Research on Hardness Detection Method of Crisped Grass Carp Based on Visible - Near Infrared Hyperspectral Technology

Qingxiu Wang, Li heng Su, Juan Zou, Ningxia Chen, Ting Wu, Ling Yang*

*Guangdong Provincial Food Safety Traceability and Control Engineering Technology Research Center, College of Information Science and Technology, Zhongkai University of Agriculture and Engineering, Guangzhou, Guangdong 510225, China

*yang98613@163.com

Abstract. With the fish of crisped grass carp as the research object, this paper analyzes the hardness-hyperspectral data of crisped grass carp with a texture analyzer and a visible - near infrared hyperspectral imaging system (400-1100nm), and then proposes a method to quickly detect the hardness of crisped grass carp. In this study, the hardness of 15 fish crisped grass carp was analyzed with a texture analyzer, and it was found that there was a difference in hardness between different fish with a significance P<0.05. Four spectral bands affecting the hardness of crisped grass carp were found by using the random forest algorithm, which indicated that there was a connection between hardness and hyperspectrum. Four pretreatment methods were used, among which SNV pretreatment method had the best effect, R² was 0.80. PLS, SVM and BP-NN prediction models were established respectively, and R² and RMSEP of the models were used as evaluation indexes to compare the advantages and disadvantages. The results are as follows: R² is 0.8033, 0.8564, 0.8814 and RMSEP are 3.6417, 2.6891 and 2.6128 respectively, among which BP-NN prediction model R² is 0.8814 and RMSEP is 2.6128, which has the most significant effect. Therefore, BP-NN prediction model is more suitable for nondestructive testing of crisped grass carp hardness.

Keywords: Crisped grass carp, Hardness, Texture device, Visible-near infrared hyperspectral technology.

1. Introduction
Crisped grass carp is one of Guangdong characteristic aquatic products because its meat is tender and crisp. It is widely welcomed by consumers. The quality of crisped grass carp is so especially because a certain amount of broad beans is fed during the grass carp growth. During feeding of broad bean, the muscular structure and nutritional content of crisped grass carp are changed to different degrees, for example, the hardness and toughness of the muscle are increased [1].

How to determine the hardness and toughness of crisped grass carp when it comes to the market? Many scholars have made contributions in this respect. However, the brittleness detection of crisped grass carp in most of these studies is based on mechanism research, and the evaluation method for crisped grass carp brittleness index is very traditional and there are many limiting factors in these methods. For example, a large number of participants are required, the participants need to have
complete requirements for health indicators such as smell and taste, and the test samples must be cooked to the point where they can be eaten [2-3]. Compared with sensory evaluation, texture detection is improved to some extent, but there are still some problems, such as complicated testing process, destructive testing of samples, and unstable testing data caused by large differences between samples. People tend to adopt safe and rapid non-destructive testing methods for meat quality detection. Among them, spectroscopy technology has been increasingly popularized in the field of food quality detection. Achievements have been made in the quantitative detection of food ingredients, such as water, fat, protein, amino acid, etc., which are mainly applied in the detection of food freshness [4-6] and food forgery and adulteration [7-9]. But few studies have been conducted on the hardness testing of crisped grass carp by using spectroscopy.

With fish crisped grass carp as the research object, this project uses hyperspectral imaging technique (HSI) combined with chemometrics method and computer programming technology to study the change rule between hardness and spectrum of crisped grass carp and establish a hyperspectral imaging detection method to characterize the hardness of crisped grass carp. It is hoped that it can provide important scientific basis for intelligent monitoring of aquatic product quality and rapid nondestructive analysis of quality safety, and contribute to the development of real-time online testing equipment.

2. Materials and methods

2.1. Sample collection and preparation

A total of 15 adult fish are purchased from the shop of crisped grass carp in Guangzhou market, whose length are about 72–78cm and weight are about 7.5~9kg. After slaughter, the dorsal muscles on both sides parallel to the outer pectoral fins and above the midline are taken (Fig.1), which are about 12cm long. Then, clean with tap water, scale and skin off, and cut the red meat on the surface of crisped grass carp. 5 samples of about 2cm*1.5cm*2cm (length * width * thickness) were cut from the head to the tail. There are 10 samples for each crisped grass carp, a total of 150 samples. Number the samples obtained and store them in a low-temperature crisper for testing.

![Fig.1 Sample collection of Crisped Grass carp.](image)

2.2. Spectral data acquisition

The experiment uses Gaiasky-Mini (Sichuan Shuang Li He Pu Technology Co., LTD, China), which is mainly composed of the following parts: Gaiasky-mini (Sichuan Shuang Li He Pu Technology Co., LTD.), with a wave number range of 400-1100cm; Four 50wELC halogen lamps; LENOVO computer; Sample stage; Data acquisition black box (60cm×70cm×80cm) (Fig.2). The sample to be measured is placed on the carrier platform of the hyperspectral imager. In order to make the sample clearly visible and well-defined, the distance between the sample and the lens shall be adjusted to 52cm, the moving speed of the platform shall be set to 0.08mm/s and the exposure time to 9.98 seconds. Then the sample shall be photographed one by one. The collected hyperspectral images were imported into ENVI 5.3, and the region of interest (ROI) included in the software was used to extract the image of fish crisped grass carp. The extracted area was mainly the relatively uniform and smooth part in the middle of the fish with an area of about 1.5cm*1cm.
2.3. Texture detection
Texture detection adopts FTC texture detector with 500N force-sensing element. In the experiment, a cylindrical stainless steel probe with a diameter of 6mm was used, the triggering force was set at 0.75N, the test speed was 30mm/min, and the deformation rate was 35%. The samples collected with hyperspectral images were sampled with TPA mode in sequence according to their number. Three sites were collected for each sample, and each site was tested twice. Finally, the average value of the three sites was taken for analysis. Hardness values are read and calculated by the TMS-Pro physical property analysis system.

2.4. Methods
In this paper, three modeling methods, PLSR, SVM and BP-NN, are mainly used to compare their abilities in processing non-linear characteristics of hyperspectral data. The following are the characteristics of the three modeling methods, PLSR, SVM and BP-NN respectively.

Partial least squares regression analysis (PLSR) has two or more independent variables and dependent variables, when PLSR effect is significant, the internal variables are highly linearly correlated. PLSR as a kind of widely used multivariate statistical methods, focus on the correlation analysis, multiple linear regression analysis and principal component analysis, the advantages of flexibility to solve the sample number less than the number of variables and multiple common problems between X [10].

As a common machine learning algorithm, support vector machine (SVM) is subordinate to supervised learning. It is mainly used to divide data through an ultra-lat surface in m-space. When linear indivisible data is encountered, SVM skillfully maps the sample to a high-dimensional feature space by introducing kernel function, and the processed sample data can be linearly separable[11-13].

BP(Back Propagation) neural network is a concept proposed by scientists led by Rumelhart and McClelland in 1986. As one of the most widely used neural networks in the field of deep learning, it is a multi-layer feedforward neural network training algorithm based on error reverse propagation. Its main method is the gradient descent method, which minimizes the error between the actual value calculated by the algorithm and the expected value [14]. In this study, the function SIGMIOD is used as the transfer function, and the characteristics of forward propagation of signals and back propagation of errors are utilized to calculate the error output in the direction from input to output, while the adjustment weights and thresholds are carried out in the direction from output to input [15-16].

3. Results and analysis

3.1. Analysis on the texture of crisped grass carp
The changes in the internal muscle composition of crisped grass carp can be represented by its physical characteristics, among which crispness and non-crispness are the particularity inherent in crisped grass carp. Moreover, studies have shown that hardness effectively represents the brittleness of crisped grass carp [17]. Therefore, the hardness of the fish on the back of crisped grass carp is tested by a texture analyzer in this paper to analyze whether there is any difference in the hardness of crisped grass carp sold on the market. Tab.1 represents 15 crisped grass carp purchased randomly on the market. Ten fish samples are taken from each fish. Through analysis, it is found that the hardness of each individual with different crisped grass carp is different with a significance P<0.05 and the hardness range is between 14 and 36, which indicates that the taste and quality of the fish sold on the market are different.

| Hardness variance analysis statistics (N) | 36.45±3.05abc | 36.7±3.23ab | 34.92±5.10ab | 32.74±2.96abc | 31.49±1.43abcd |
|-----------------------------------------|----------------|-------------|--------------|---------------|----------------|
| 29.94±2.28abcde                         | 29.83±3.63abcd | 28.76±4.33bcde | 26.48±4.25cde | 24.68±1.81def |
| 23.33±1.25efg                           | 17.17±1.25fgih | 15.83±0.89gh | 15.36±0.92h   | 14.32±0.90h   |

Tab.1 Variance analysis of hardness of fish on the back of crisped grass carp

3.2. Original spectral curve
In this passage, we analyze the changes in the nutritional composition of the fish on the back of crisped grass carp and find the characteristic bands that affect the hardness of crisped grass carp, so as to judge the relationship between the hardness and spectral bands. It can be seen from Fig.3 that the spectral value of crisped grass carp varies significantly within the spectral band of 400-1000nm. The variation trend of spectral bands among individuals with different crisped grass carp is the same, but the extent is different to some extent. The random deep forest algorithm[18-19] was used to find the spectral band factors affecting the hardness of crisped grass carp and it was found that the four spectral bands of 450nm, 599nm, 602nm and 745nm were the influence factors with the highest proportion. It further indicates that the hardness of crisped grass carp is correlated with the hyperspectral band (400-1000nm) and can be reflected by the changes in the band.

![Fig.3 The original spectra of three crisped grass carp.](image)

3.3. Pretreatment
In order to reduce the interference of dark current floodlight to the data, we used Matlab2016b software platform to conduct black and white correction for the original hyperspectral data [20]. In order to
exclude the influence of equipment, environment, sample preparation and other factors in the original spectrum acquisition process, Unscrambler X 10.2 software was used in this paper to conduct transformation analysis of preprocessing methods such as multiple scattering correction (MSC), standard canonical transformation (SNV), Smoothing-Sgolay (SG), and Area normalization on the original spectrum, as shown in Tab.2:

| pretreatment | model | Calibration set | Cross validation set | Prediction set |
|--------------|-------|-----------------|----------------------|---------------|
|              |       | RMSEC          | R^2_cal              | RMSECV        | R^2_cv        | RMSEP         | R^2            |
| Smoothing    | PLS   | 2.3            | 0.84                 | 2.78          | 0.79          | 0.7588        | 2.3            |
| Normalize    | PLS   | 2.3            | 0.85                 | 2.76          | 0.79          | 0.7643        | 2.3            |
| SNV          | PLS   | 2.33           | 0.84                 | 2.78          | 0.82          | 0.7639        | 2.33           |
| MSC          | PLS   | 2.15           | 0.87                 | 2.65          | 0.80          | 0.7869        | 2.15           |

Tab.2 Comparison of different pretreatment methods

As can be seen from Tab.2, after the original spectrum was treated with Smoothing-Sgolay and Normalize, the determination coefficient and error of the prediction set did not change very much, indicating that these two pretreatment methods had little effect on the baseline translation and drift correction of spectral data, and did not improve the spectral accuracy. After treatment with SNV and MSC, the determination coefficient of the prediction set increased by 0.0445 and 0.0281 relative to the original spectrum, respectively, indicating that SNV and MSC have certain effects on improving the prediction accuracy of the model, among which SNV pretreatment effect is more obvious, with a determination coefficient of 0.8033.

3.4. Model establishment
In order to more effectively establish the correspondence between the hardness value of crisped grass carp and the spectral value, two-thirds of the data samples were randomly selected as the correction set during the modeling process, and the remaining one-third of the data samples were used as the detection set to establish the PLS model and the SVM model respectively. In the establishment of BP-NN model, the k-fold cross validation method is adopted to reduce the error caused by the relatively small amount of data, where k is 4, and the modeling results are shown in the following Tab. 3.

| model | Calibration set | Cross validation set | Prediction set |
|-------|-----------------|----------------------|---------------|
|       | RMSEC R^2_cal   | RMSECV R^2_cv        | RMSEP R^2     |
| PLS   | 2.3 0.84        | 2.68 0.80            | 3.6417 0.8033 |
| SVM   | 1.41 0.94       | 2.55 0.81            | 2.6891 0.8564 |
| BPNN  | 1.05 0.97       | 2.87 0.82            | 2.6128 0.8814 |

Tab.3 Modeling results of PLS, SVR and BP-NN
Fig. 4 Modeling result diagram.

\(a\) is the PLS result graph, \(b\) is the SVM result graph, and \(c\) is the BP-NN result graph.

As shown in Tab. 3 and Fig. 4, the PLS, SVM and BP-NN models were compared under the same preprocessing method. The correlation coefficient of PLS was 0.8033, which was the smallest among the three methods, and the root-mean-square error was 3.6417, which was the largest among the three methods. Therefore, the PLS modeling method was not suitable for predicting the hardness of crisped grass carp. The correlation coefficient and the root-mean-square error of the SVM model were 0.8564 and 2.6891, which were better than the PLS model. The correlation coefficient and root-mean-square error of BP-NN model reach 0.8814 and 2.6128, so the model has the best effect.

4. Conclusion

In this paper, the texture of crisped grass carp sold on the market was tested and corresponding spectral data were obtained and analyzed. The conclusion was that SNV as a model pretreatment method had a better effect on the pretreatment method. Both the SVM model and the BP-NN model achieved higher results than the PLS model, and the prediction set accuracy of the BP-NN model reached the highest of 0.8814, because BP-NN has strong self-learning ability and adaptive ability, and can extract rules between data through learning. This result also indicates that the PLS modeling method and SVM modeling method have a lower ability to deal with nonlinear data than BP-NN, which is the same as the existing research conclusion. Therefore, it has practical application significance to use BP-NN modeling method to predict hardness of crisped grass carp.

References

[1] Lin W L, Zeng Q X and Zhu Z W et al 2012 Relation between protein characteristics and TPA texture characteristics of crisp grass carp (Ctenopharyngodon idellus C. et V) and grass carp(Ctenopharyngodon idellus) J. Journal of Texture Studies 43(01) pp1-11

[2] Bourne M C 2002 Food texture and viscosity: Concept and measurement (2nd ed.) San Diego: Academic press

[3] Wanling L, Xianqing Y, laihao L, Xiao H, Shiqiang D, Shuxian H and Ya W, Jianchao D and Yanyan W 2013 Correlation between texture and sensory evaluation of crispy grass carp Modern food science and technology 29(01) pp1-7

[4] Yu H 2018 Preliminary study on the application of hyperspectral imaging technology in nondestructive detection of food quality J. Food safety guide 24 93

[5] Jiyong Sh, Wenting L, Xiaobo Z, Fang Z and Ying C 2019 Rapid detection of salmon quality based on near infrared spectroscopy J. Spectroscopy and spectral analysis 39(07) pp2244-2249

[6] Junhu C 2016 Study on nondestructive and rapid detection method of fish freshness based on hyperspectral imaging (South China University of technology)

[7] Yadong Z, Hongju H,Wei W, Shengqi J, Hanjun M, Xi L, Suhan L, Mingming Z, Shengming Z and Zhengrong W 2020 Rapid prediction of chicken adulterated beef by hyperspectral
imaging combined with linear regression algorithm. *J. Food industry science and technology* **41**(04) pp.184-189

[8] Yumiao L, Chunliu Y, Cui I, Fang L, Zhiqiang W and Yuzhen D 2019 Application research progress of spectral technology in identification of adulterated meat. *Meat research* **33**(02) pp.72-77

[9] Ting W, Nan Z and Ling Y 2017 Identification of salmon meat counterfeiting by infrared spectroscopy. *Spectroscopy and spectral analysis* **37**(10) pp.3078-3082 + 3149

[10] Wold S, Sjöström M and Eriksson L 2001 PLS-regression a basic tool of chemometrics, *J. Chemometrics & Intelligent Laboratory Systems* **58**(2) pp.109-130

[11] Vapnik V 1998 The support vector method of function estimation, in J.A.K. Suykens and J. Vandewalle (Eds) Nonlinear Modeling: Advanced Black-Box Techniques *Kluwer Academic Publishers Boston* pp.55-85

[12] Khan S, Ullah R, Khan A, Wahab N, Bilal M and M Ahmed 2016 Analysis of dengue infection based on Raman spectroscopy and support vector machine (SVM). *J. Biomedical Optics Express* **7**(6) pp.2249-2256

[13] Zhang Y, Dai M and Ju Z 2015 Preliminary Discussion Regarding SVM Kernel Function Selection in the Twofold Rock Slope Prediction Model. *J. Journal of Computing in Civil Engineering* **30**(3) pp.04015031

[14] Chen Q, Jing L, Chaowen Z et al. 2019 Classification and prediction of air quality model based on BP neural network. *Software* **40**(2) pp.129-132

[15] Chunxiao L, Zhenguo W, Songlin J et al. 2019 Construction of wheat cold resistance model based on BP neural network. *Journal of Henan University of science and Technology (NATURAL SCIENCE EDITION)* **47**(3) pp.72-78

[16] Tairan F, Guangxin L, Wanquan Y et al. 2019 Prediction of nitrate nitrogen concentration in water. Based on stack self-coding BP neural network. *J. Chinese Journal of Fisheries* **43**(04) pp.257-266

[17] Tuanjie W, Sai Z and Sijia Z 2020 Face recognition system based on BP neural network. *J. Fujian computer* **36**(07) pp.27-29

[18] Raschka and Sebastian 2014 Python Machine Learning *Packt Publishing*

[19] Kai Y, Yan H and Kang L 2015 Importance score of random forest variables and its research progress

[20] Zhengwei W, Jiayun W and Songlei W et al. 2015 Detection of chicken tenderness based on Vis / NIR hyperspectral imaging technology. *J. Food science and technology* **40**(11) pp.270-274