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Quality Inspection Method of Agricultural Products Based on Image Processing

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ABSTRACT

Farmers should provide high-quality agricultural products and companies should receive high-quality agricultural products, which is the purpose and pursuit of the business model of "companies plus farmers". In order to increase the stability of the cooperation mode between companies and farmers, it is necessary to detect the quality of agricultural products accurately, objectively and efficiently. Therefore, this article studies the quality inspection method of agricultural products based on image processing. Firstly, the traditional threshold calculation method and threshold function are improved to obtain more ideal denoising effect of agricultural products images. Aiming at the problem that the traditional image processing model cannot obtain fine-grained feature information of image objects, a multi-level feature dependence extraction network is constructed, and the structure and working principle of the network model are introduced in detail. Experimental results verify the effectiveness of the proposed algorithm and model for agricultural product quality inspection.

1. INTRODUCTION

The business model of "companies plus farmers" began in 1980s. As its name implies, it connects "big companies" with "small farmers" and establishes mutually beneficial supply and marketing relations in the form of contracts [1-7]. This business model has played an active role in farmers' learning production technology and improving the quality of agricultural products. The quality and safety of agricultural products is related to the stability of cooperation between companies and farmers [8-13]. In this community of interests formed through contract mechanism, companies and farmers need to clarify their respective rights and obligations and liabilities for breach of contract. It is the purpose and pursuit of the business model of "companies plus farmers" for farmers to provide high-quality agricultural products and companies to receive high-quality agricultural products [14-19]. Therefore, the quality inspection of agricultural products needs to be accurate, objective and efficient. The traditional pattern recognition method of intelligent sensor system has a single function, which is prone to over-fitting, poor generalization ability and low detection efficiency [20-22]. Therefore, it's of significance in research and practice to analyze and detect the quality of a variety of agricultural products based on image processing technology.

Current quality inspection, classification and distribution systems have the disadvantages of low yield, larger time consumption, high cost and complexity. Research on machine-controlled fruit selection using image processing aims to create higher quality fruit selection, quality maintenance and production, and reduce labor concentration. Liu et al. [23] comprehensively reviews the current work related to automatic classification and grading of agricultural products. A complete end-to-end automatic and efficient fruit classification and grading system based on image processing is also proposed. Preliminary experimental results prove the effectiveness of the structure. Chen et al. [24] takes agricultural products trademarks as the research object, and designs an image retrieval method based on the shape features of agricultural products trademarks. The boundary feature of trademark image is represented by classical Fourier descriptor, and the regional feature of trademark image is represented by the ratio of target pixel to background pixel. Agricultural products trademarks are retrieved based on the similarity measurement of boundary and regional features. Abbas et al. [25] attempts to identify important features by using weighted feature vectors, rough theory and fuzzy logic, and find higher accuracy in retrieval results, so as to identify the importance of each feature according to users' opinions in each feedback stage. This method is compared with fuzzy color histogram, combination method and fuzzy neighborhood entropy characterized by color location. Simulation results show that compared with the existing methods, the proposed method has higher applicability in image marketing. It's essential to understand the optical properties of food and agricultural products for quality and safety assessment using optical technology. Wang et al. [26] aims to optimize the frequency region by inverse algorithm, so as to better quantify the optical absorption and reduce the scattering coefficient of double-layer food and agricultural products from the spatial frequency domain reflectivity. The frequency region defined by the start frequency and the end frequency is firstly optimized for the parameter estimation of the first layer and the second layer, respectively [27, 28].

The existing target detection model has too many parameters and computation, and its detection performance is inefficient. However, the above-mentioned methods mainly weigh the extracted image target features from spatial domain, channel domain and mixed domain, which is not conducive to obtaining more layers of attention from more detailed image target feature information, and finally leads to the limitation of image target detection effect. Therefore, this article studies the quality inspection method of agricultural products based on image processing. Firstly, in the second chapter, the traditional threshold calculation method and threshold function are improved to obtain more ideal denoising effect of agricultural products images. As the traditional image processing model ignores the relationship between the low-level features and the high-level features of the image object, it is impossible to obtain the fine-grained feature information of the image object. In the third chapter, a multi-level feature dependence extraction network is constructed, and the structure and working principle of the network model are introduced in detail. Experimental results verify the effectiveness of the proposed algorithm and model for quality inspection of agricultural products.

2. IMAGE DENOISING OF AGRICULTURAL PRODUCTS BASED ON OPTIMIZED DISCRETE WAVELET TRANSFORM

Traditional thresholding denoising theories have some limitations in the field of image processing. Some scholars mainly improve the traditional algorithm through threshold optimization and threshold function optimization, but these improvements are carried out unilaterally. This article improves the threshold calculation method as well as threshold function in order to obtain more ideal denoising effect of agricultural products images. Figure 1 shows the schematic diagram of agricultural product image denoising process.

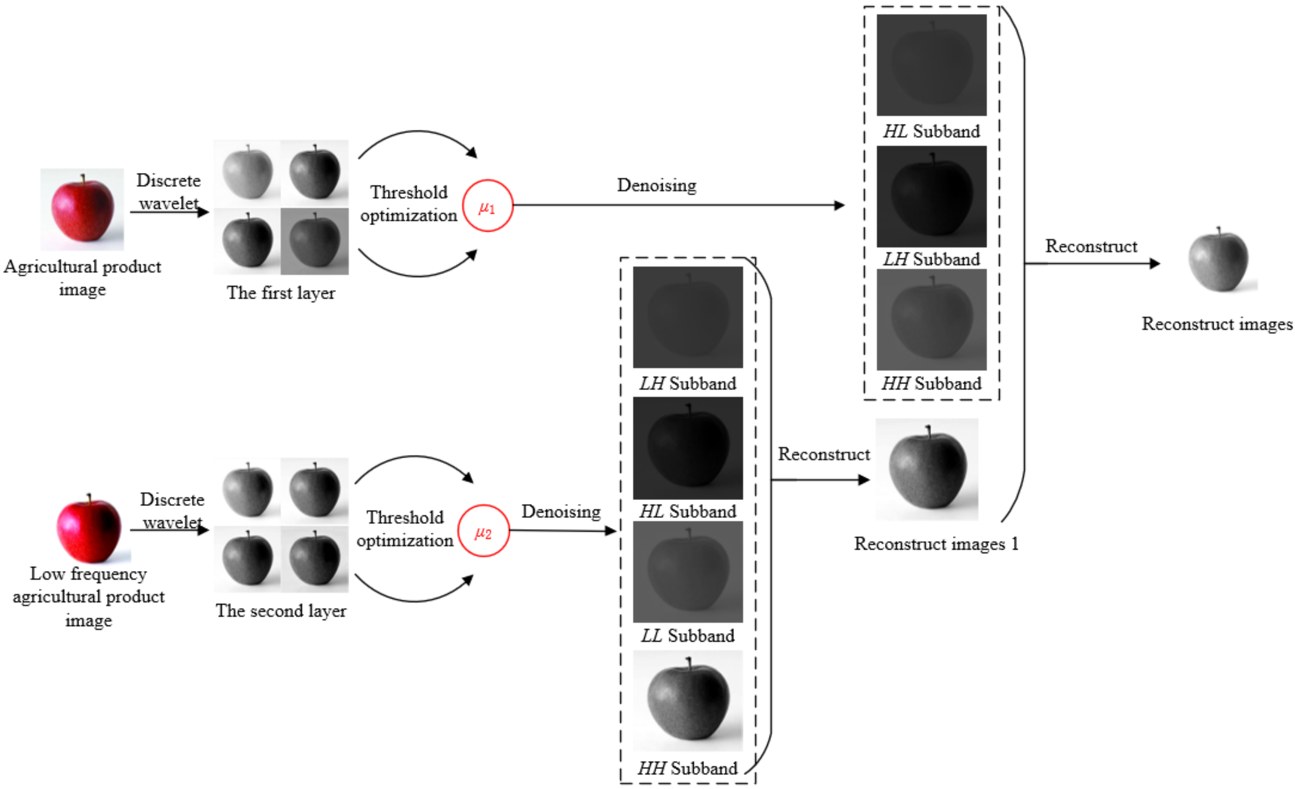

Figure 1. Schematic diagram of agricultural product image denoising process

The more the wavelet basis function matches the image of agricultural products, the more accurate the quality information of agricultural products extracted by this function will be. The matching degree between wavelet basis function and noisy image of agricultural products can be characterized by the cross-correlation coefficient between the approximate coefficient obtained by discrete wavelet transform and the original agricultural product image. Assuming that the size of the original agricultural product image $a(m)$ is represented by M, the l-th wavelet coefficient of $a(m)$ on the x-th decomposition layer is represented by $\theta P(x,l)$, the approximation coefficient on the x-th decomposition layer is represented by $\theta P(x)$, and the average value of the noisy image of agricultural products is represented by a^*, the following formula gives the definition formula of the cross-correlation coefficient between the approximation coefficient of noisy image of agricultural products and the original agricultural product image:

$$s=\frac{\sum_{l=1}^{M}\left[a(l)-a^*\right]\left[\theta P(x,l)-\overline{\theta P(x)}\right]}{\sqrt{\sum_{l=1}^{M}\left[a(l)-a^*\right]^2\sum_{l=1}^{M}\left[\theta P(x,l)-\overline{\theta P(x)}\right]^2}} \tag{1}$$

Traditional threshold calculation methods do not calculate thresholds independently for each decomposition layer. In this article, threshold calculation is regarded as a numerical optimization problem, and the threshold of wavelet coefficients on each decomposition layer is solved based on genetic algorithm.

Firstly, the noisy image of agricultural products is transformed by wavelet basis function to obtain the noisy wavelet coefficients $\theta_{j,l}$ of each decomposition layer. Then the optimal thresholds μ_1, μ_2, … μ_m are obtained by using genetic algorithm to optimize $\theta_{j,l}$. In this article, SNR is selected to evaluate the optimal threshold μ_m obtained on each decomposition layer of agricultural product image. Assuming that the size of agricultural product image is represented by $N\times M$, the original agricultural product image is represented by $g(i,j)$, and the denoised agricultural product image is represented by $h(i,j)$, the following formula gives the definition formula of signal-to-noise ratio:

$$XZ = 101h\left(\frac{\sum_{i=1}^{N}\sum_{j=1}^{M} g^2(i,j)}{\sum_{i=1}^{N}\sum_{j=1}^{M}\left[g(i,j)-h(i,j)\right]^2}\right) \tag{2}$$

Hard threshold function, soft threshold function and soft-hard compromise threshold are three common threshold functions. Figure 2 shows a schematic diagram of a common threshold function. It is assumed that the wavelet coefficients generated by discrete wavelet transform of noisy image of agricultural products are represented by $\theta_{j,l}$, and the denoising wavelet coefficients obtained by threshold function are represented by $\theta'_{j,l}$.

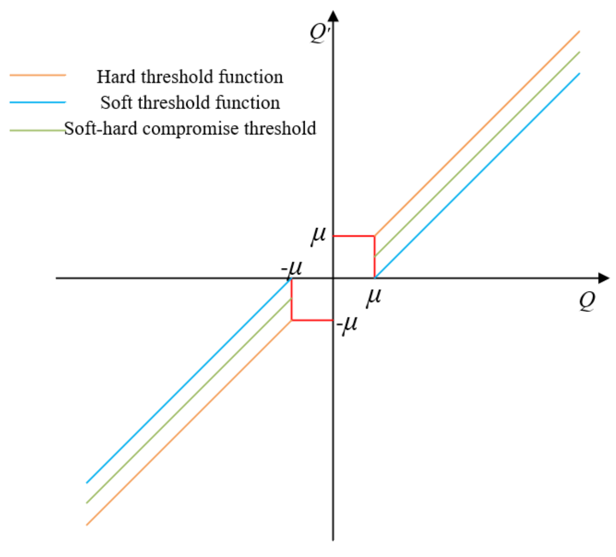

Figure 2. Schematic diagram of common threshold function

Hard threshold function, soft threshold function and soft-hard compromise threshold have some limitations in the application scenarios of wavelet denoising of agricultural product images. At μ and a μ, the soft threshold function is continuous and the hard threshold function is discontinuous, and $\theta_{j,l}$ is not equal to $\theta'_{j,l}$. With the increase of $\theta_{j,l}$, the proportion of wavelet coefficients of effective feature information of agricultural products images will gradually increase, which can make $|\theta'_{j,l}-\theta_{j,l}|$ approach 0 as much as possible. However, the soft-hard threshold compromise function, which combines hard threshold function and soft threshold function simply, has no obvious denoising advantage. Therefore, as to the shortcomings of traditional threshold functions, this article constructs the following nonlinear two-parameter threshold functions:

$$\theta'_{j,l} = \begin{cases} \operatorname{sgn}\left(\theta_{j,l}\right)\bullet\left[\left|\theta_{j,l}\right| - \dfrac{x\mu}{\left(\dfrac{\left|\theta_{j,l}\right|-\mu}{y\mu}\right)+1}\right], \left|\theta_{j,l}\right| \ge \mu \\ 0, \left|\theta_{j,l}\right| < \mu \end{cases} \tag{3}$$

In order to determine the image denoising advantage of the above function, after determining x and y, only $|\theta'_{j,l}|\geq\mu$ is considered, set:

$$g(a) = \operatorname{sgn}(a)\left[|a| - \frac{x\mu}{\left(\dfrac{|a|-\mu}{y\mu}\right)+1}\right] \tag{4}$$

$$\begin{aligned} &\text{When a}>0,\ g(a) = a - \frac{x\mu}{\left(\dfrac{a-\mu}{y\mu}\right)+1} \\ &a<0,\ g(a) = a + \frac{x\mu}{\left(\dfrac{-a-\mu}{y\mu}\right)+1} \end{aligned} \tag{5}$$

When x=1, $g(a)$ is continuous at $\pm\mu$ and $g(\theta_{j,l})$ is continuous in wavelet domain, which makes up for the discontinuity of hard threshold function at μ and a μ. The function takes $b=a$ as asymptotic and $\theta_{j,l}\rightarrow\infty$, $g(\theta_{j,l})$ gradually approaches $\theta_{j,l}$, which overcomes the disadvantage that the soft threshold function $\theta'_{j,l}$ is not equal to $\theta_{j,l}$.

In Formula 3, x and y are the adjustment factors for the position and bending degree of conditional threshold function, and are the key to denoising noisy image of agricultural products based on two-parameter threshold function. In this article, x and y are determined based on particle swarm optimization. It is assumed that the velocity component of the i-th particle in c dimension at time p is represented by U^{t}_{ic}, the updated velocity component of the i-th particle is represented by U^{t+1}_{ic}, the inertia weight is represented by θ, and the random numbers from 0 to 1 are represented by SJ (m'). The number of random numbers is represented by m, the learning factor is represented by d_1 and d_2, the individual extreme value is represented by t_{best}, the global extreme value is represented by h_{best}, the position component of the i-th particle in c dimension at p time is represented by A^{p}_{ic}, the updated position component of the i-th particle is represented by A^{t+1}_{ic}, and the p-th iterative operation is represented by p. The following formula gives the calculation formula of particle iteration speed and position in particle swarm optimization:

$$\begin{aligned} U_{ic}^{p+1} &= \theta\cdot U_{ic}^{p} + d_1\cdot SJ\left(m'\right)\cdot\left(t_{best}-A_{ic}^{p}\right) \\ &+ d_2\cdot SJ\left(m'\right)\cdot\left(h_{best}-A_{ic}^{p}\right) \end{aligned} \tag{6}$$

$$A_{ic}^{p+1} = A_{ic}^{p} + U_{ic}^{p+1} \tag{7}$$

In order to make the fitness function of particle swarm optimization have ideal convergence rate, this article set the convergence factor as L, set $L=2/|2-\psi-(\psi^2-4\psi)^{1/2}|$, $\psi=d_1+d_2$, $\psi>4$, then:

$$U_{ic}^{p+1} = L\begin{bmatrix} U_{ic}^{p} + d_1 \cdot SJ(m') \cdot \left(t_{best} - A_{ic}^{p}\right) \\ +d_2 \cdot SJ(m') \cdot \left(h_{best} - A_{ic}^{p}\right) \end{bmatrix} \tag{8}$$

3. QUALITY INSPECTION OF AGRICULTURAL PRODUCTS BASED ON MULTI-LEVEL FEATURES

Traditional image processing models ignore the relationship between low-level features and high-level features of image objects, so they cannot obtain fine-grained feature information of image objects, which affects the performance of target detection. That's, it is difficult for low-level neurons in shallow network to obtain effective discriminative features, while the local features extracted by high-level neurons in deep network are prone to lack diversity. Therefore, this article constructs a multi-level feature dependence extraction network to solve the above problems.

In order to extract the local information of each decomposition layer, this article constructs the correlation between convolution channels of convolution neural network to obtain the channel information of each decomposition layer $\{X_1, X_l, \ldots, X_L\}$, and then generates the bottom-up path from X_L to X_1. This path is combined with the existing top-down path with opposite direction, and can realize the connection of bidirectional paths of the model. It is assumed that the learnable parameters in the fully connected layer are represented by Q_s and Q_r, and the width, height and position coordinates of G_l in the spatial domain are represented by Q, F and (i,j), respectively. Through the processing of global average pooling layer and two fully connected layers, $X_L \in R^{F\times Q\times D}$ can be generated, specifically as follows:

$$X_l = sigmoid\left(Q_r \cdot \mathrm{Re}LU\left(Q_S \cdot GAP(G_l)\right)\right) \tag{9}$$

$$GAP(G_l) = \frac{1}{Q\times F}\sum_{i=1}^{F}\sum_{j=1}^{Q} G_l(i,j) \tag{10}$$

Then, G_l is weighted and pooled by global average, and the key information in each decomposition layer is extracted to obtain the multi-level feature $N_l \in R^{1\times D}$ of agricultural product image:

$$N_l = GAP(G_l \cdot X_l) \tag{11}$$

In order to reduce the redundant information of local features of agricultural products, this article evaluates and selects the first largest feature map of agricultural products after descending order by using non-maximum inhibition method, and obtains the average value G_x of the feature map. The image region exceeding $\omega\times G_x$ is set to 0, and suppression is performed by a suppression mask R shown by the following formula:

$$R(i,j) = \begin{cases} 0, N_l > \omega\times G_X \\ 1, otherwise \end{cases} \tag{12}$$

In order to further realize the mining of fine-grained features of agricultural product quality, this article gradually combines the more detailed local information in N_l with the key feature information learned in each decomposition layer, and introduces *LSTM* modeling and attention gating to solve the adaptive adjustment of attention degree of complementary fine-grained features among each decomposition layer. Figure 3 shows the framework of agricultural product quality inspection network model.

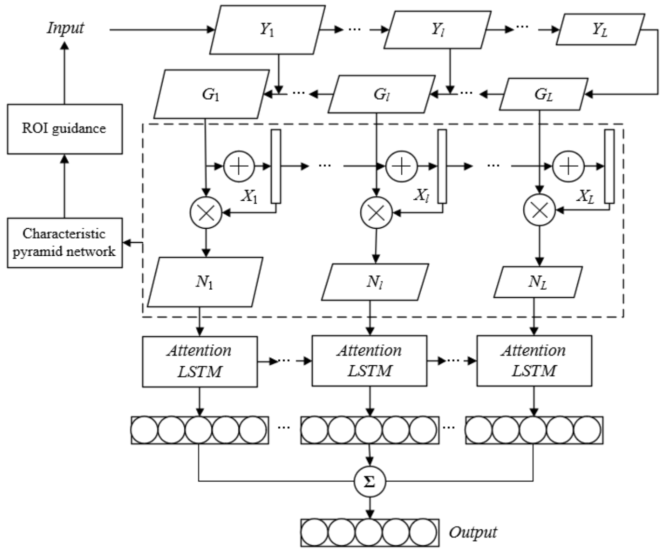

Figure 3. Network model framework of agricultural product quality inspection

A conventional *LSTM* unit contains three gate structures, namely forgetting gate g^k_l, input gate i^k_l and output gate e^k_l, with the introduced attention gate represented by x^k_l. Assuming that the cell state is represented by d^k_l, in the network attention module, the input of the $(k+1)$ layer is obtained based on the calculation of f^k_l and d^k_l. Let $k\in[0,K]$, the number of layers of *LSTM* is denoted by K, the multiplication and addition of corresponding elements are denoted by ⊕ and ⊗ respectively, the forgetting gate of layer k is denoted by g^k_l, the cell state of the previous feature is denoted by d^k_{l-1}, the candidate state before entering the cell state is denoted by h^k_l, and the input gate and output gate of each cell are denoted by i^k_l and e^k_l respectively. The d^k_l and f^k_l of layer k can be calculated by the following formula:

$$d_l^k = g_l^k \otimes d_{l-1}^k \oplus i_l^k \otimes h_l^k \tag{13}$$

$$f_l^k = e_l^k \otimes \tanh\left(d_l^k\right) \tag{14}$$

The attention gate x^k_l can be regarded as a vector with the same size as N_l at the k-th layer. Figure 4 shows the structure diagram of *LSTM* unit with attention gating. x^k_l is set mainly for adaptively adjusting different inputs. Assuming that the weight of current input, the weight of previous hidden layer and the weight of offset in x^k_l are represented by Q_x, Q_y and y_h respectively, then:

$$x_l^i = sigmoid\left(Q_x \cdot N_l^k + Q_c \cdot f_{l-1}^k + y_h\right) \tag{15}$$

x^k_l can effectively characterize the importance of the l-level feature N^k_l and the l-level hidden layer f^k_{l-1} to the fine-grained information of agricultural product quality in N^k_l. Then, the response of N^k_l in each decomposition layer to the fine-grained information of agricultural product quality is effectively adjusted by the gating of attention gate, and updated as $d^l_k c^k_l$:

$$c_l^i = N_l^k \cdot x_l^k \tag{16}$$

Therefore, based on the updated input c^k_l, the calculation results of other activation and gating modules of the *LSTM* unit can be obtained, and the specific calculation formulas of g^k_l, i^k_l, h^k_l and e^k_l are given by the following formula:

$$g_l^k = sigmoid\left(Q_g{}' \cdot c_l^k + Q_g \cdot \left[f_{l-1}^k, f_f^{k-1}\right] + y_g\right) \tag{17}$$

$$i_l^k = sigmoid\left(Q_i{}' \cdot c_l^k + Q_i \cdot \left[f_{l-1}^k, f_l^{k-1}\right] + y_i\right) \tag{18}$$

$$h_l^k = sigmoid\left(Q_h{}' \cdot c_l^k + Q_h \cdot \left[f_{l-1}^k, f_l^{k-1}\right] + y_h\right) \tag{19}$$

$$e_l^k = sigmoid\left(Q_e{}' \cdot c_l^k + Q_e \cdot \left[f_{l-1}^k, f_l^{k-1}\right] + y_e\right) \tag{20}$$

After splicing $\{f^k_1, f^k_2, \ldots, f^k_l, \ldots, f^k_L\}$ and then inputting them into the fully connected layer and *softmax* classifier for processing, the fine-grained feature classification of agricultural product quality can be realized, and finally the evaluation results of agricultural product quality can be obtained.

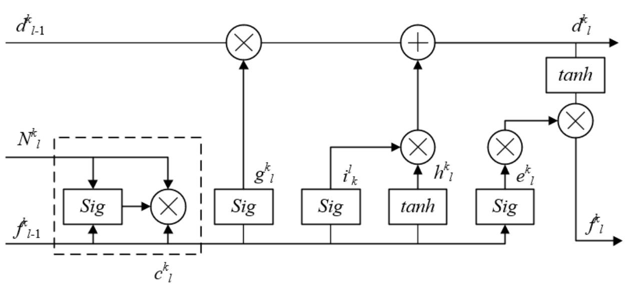

Figure 4. Structure diagram of *LSTM* unit with attention gating

4. EXPERIMENTAL RESULTS AND ANALYSIS

Six sample images of agricultural products were processed by five-layer discrete wavelet transform using six different series of wavelet basis functions. Based on six sample images of agricultural products and wavelet coefficients decomposed by wavelet basis functions, the cross-correlation coefficients corresponding to a single wavelet with the best performance are calculated. Figure 5 shows the change of cross-correlation coefficient under different decomposition levels. Based on Figure 5, the wavelet basis functions are selected, and *Haar* wavelet basis functions are selected as the most suitable wavelet basis functions for further experiments. Table 1 gives the final result of threshold calculation based on genetic algorithm after twice wavelet decomposition, and gives the maximum fitness function value after 200, 330, 250, 350, 430 and 470 iterations and the threshold of each decomposition layer at corresponding time.

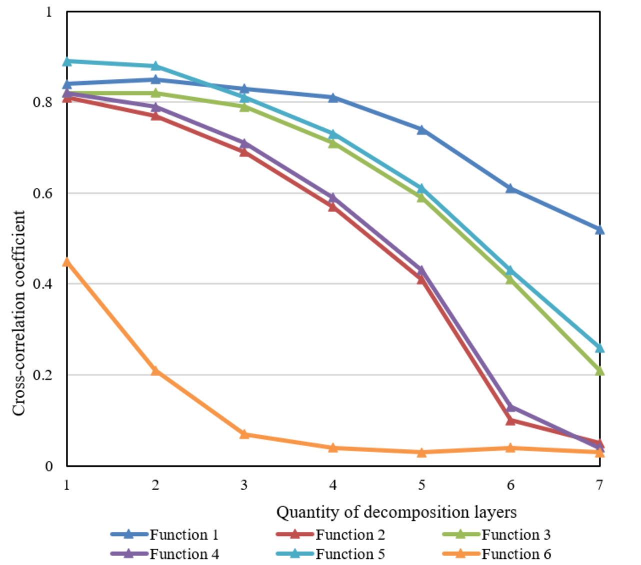

Figure 5. Change of cross-correlation coefficient under different decomposition layers

Table 1. Final result of threshold calculation

	Sample 1	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**	**Sample 6**
Wavelet basis function	Haar	Haar	Haar	Haar	Haar	Haar
Decomposition layer	2	5	4	5	6	6
Iterations of SNR convergence	200	330	250	350	430	470
Maximum SNR	6.85	6.12	6.67	4.08	3.42	5.24
Maximum iterations	600	600	600	600	600	600
Optimal threshold value at each decomposition level	μ_1=25 μ_2=17	μ_1=25 μ_2=17 μ_3=13 μ_4=11	μ_1=21 μ_2=18 μ_3=13	μ_1=23 μ_2=16 μ_3=15 μ_4=11	μ_1=23 μ_2=18 μ_3=11 μ_4=8 μ_5=6	μ_1=27 μ_2=18 μ_3=14 μ_4=9 μ_5=3

Two different threshold calculation methods, general method and genetic algorithm, are used to denoise agricultural product images, and can retain valuable agricultural product quality feature information and improve the identifiability of the model to image feature areas. For this article, SNR, PSNR, MSE and RMSE are selected to compare the advantages and disadvantages of the two threshold calculation methods. The experimental results are given in Table 2. It can be seen from Table 2 that the performance index values of the two threshold calculation methods after denoising agricultural product images are quite different. The threshold calculation based on genetic algorithm proposed in this article has better performance after denoising six samples of agricultural products, with SNR mean and PSNR mean increased, and MSE mean and RMSE mean decreased.

Table 2. Comparison results of threshold calculation methods

Threshold	Evaluation parameter	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Mean
Universal threshold	*SNR*	4.45	5.42	3.87	1.09	2.23	1.86	3.15
	PSNR	32.08	32.86	34.62	28.91	29.72	2.53	26.79
	MSE	40.16	33.07	45.53	85.03	67.08	73.45	57.39
	RMSE	6.45	5.63	6.4	9.23	8.21	8.62	7.42
Calculate threshold with genetic algorithm	*SNR*	9.87	9.35	10.52	10.81	9.68	10.61	10.14
	PSNR	37.62	37.12	38.69	38.49	37.42	38.62	37.99
	MSE	10.84	12.26	9.26	9.16	12.04	9.45	10.50
	RMSE	3.41	3.51	3.05	3.05	3.42	3.12	3.26

Table 3. Results of ablation experiment

Method	Computation	Parameters	Classification accuracy
Before the construction of channel correlation (A curve)	17.1	26.4	84.2
Before non-maximum suppression method (B curve)	26.5	26.4	85.1
Before key feature information fusion (C curve)	26.5	26.4	86.8
Before the introduction of attention gating (D curve)	30.2	29.2	88.7
Final model (E curve)	31.9	30.5	90.9

In order to prove the effectiveness of the multi-level feature dependence extraction network for agricultural product quality inspection, this article designs an ablation experiment, and the experimental results are shown in Table 3. As can be seen from the table, the correlation between convolution channels of convolution neural network is constructed, the non-maximum inhibition method is used to evaluate and select the first largest agricultural product feature map after descending order, and the more detailed local information is gradually combined with the key feature information learned in each decomposition layer, and the model optimization measures such as attention gating are introduced to effectively improve the accuracy of the model for agricultural product quality detection.

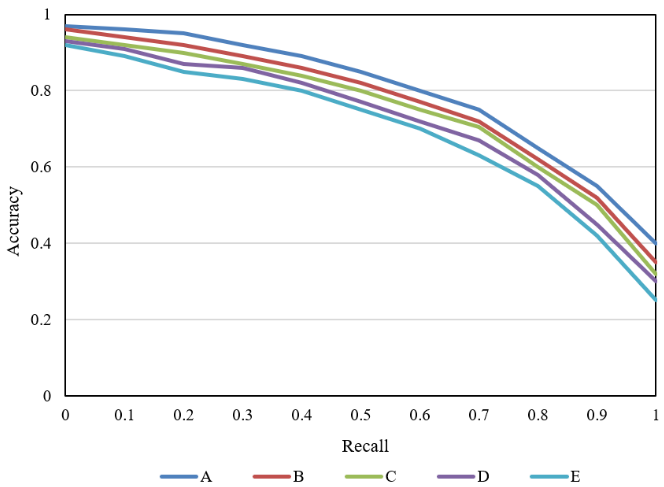

Figure 6. PR curves before and after the implementation of different optimization measures

Figure 6 shows the PR curves before and after the implementation of different optimization measures. As can be seen from the figure, the PR curve of the model after the implementation of optimization measures is lower, and the mAP value is correspondingly reduced. This shows that the key feature information fusion effectively provides more detailed features of agricultural product quality, equivalent to data enhancement; by introducing attention gating, the salient areas in the image are suppressed and the background areas are eliminated at the same time, and the attention of the features of each decomposition layer to the fine-grained feature information of agricultural product quality is adaptively adjusted. Finally, the purpose of improving the effective classification of agricultural product quality evaluation results based on the network model is achieved.

5. CONCLUSION

This article studies the quality inspection method of agricultural products based on image processing. Firstly, the traditional threshold calculation method and threshold function are improved to obtain more ideal denoising effect of agricultural products images. Aiming at the problem that the traditional image processing model cannot obtain fine-grained feature information of image objects, a multi-level feature dependence extraction network is constructed, and the structure and working principle of the network model are introduced in detail. The experimental results show the change of cross-correlation coefficients under different decomposition levels. *Haar* wavelet basis function is selected as the most suitable wavelet basis function for further experiments. The final result of threshold calculation is given, which verifies the effectiveness of threshold calculation based on genetic algorithm proposed in this article. Ablation experiment is designed to verify the effectiveness of the multi-level feature dependence extraction network for agricultural product quality inspection.

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