in total mass (g/g%) Shell thickness was measured with calipers at three locations, egg white dry matter was determined based on the weight loss of egg white samples after drying at 105°C for eight hours.

During processing of the audio files, a wavelet-based denoising was conducted first (built-in function of MATLAB, optimized for the present measurements), then the Fourier transforms were calculated by Fast Fourier Transformation (FFT) for the NS and EW signals separately, yielding spectra of 512 data points between 0 Hz and 3000 Hz, and PLS regression was carried out on each of the measured parameters using these spectra. A continuous wavelet decomposition with linear scaling factors and Paul wavelet was also conducted on the signals, the wavelet coefficients were aligned in a vector to carry out principal component analysis (PCA). The 512 coefficients that explained most of the variance of the original dataset were chosen for further processing and aligned in a descending order of contribution to the explained variance. The resulting vector was realigned with the measured variables, and the new dataset was also subjected to a PLS regression. GOF was tested by the adjusted R^2 (R^2adj), minimum of the root mean squared error percentages of prediction and cross validation (RMSEP%, RMSECV%) values defined as RMSE/(range), and maximum of the residual predictive deviation (RPD, ratio of the standard deviation to RMSE) for the prediction and cross-validation. R^2adj is superior to the original R^2 in respect to avoiding overfitting, because it is corrected for the number of estimators in the linear model and sample size. Although the prediction residual sum of squares (PRESS) metric is advisable to be calculated when regressing with multiple variables, in the case of the present dataset it would take an immense amount of calculation power and time to conduct a leave-one-out (LOO) cross-validation (CV). This would be required to calculate PRESS for 512 variables and over 700 observations for each parameter, therefore a ten-fold CV was carried out instead, which also yields reliable results to evaluate the GOF. The value of R^2adj can be comprehended similarly as the normal R^2 but for a large number of variables, also their relation (i.e. their difference) can give an insight on the limits of the regression. For this reason, as a reference point, the number of latent variables in the regression was increased until reaching the value of 0.9 for the non-adjusted R^2. RMSE% should ideally be lower than 15%. Also the number of latent variables used can be important because it has an effect on the speed of the algorithm applied in practice, and therefore the applicability of the method on an industrial scale, the number of latent variables was maximized in 250.

LDA classifications were carried out to estimate the presence of cracks and the age (counted in weeks) of the individual samples and the misclassification matrix was analysed. In this method, different FFT window sizes (2048, 4096, 8192) and multipliers (2, 4, 8) were used, the latter were applied to the extracted signal and the created empty signal part was padded with zeros. This process increases the resolution of the FFT, and provides an increased amount of spectral data to base the estimation on. Results of the LDA were also validated by ten-fold CV.

Results

The signals of the individual measurements in the different positions showed high correlation with each other with a median of R=0.96 and R=0.92 for the NS and the EW positions respectively. The typical shapes and spectra of the signals are shown in figure 2.

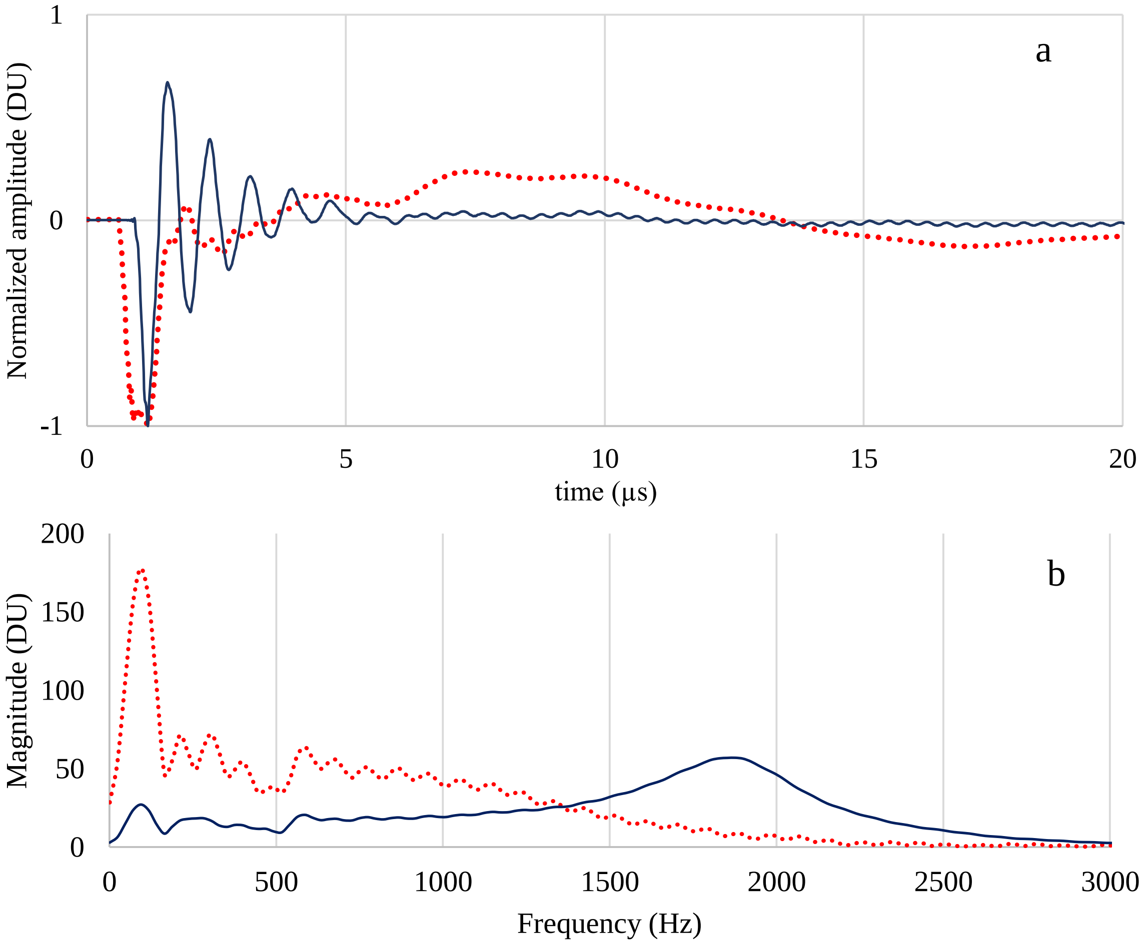

Figure 2.: Typical shape of the signals of the NS (continuous line) and SW (dotted line) positions (a) and the spectrum of the same signals (b)

The PLS GOF metrics for each estimated parameter can be found in table 1., based on wavelet coefficients and spectral data, R^2adj, RPD and RMSECV% are shown for the cross-validation and RMSEP% for the prediction.

The results of the LDA can be found in table 2.

Table 1. GOF parameters for PLS models based on wavelet coefficients (a) and spectral Fourier-coefficients (b)

a		mass (g)	loss (g/g %)	yolk mass (g)	shell mass (g)	shell thickness (mm)	yolk/white (g/g)	egg white dm (g/g%)
NS	R^2adj	0.81	0.86	0.87	0.87	0.87	0.87	0.87
	RPD	1.50	1.25	1.02	1.05	1.02	1.14	1.06
	RMSEP%	5.01	3.63	7.61	4.24	4.20	7.44	5.16
	RMSECV%	10.61	9.25	23.70	12.96	13.10	20.96	15.67
EW	R^2adj	0.71	0.84	0.80	0.81	0.81	0.81	0.79
	RPD	1.27	1.28	1.01	1.04	1.01	1.08	1.01
	RMSEP%	6.17	3.63	7.58	4.27	4.18	7.50	5.17
	RMSECV%	12.46	9.01	24.10	13.03	13.29	22.12	16.40

b		mass (g)	loss (g/g %)	yolk mass (g)	shell mass (g)	shell thickness (mm)	yolk/white (g/g)	egg white dm (g/g%)
NS	R^2adj	0.89	0.88	0.87	0.87	0.88	0.88	0.87
	RPD	1.59	1.22	1.14	1.09	1.00	1.17	1.06
	RMSEP%	5.01	5.62	7.62	4.26	4.15	7.43	5.16
	RMSECV%	11.31	9.47	22.51	12.08	13.25	19.48	15.80
EW	R^2adj	0.82	0.89	0.88	0.88	0.89	0.88	0.88
	RPD	1.32	1.43	1.04	1.10	1.01	1.14	1.02
	RMSEP%	5.03	3.62	7.43	4.19	4.18	7.39	5.01
	RMSECV%	11.39	9.11	24.30	12.36	12.77	22.40	15.57

Predictions for both positions and both attribute show a decrease in misclassification error with increasing window sizes as expected, but the multiplier, which is affecting the resolution heavily did not show such a clear trend. EW positions yielded a lower error than the NS positions, these differences became smaller with cross-validation, resulting in a high error rate.

Table 2. Results of the LDA and cross-validation

		Misclassification Prediction (%)				Misclassification of CV (%)			
Window Length	Multiplier	Crack		Date		Crack		Date	
		NS	EW	NS	EW	NS	EW	NS	EW
2048	2	6.96	9.38	2.98	6.39	15.20	15.34	10.37	11.51
	4	10.08	3.41	3.13	0.85	21.59	21.88	21.02	19.17
	8	10.65	0.43	5.11	0.00	29.97	30.26	31.96	31.96
4096	2	3.84	4.40	0.14	0.42	22.59	23.72	11.93	12.93
	4	2.98	0.00	0.28	0.00	30.82	34.09	20.60	22.02
	8	5.53	0.00	0.71	0.00	28.41	29.26	22.30	18.89
8192	2	0.28	0.43	0.00	0.00	29.26	31.25	12.64	14.49
	4	1.27	0.00	0.00	0.00	25.43	23.44	7.10	6.53
	8	2.27	0.00	0.00	0.00	21.59	23.86	5.54	4.97

Discussion

As for the PLS regression, GOF metrics showed a better result for almost every variable when calculated from the FFT coefficients of the spectrum, in some cases the RMSE% values were lower for the wavelet-based estimation. This may be also caused by improper selection of the relevant wavelet coefficients for the regression, but it suggests that this calculation-heavy process is superfluous. Geometry variables were estimated with the worst results, but fortunately these are less relevant attributes for the industry, whereas more important parameters such as total mass, shell mass and egg white dry matter gave better estimations

GOF metrics were satisfactory, but not as good as expected; this can be partially attributed to the limitation of R^2 to 0.9 during the process, probably another limit should be set in further processing of the raw data, and more sophisticated pre-processing of the spectral data should enhance the acquired metrics.

In the results of the LDA, adjustments for the least resubstitution (misclassification) error should be considered the best, but it is important to note, that the window size and the multiplier affects the process time inversely, therefore their value should be taken into account when choosing the right adjustments, and for reliability, this should be done to the CV results. Since the multiplier increases process time more than window size, hence a lower multiplier should be preferred over a lower window size, although the classification process is still much less time consuming, than the parameter-estimation from the PLS regression model. It is also important to choose a position that will provide the most valuable data, therefore no intermittent realignment of the sample is necessary in an industrial case, and the NS position gave the better estimation altogether. With that being said, the acoustic tests' results were found to be consistent regarding the most important quality parameters, and can be simultaneously used for crack detection and age estimation as well in real time, which is a major advantage over other NDT methods used to date.

Further experimentation is suggested using a wider mass range of egg samples. As for signal processing method refinement, enhanced pre-processing of estimator variables, the application of different mother wavelets and non-linear regression methods, for classification, the use of SVM and neural network methods are suggested.

References

1. Attar, M. Z., Fathi, M. M. (2014): Non-Destructive Acoustic Resonance Method for Evaluating Eggshell Strength and Thickness, *International Journal of Biophysics*, 4 (1), 9-15.
2. Bain, M. M., Dunn, I. C., Wilson, P. W., Joseph, N., De Ketelaere, B., De Baerdemaeker, J., Waddington, D. (2006): Probability of an egg cracking during packing can be predicted using a simple non-destructive acoustic test, *British Poultry Science*, 47 (4), 462-469.
3. Cho, H. K., Choi, W. K., Paek, J. H., (2000): Detection of surface cracks in shell eggs by acoustic impulse method, *Transactions of the ASAE*, 43 (6), 1921-1926.
4. Deng, X., Wang, Q., Chen, H., Xie, H. (2010): Eggshell crack detection using a wavelet-based support vector machine, *Computers and Electronics in Agriculture*, 70 (1), 135-143.
5. Jin, Ch., Xie, L., Ying, Y. (2015): Eggshell crack detection based on the time-domain acoustic signal of rolling eggs on a step-plate, *Journal of Food Engineering*, 157, 53-62.
6. Li, P., Wang, Q., Zhang, Q., Cao, Sh., Liu, Y., Zhu, T. (2012): Non-destructive Detection on the Egg Crack Based on Wavelet Transform, *International Conference on Future Computer Supported Education, IERI Procedia 2*, 372-382.
7. Pan, L., Tu, K., Zhao, L., Pan, X. (2005): Preliminary research of chicken egg crack detection based on acoustic resonance analysis, *Transactions of the Chinese Society of Agricultural Engineering*, 21 (4), 11-15.
8. Zhang, W., Pan, L., Tu, S., Zhan, G., Tu, K. (2015): Non-destructive internal quality assessment of eggs using a synthesis of hyperspectral imaging and multivariate analysis, *Journal of Food Engineering*, 157, 41-48.
9. Zhu, Z., Wu, L., Hu, D., Wen, Y. (2012): Cracked-Shell Detection of Preserved Eggs Based on Bayes Theory in Mechacincal Engineering, *2012 International Conference on Mechanical and Electronic Engineering*
10. Zsom-Muha, V., Felföldi, J., (2007): Vibration Behavior of Long Shape Vegetables, *Progress in Agricultural Engineering Sciences*, 3, 21-46.