Identification of diseases for soybean seeds by computer vision applying BP neural network

Tan Kezhu, Chai Yuhua*, Song Weixian, Cao Xiaoda

(*College of Electrical Engineering and Information, Northeast Agricultural University, Harbin 150030, China*)

Abstract: The use of computer vision for estimating quality in agriculture products has become wide spread in recent years and the composition, variety, or ripeness can be estimated. On the other hand, the appearance is one of the most worrying issues for producers due to its influence on quality. In this research, computer vision technology combined with BP artificial neural network (ANN) was developed to identify soybean frogeye, mildewed soybean, worm-eaten soybean and damaged soybean. Thirty-nine characteristic parameters from color, texture and shape characteristics were computed after preprocessing the acquired soybean images. The dimensionality of the characteristic parameters was reduced from 39 dimensionalities to 12 dimensionalities using the method of principal component analysis (PCA). MALAB software was used to build a prediction model according to 12 characteristic parameters. The identification accuracies of soybean frogeye, mildewed soybean, damaged soybean and worm-eaten soybean are 96%, 95%, 92%, and 92%, respectively. And the accuracy for heterogeneous soybean seeds with several diseases is 90%. The results show that the prediction model constructed by BP neural network can identify the diseases of soybean seeds. And it is useful to estimate appearance quality of soybean by computer vision applying BP neural network.

Keywords: soybean seed, disease identification, computer vision, BP neural network, characteristic parameters, data reduction

DOI: 10.3965/j.ijabe.20140703.006

Citation: Tan K Z, Chai Y H, Song W X, Cao X D. Identification of diseases for soybean seeds by computer vision applying BP neural network. Int J Agric & Biol Eng, 2014; 7(3): 43－50.

1 Introduction

Among different soybean producing provinces of China, Heilongjiang Province is the largest producer of soybean, producing up to 18 400 thousand metric tons with an export of nearly 86%. The soybean industry contributes significantly to the economy of China, which has more than one-third of its agricultural land (4.05 million hectares) under soybean plantation[1]. There is a constant demand for the production of soybean with high quality. Besides chemical composition, soybean appearance is one of the most important characteristics as it is closely associated with quality and consumer preferences[2]. However the appearance quality of soybean could be affected by some factors. For example, soybean is susceptible to mildew in long-term storage in wet environment; there are some soybean diseases caused by bacteria; during harvesting or transporting, soybean seeds could be damaged by machinery handling. The shape of soybean seeds and various plant diseases such as soybean frogeye, mildew infection, soybean purple spot, virus blotches, and worm damage will affect the appearance quality. Soybean diseases greatly reduce the economic value of soybean products and result in economic losses for the soybean industry and farmers. Thus, it is of great significance for soybean farmers and soybean industry to develop a rapid and reliable technique

Received date: 2014-01-05 **Accepted date:** 2014-03-26

Biographies: Tan Kezhu, PhD student, Lecturer; research interests: digital image processing and pattern recognition; Email: kztanneau@126.com; **Song Weixian**, PhD student, Lecturer; research interests: digital signal processing; Email: weixiansong@126.com; **Cao Xiaoda**, postgraduate, research interests: digital image processing; Email: xiaodacao @126.com.

*** Corresponding author: Chai Yuhua,** Professor, doctoral supervisor, research interests: pattern recognition; Email: yhchai@163.com.

for detecting the appearance quality of soybean.

At present, the traditional soybean appearance quality detection technology still relies on manual inspection. The manual detection of soybean is a time-consuming, labor-intensive process resulting in bias and human error which drastically affects the efficiency[3-4]. In order to address these challenges, an efficient and effective discrimination system was required. An automated machine vision-based discrimination system might offer better consistency, accuracy, non-destructive and quicker performance. This can greatly improve production efficiency and automation[4]. Many domestic and foreign scholars researching on appearance quality inspection and grading of agricultural products have obtained many research results. Machine vision has been shown to be successfully used in grading process for fruits and vegetables[5-8]. Ling Yun et al.[9] designed a set of rice appearance quality parameters detection device based on machine vision. In this research, rice appearance quality traits mainly referred to grain length (GL), grain width (GW), ratio of length and width (L/W), chalkiness (CH), degree of white core (DWC), milling rice (MR) and transparence (TR) were detected. Yang Fei et al[10] realized the indexes detection of particle uniformity, pepper seed rate, closing rate and ear stem ratio. Experimental results show the ear recognition accuracy of pepper seed at 100%, and closing and the skin recognition accuracy at 89% and 96.8%, respectively. The previous research provides the theoretical basis and technical support in order to further improve the Chinese prickly ash appearance quality of computer vision detection. Xu Li et al.[11] applied machine vision technology and colorimetric theory and researched the method to distinguish different color features of endosperm, embryo and cortex of the stained rice. Jarimopsa B[12] studied analysis method for tamarind using machine vision. The size and the surface defects of tamarind were detected in the research. Onur Yorulmaz et al[13] detected fungal damaged popcorn using image property covariance features. Images of kernels were obtained to distinguish damaged from undamaged kernels using image-processing techniques.

This research is focused on development of a discrimination method for soybean seeds diseases such as soybean frogeye, mildewed soybean, worm-eaten soybean and damaged soybean. The mathematical morphology theory, digital image processing technology, neural network and pattern recognition technology were employed together to discriminate appearance quality of soybean seeds. It is nondestructive, rapid and automatic. And a machine vision detection platform was designed in this research.

2 Materials and methods

2.1 Samples

One hundred and seventy six soybean seeds were used in this study which came from the Northeast Agricultural University's National Soybean Research Laboratory. Dongnong 40567, Dongnong 47, Dongnong 42, Dongnong 410, Dongnong 634 were chosen because they are largely popularized around Heilongjiang Province. Dongnong 46 with high oil and rich nutrition composition was also considered.

The study focused on the soybean samples infected by common diseases such as soybean frogeye. And mildewed soybean, worm-eaten soybean and damaged soybean were also considered. These defects affect the appearance quality of soybean seriously. Soybean seed samples with diseases are shown in Figure 1. Five hundred soybean seeds with soybean frogeye, 420 mildewed soybean seeds, 450 worm-eaten soybean seeds and 300 damaged soybean seeds were used in this study.

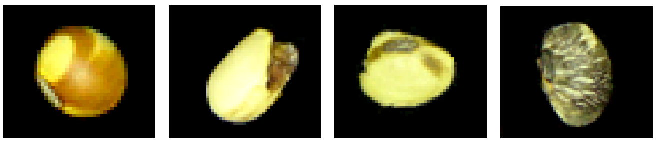


Figure 1 Soybean seeds with disease

The optical sensor system consists of a CCD camera, computer, a light source, a small hand-held box of light source and an illuminometer. The system is shown in Figure 2.

2.2 Image acquisition

A light source box with the size of 100 cm × 30 cm × 30 cm was designed in the experiment. Black cotton cloth with no light penetration and no light reflection was laid over the floor of the light source box. The system

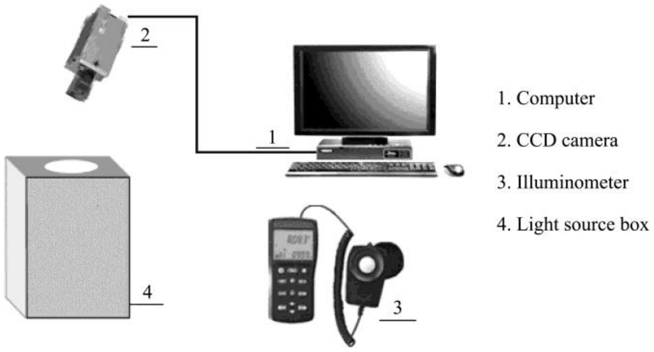


Figure 2 Hardware composition of the system

coupled with a ring light source which connected to a current stabilizer. The light source distributed the light evenly. We could acquire the images of samples primly. The light source designed avoided color difference and shadow noise under the condition of natural light. Thus the images acquired were clearer, more accurate and easier to be analyzed. The hardware platform of image acquisition was constructed with camera, illuminometer, computer and light source.

Sixteen grains as a group were under the camera at 60 cm distance. For every group, the camera angle, the distance between sample and camera, light intensity and the number of soybean grains should be consistent. And then, the images of disease soybean seeds and normal soybean seeds were acquired respectively.

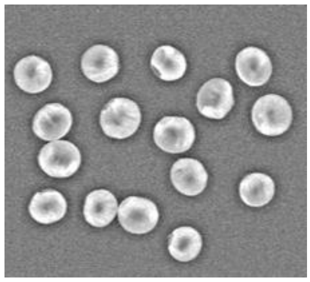
2.3 Image preprocessing

2.3.1 Image enhancement

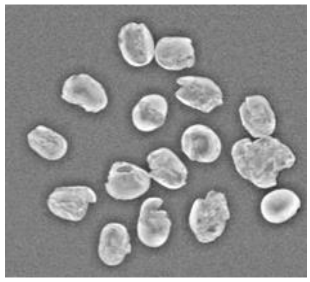
The distorting phenomenon still exists for ill spot in the chrome image. It is troublesome in the late work and affects the segmentation accuracy. In this study, the gray linear transformation method was adopted to stretch gray level difference between background and target. The gray linear transformation for chrome images are shown in Figure 3.

2.3.2 Image segmentation

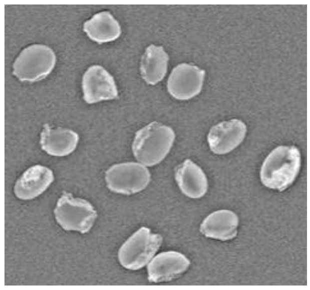
Comparing performance of some segmentation methods, we selected the minimum error threshold selecting method (METS) to separate the target from background. The optimal threshold should make the error probability least for the target and the background. Thus, the function of error segmentation probability was employed as criterion function. It was obvious that the smaller the criterion function was, the fewer the errors, the better the segmentation effect. The results are shown in Figure 4.



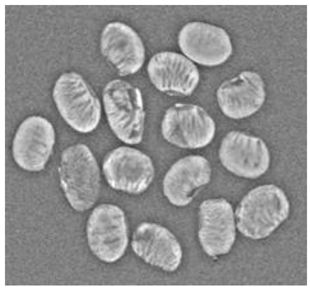
a. Frogeye soybean



b. Mildewed soybean



c. Worm-eaten soybean



d. Damaged soybean

Figure 3 Images after gray-scale transformation

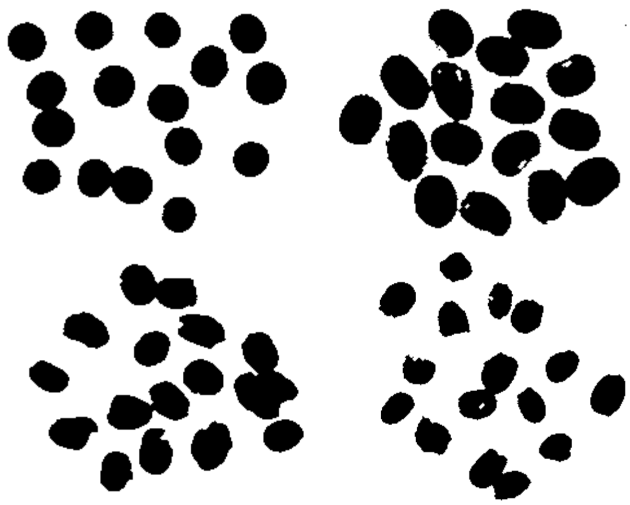


Figure 4 Binary images after segmentation by minimum error threshold selection method

2.3.3 Holes filling

Soybean seeds were distinguished in the binary image. However, there was weak noise in the segmented image because of interference of the environment. Therefore, there were some holes inside the target. The holes can be eliminated by morphological operation.

After the image threshold, the segmented soybean seeds were eroded using a morphological structured element of five pixels and spherical shape. This operation allowed the exclusion of the soybean perimeter that suffered an intense reflection from the background.

Opening operation applied to eliminate small noise and closing operation was used to eliminate connections. Binary image filled in this way with good effect is shown in Figure 5.

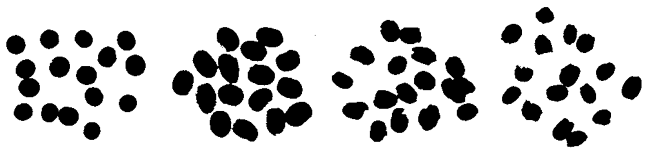


Figure 5 Binary images by filling

2.3.4 Adhesion segmentation

The watershed algorithm was used to deal with the adhesion problems and the results are shown in Figure 6.

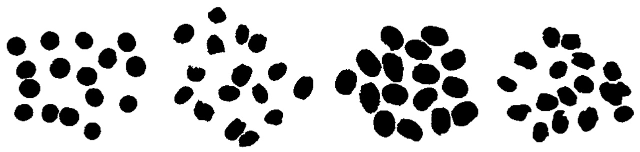


Figure 6 Binary images by watershed algorithm

3 Results and analysis

3.1 Feature extraction

3.1.1 Extraction of morphological characteristics

Morphological characteristic is the most intuitive description for appearance quality. The saturation, damage degree and a lesion can be reacted by morphological parameters directly. Characteristic morphological parameters are shown in Table 1.

3.1.2 Extraction of color feature

Color feature is another important characteristic of soybean. Besides different colors in different varieties, mildew, plaque grain and immature grains are different in color compared with normal soybean. Color feature is important for defects detection of soybean.

Mean value, deviation, the 3rd order moment of R, G and B are shown in Table 2.

Table 1 Morphological characteristic parameters

Sample ID	Circularity	Compaction	Arc degree	Fluffy degree	Eccentricity	Elliptic long axis	Elliptic short axis	Central moment
1	0.92	1.04	0.96	1.00	0.26	15.82	18.64	4590968686.00
2	0.95	1.00	0.95	1.00	0.25	16.95	14.00	4590965624.32
3	0.90	1.34	0.89	1.08	0.29	19.90	17.34	4590959544.74
4	0.94	1.25	0.69	1.05	0.29	14.94	12.40	4590956456.05
5	0.45	1.27	0.85	1.00	0.24	15.45	15.27	4591000068.70
6	0.50	1.40	0.79	1.04	0.31	15.50	12.35	4590968686.85
7	0.92	1.46	0.96	1.00	0.46	14.92	14.46	4590945678.21
8	0.79	1.25	0.83	1.02	0.23	16.79	17.25	4590899938.74
9	0.78	1.15	0.67	1.01	0.29	17.78	16.15	4590952785.56
10	0. 99	1.62	0.90	1.03	0.21	15. 99	19.62	4590965787.47

Table 2 Color characteristic parameters

Sample ID	R mean	G mean	B mean	R deviation	G deviation	B deviation	R3 moments	G3 moments	B3 moments
1	170.35	149.51	63.65	32.61	42.14	39.80	-7.96	6.64	11.59
2	150.25	129.70	64.45	32.56	45.95	40.35	-6.35	6.39	10.26
3	173.52	142.65	65.09	29.86	44.53	37.56	-6.39	5.63	15.26
4	192.34	147.25	57.69	42.63	39.65	46.23	-7.86	6.93	12.35
5	177.40	145.77	72.65	37.25	40.21	36.70	-9.35	8.25	13.65
6	177.05	151.64	73.79	40.34	36.54	38.62	-5.56	7.23	14.23
7	169.32	139.46	77.83	32.00	37.89	49.12	-9.86	5.65	10.32
8	163.47	146.80	71.93	35.12	35.65	47.86	-8.96	5.33	9.65
9	178.28	144.60	75.67	26.37	39.98	48.65	-6.95	5.26	13.65
10	179.24	147.25	35.20	38.90	35.32	35.63	-9.22	5.68	7.25

Note: Mean value, deviation, 3rd order moment of H, S and V are shown in Table 3.

Table 3 Color characteristic parameters

Sample ID	H mean	S mean	V mean	H deviation	S deviation	V deviation	H 3 moments	S 3 moments	V 3 moments
1	34.67	166.51	210.21	5.63	45.14	32.80	1.96	-6.64	-7.80
2	35.24	129.70	204.56	5.56	44.95	40.35	1.35	-6.39	-9.26
3	29.54	132.65	215.49	4.86	44.53	37.56	1.39	-5.63	-6.26
4	32.64	147.25	217.79	5.63	39.65	46.23	1.86	-6.93	-7.35
5	37.50	145.77	212.35	6.25	40.21	36.70	1. 53	-8.25	-8.65
6	37.45	151.64	213.29	4.34	36.54	38.62	1.96	-7.23	-6.23
7	29.22	139.46	207.24	5.35	37.89	49.12	1.76	-5.65	-8.32
8	30.69	146.80	201.46	5.12	35.65	47.86	1.63	-5.33	-7.65
9	33.27	194.60	205.28	6.37	34.98	48.65	1.95	-6.60	-8.65
10	38.98	147.25	35.20	3.65	35.32	35.63	1.22	-5.68	-7.25

Note: Mean value, deviation, 3rd order moment of L, a and b are shown in Table 4.

Table 4 Color characteristic parameters

Sample ID	L mean	a mean	b mean	L deviation	a deviation	b deviation	L3 moments	a 3 moments	b 3 moments
1	210.21	126.19	149.20	19.33	1.00	7.20	-5.13	0.24	1.92
2	220.25	129.70	134.45	18.56	0.95	6.70	-5.35	0.20	1.93
3	209.00	132.65	135.09	19.86	0.83	6.56	-6.39	0.33	193
4	199.34	127.25	137.69	22.25	0.65	7.52	-5.86	0.39	1.95
5	207.45	115.47	132.65	17.25	1.21	6.23	-6. 43	0.25	1.95
6	207.50	131.34	133.79	20.34	1.25	8.69	-5.94	0.43	1.85
7	209.32	129.46	155.96	22.00	0.89	6.48	-4.94	0.35	2.26
8	203.59	126.82	151.33	15.12	0.94	6.24	-6.09	0.33	1.65
9	188.28	124.40	135.67	16.37	0.98	8.65	-5.90	0.45	1.96
10	199. 39	133.25	135.20	18.06	0.86	8.63	-5.28	0.39	2.23

3.1.3 Extraction of texture feature

Texture refers to structure of object's surface; it can represent the properties such as crisscross, uneven surface, and rough or smooth texture change. Texture characteristics reflect the degree of smoothness of soybean surface; mildewed soybean will have folds on the surface which can be described by texture parameters quantitatively. Texture characteristic parameters of soybean are shown in Table 5.

Table 5 Texture characteristic parameters

Sample ID	Energy's mean	Energy's deviation	Difference's mean	Difference's deviation
1	0.00021	2.64	508.35	151.40
2	0.00022	3.00	509.56	153.23
3	0.00024	2.34	502.69	144.02
4	0.00025	2.40	511.35	147.50
5	0.00024	2.27	522.24	168.09
6	0.00021	2.65	495.31	156.54
7	0.00024	2.46	524.29	158.32
8	0.00022	2.65	534.55	138.26
9	0.00023	2.15	516.29	165.56
10	0.00023	2.62	510.23	157.45

3.2 Dimension reduction of feature data

Feature selection is crucial in pattern recognition and image analysis. It affects the performance of classifiers greatly. Multiple parameters of color, shape and other aspects were extracted in this study, but fewer parameters were used as the inputs of pattern recognition. As the number of inputs increases, the number of training samples will grow exponentially. In addition, some repeated and unimportant features will also weaken the ability of classification and reduce the accuracy of recognition. So it is important to reduce the dimension of feature data.

Thirty nine characteristic parameters of the color, texture and shape were extracted in this study. Principal component analysis (PCA) algorithm was used to reduce dimensions of feature data. The correlation between input vectors was eliminated by the transformation. The most information of original data was reserved after PCA transformation. More than 99% primary data were kept in this experiment. And the feature vectors were reduced from 39 dimensions to 12 dimensions. The neuron numbers of input layer in the neural network was reduced. Thus, it is easer to design neural network. The dimensionality was determined using the following equation:

$$pc_{m}=\sum_{i=1}^{n}\partial_i I_i \tag{1}$$

where, pc_m is the Mth principal component (PC-m); ∂_i is the weight coefficient of the principal component; I_i is the original characteristic parameters.

3.3 Modeling and analysis of BP neural network

3.3.1 Modeling method

The reasonable neural network was designed based on 12 dimension-reduced characteristics data. The specific process is shown as follows:

1) Input matrix was established with training samples (1500), testing samples (300) and expectations.

2) Comparing tramnmx function and premnmx function for normalization of input matrix, we selected premnmx function to normalize the input matrix which make the data distribute in the range of [-1, 1].

3) Newff function in the Matlab toolbox was used to designed BP neural network with three layers. There were12 neurons at input layer, 1 neuron at output layer.

4) Trainlm function was selected as the training function of the network which has a high speed of convergence and high precision.

5) Test the trained network.

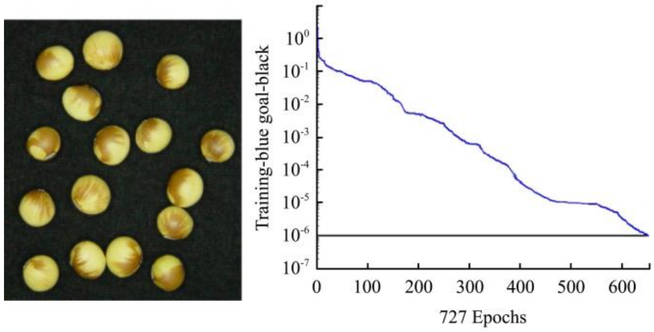
In the experiment, the number of iterations was 150. The learning rate was 0.2. The momentum factor was 0.9. The maximum number of training was 1 000. The training accuracy was le^{-6}.

3.3.2 Results of soybean diseases identification

In the process of neural network training, the weight value and threshold value need to be corrected constantly to make sure the output error minimum. After comparison, minimum mean square error (MSE) network was used for single sample identification in this study.

1) Identification of frogeye soybean

In the study, frogeye seeds should be distinguished from standards accurately. So we selected 640 images of normal soybeans and frogeye seeds for training, 160 samples for testing. From Figure 7, it can be concluded that the mean square error approximates error fits convergence goals; the predetermined precision can be achieved.

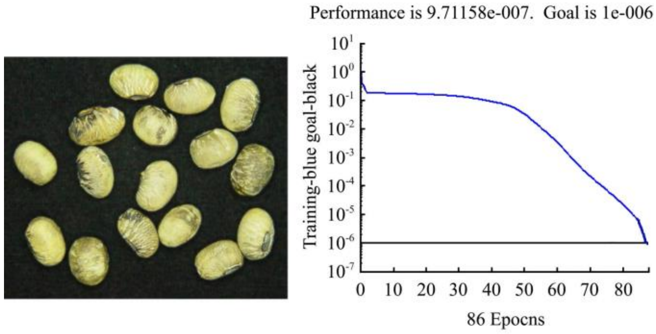


a. Image of frogeye seeds b. Network training result of frogeye seeds

Figure 7 Test results for frogeye seeds

2) Identification of mildewed soybean

There was obvious change for mildew soybeans. The volume became larger, soybean seeds softer, cotyledon color darker, and there was red circle in embryo. As shown in Figure 8, in the process of mildew soybean identification, 86 training steps generated better training effect.



a. Sample of mildewed seeds b. Network training result of mildewed seeds

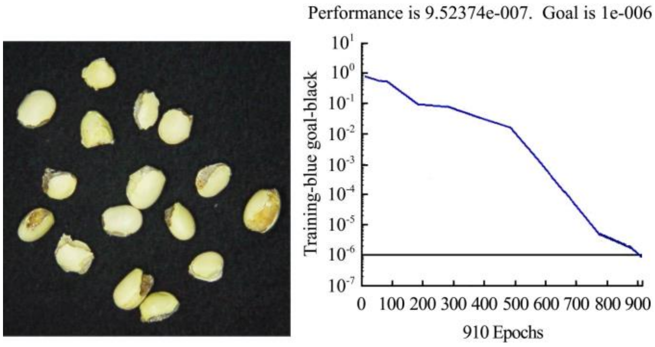
Figure 8 Test results for mildewed seeds

3) Recognition of worm-eaten soybean

It is generally irregular in the edge for worm-eaten soybean, and the color is dark brown. So good results can be achieved using morphological characteristics and color features to train the neural network. The result is shown in Figure 9.

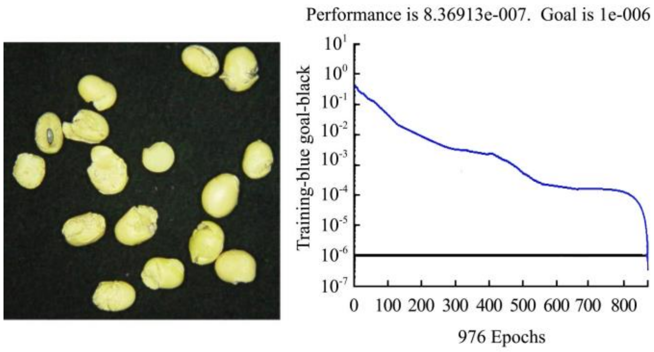
4) Identification of damaged soybean

Soybean seeds are mainly damaged during loading, transporting, and unloading process. At present, there is no effective way to avoid. It can be seen from Figure 10; the main defects of soybean seeds crushed perform in shape. It has the same color as normal soybean. So the morphological features were chosen as the main characteristic parameters. The result of damaged soybean classification of the classifier is shown in Figure 10.



a. Sample of worm-eaten seeds b. Network training result of worm-eaten seeds

Figure 9 Test results for worm-eaten seeds



a. Sample of damaged seeds b. Network training result of damaged seeds

Figure 10 Test results for damaged seeds

Identification results for normal seeds, frogeye seeds, mildewed seeds, damaged seeds, worm-eaten seeds and heterogeneous seeds are shown in Table 6 in this study. From Table 6, it is clear that the classification of single defect is better than that of mixed soybean. The identification accuracy is 100% for normal soybean. The average accuracy for other defect soybean is 93.75%. The accuracy for mixed soybean is 90%. Due to the uncertain place of soybean seed that is eaten by worm or damaged by machine, and the angle of lens, the part cannot be detected sometimes, and therefore the identification accuracy for damaged seeds and worm-eaten seeds were lower. The study also tested the classifier using mixed seeds infected with several diseases. The result illustrated that the identification accuracy for mixed seeds was lower than seeds with single disease. Zhao Danting, Chi Yuhua, et al. inspected soybean frogeye spot using image processing technique. In their research, the identification rates for peronospora hyoscyamin, break soybean and worm-eaten soybean are 92%, 86% and 87% respectively. Comparing with their results, the method used in the study in-conjunction with the ANN classifier could achieve overall classification accuracy of about 93.75%. The study illustrates that the classifier based on ANN can identify single defect soybean with high accuracy. However in practice it is possible that some diseases are infected in a single soybean, thus it is significant for comprehensive assessment of the appearance quality.

Table 6 Results of disease identification

Disease	Normal seeds	Frogeye seeds	Mildewed seeds	Damaged seeds	Worm-eaten seeds	Heterogeneous seeds
Number of test samples	100	100	100	100	100	100
Number of correct identification	100	96	95	92	92	90
Identification rate/%	100	96	95	92	92	90

4 Conclusions

The results indicated that it was useful to identify diseases of soybean applying neural network classifier. The recognition accuracy was 100% for the standard soybean, and 93.75% for seeds with deficiencies. The performance of the classifier for damaged soybean and worm-eaten soybean was relatively poorer, but the accuracy also reached 92% for both. Good detection result was obtained for heterogeneous seeds; the recognition accuracy was 90%. This study demonstrates that BP neural network can provide good technical support for single defect detection on soybean. However it is more likely that some defects coexist on the same soybean seed, therefore, it is more practical and valuable to evaluate the quality of soybean comprehensively. Future study will focus on designing a comprehensive classifier to recognize standard seeds, worm-eaten seeds, plaque seeds, damaged seeds, and mildewed seeds at one time.

Acknowledgements

We acknowledge the financial support of Heilongjiang Provincial Natural Science Foundation (ZD201303) and Youth Scientific Research Fund of Northeast Agricultural University.

[References]

[1] Feng X. Research on the development strategy of soybean industry in Heilongjiang Province. Beijing: China Science Press, 2011.

[2] Wang J F, Zhao X M, Song Y F, Bao D H, Chen G Y. Effects of appearance quality on the chemical quality of soybean. Heilongjiang Agricultural Sciences, 2006; (5): 23－24. (In Chinese with English abstract)

[3] Hernández-Hierro J M, Valverde J, Villacreces S, Reilly K, Gaffney M, González-Miret M L, et al. Feasibility study on the use of visible-near-infrared spectroscopy for the screening of individual and total glucosinolate contents in broccoli. Journal of Agricultural and Food Chemistry, 2012; (60): 7352－7358.

[4] Fernández-Vázquez R, Stinco C, Meléndez-Martínez A J, Heredia F J, Vicario I M. Visual and instrumental evaluation of orange juice color: a consumers' preference study. Journal of Sensory Studies, 2011; (26): 436－444.

[5] Zhao D T, Chai Y H, Zhang C L. Research on detection technology of soybean frogeye based on image processing technology. Journal of Northeast Agricultural University, 2010; 41(4): 119－123. (In Chinese with English abstract)

[6] Li C, Wang B, Wang J, Li F. Extracting vein of leaf image based on K-means clustering. Transactions of the CSAE, 2012; (28): 157－162. (In Chinese with English abstract)

[7] Arzate-Vázquez I, Chanona-Pérez J J, de Perea-Flores M J, Calderón-Domínguez G, Moreno-Armendáriz M A, Calvo H, et al. Image processing applied toclassification of avocado variety hass (Persea americana Mill.) during theripening process. Food and Bioprocess Technology, 2011; (4): 1307－1313.

[8] ElMasry G, Sun D W. Meat quality assessment using a hyperspectral imaging system. In: Sun, P.D.-W. (Ed.), Hyperspectral Imaging for Food Quality Analysis and Control. Academic Press, San Diego, 2010; 175－240.

[9] Mathiassen J R, Misimi E, Bond M, Veliyulin E, tvik S O. Trends in application of imaging technologies to inspection of fish and fish products. Trends in Food Science and Technology, 2011; (22): 257－275.

[10] Ling Y, Wang Y M, Sun M, Sun H, Zhang X C. Rice appearance quality detection device based on machine vision. Transactions of the CSAM, 2005; 36(9): 89－92. (In Chinese with English abstract)

[11] Yang F, Zhu S P, Qui Q M. Chinese prickly ash appearance quality detection based on computer vision and MATLAB. Transactions of the CSAE, 2008; 24(1): 198－202. (In Chinese with English abstract)

[12] Xu L, Qian M J, Fang R M. Rice processing precision identification method. Transactions of the CSAE,, 1996; 12(3): 34－38. (In Chinese with English abstract)

[13] Jarimopas B. An experimental machine vision system for sorting sweet tamarind. Journal of Food Engineering, 2008; (89): 291－297.

[14] Blasco J, Aleixos N, Moltó E. Machine vision system for auto-matic quality grading of fruit. Biosystems Engineering, 2003; 85(4): 415－423.

[15] Alireza Yadollahinia, Mehdi Jahangiri. Shrinkage of potato slice during drying. Journal of Food Engineering, 2009; (1): 52－58.

[16] Zhan H, Li X Y, Wang W. Chestnut hierarchical detection method based on machine vision. Transactions of the CSAE,, 2010; 26(4): 327－331. (In Chinese with English abstract)

[17] He M, Ma S S, He X D. Potato shape detection based on the Zernike moment. Transactions of the CSAE, 2010; 26(2): 347－350. (In Chinese with English abstract)

[18] Guan Z X, Kang J, Yang B J. Research on rice disease recognition method based on image. The Chinese Rice Science, 2010; 24(5): 497－502. (In Chinese with English abstract)

[19] Xiong Kai, Li Xianghong, Li Yanzhao. Characteristics of corn varieties analysis and recognition based on ANN and PCA. Grain and Oil Food Science and Technology, 2010; 18(4): 1－5. (In Chinese with English abstract)

[20] Han Z Z, Zhao Y G. Study on the detection of peanut quality grading based on computer vision. Agricultural Sciences in China, 2010; 43(18): 3882－3891. (In Chinese with English abstract)

[21] Yang J H, Liu J. Segmentation algorithm based on watershed and automatic seeded region growing image. China Journal of Image and Graphics, 2010; 1(15): 63－68. (In Chinese with English abstract)

[22] Piotr Zapotoczny. Discrimination of wheat grain varieties using image analysis and neural network. Part I. Single kernel texture. Journal of Cereal Science, 2011; (54): 60－80.

[23] W Medina, Skurtys O, Aguilera J M. Study on image analysis application for identification Quinoa seeds (Chenopodium quinoa Willd) geographical provenance. Food Science and Technology, 2010; (43): 238－246.

[24] Siriluk Sansomboonsuk, Nitin Afzulpurkar. Machine vision for rice quality evaluation. Technology and Innovation for sustainable development conference, 2008; 343－346.