

An image processing method for green apple lesion detection in natural environment based on GA-BPNN and SVM

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Abstract - The technologies of information processing, especially the image processing, are important technical means to realize intelligent management and control of modern orchard. In order to realize the intelligentization of orchard production, the orchard image database, especially the lesion image database needs to be set up. Because of the uneven illumination and the complex background under the natural light condition, traditional image segmentation methods cannot solve the adaptive threshold issue during the lesion image processing of green apples. This paper proposes an image processing method based on a BP neural network updated by genetic algorithm (GA-BPNN) and support vector machine (SVM) to realize lesion image processing of green apples in orchard. With this method, apple images can be processed in batch and the lesion image database can be consummated automatically. Furthermore, the recognition of the diseased apple is realized. The experimental results show that the proposed method can obtain green apple segmentation and lesion detection with good efficiency and robustness in complex natural orchard environment.

Keywords - GA-BPNN; ROI; SVM; Lesion Image Database; Recognition of the diseased apple;

I. INTRODUCTION

Nowadays, with the popularization of large farms and big orchards, it is an important task to accurately judge the real time status of crops, identify and respond to the occurrence of pests and diseases in time by image information. So it's essential to build crop image databases [1]. Computer vision technology, including object recognition, image segmentation, feature extraction, etc. has been widely applied in agriculture [2,3]. With the growing requirement of recognition accuracy, some new or improved image processing methods are constantly being proposed to improve the traditional ones, such as background light compensation method [4], CVS-MLP method [5], region-based image segmentation method [6] and so on.

Image segmentation technology is widely used in target recognition [7]. The foreground and background are separated in the image to accurately extract the target information and identify the target object. Image segmentation method based on threshold has been widely applied into the detection of crops in the past. Li Q et al. set a fixed threshold manually to separate the foreground and background [8]. In the application of apple images segmentation, a multi-threshold method was used to separate images of apples and background [9]. Mizushima et al.

used SVM to generate new grayscale images, and then achieved image segmentation combined with Otsu algorithm [10]. However, these methods were carried out under a fixed background and cannot be well applied into the environment with uneven illumination conditions and complex backgrounds. Liu et al. used six components in RGB and HSI color spaces to train a neural network, and carried out image segmentation of apples illuminated by intense light at night [11]. This method has good timeliness, but the black background at night and the mirror reflection on apple surface reduce the difficulty of image segmentation. The applicability of the algorithm is poor when the background is complex during the daytime. Raphael et al. proposed an algorithm for counting the number of green apples in RGB space [12]. The experiment result under uniform illumination at sunset is better than that under uneven illumination during the daytime.

The lesion image of fruit is one of the important sources for the agronomist to identify the diseased fruit and the type of lesion. In the study of recognition and processing of fruit lesion images, Tan et al. used CNN method to extract the lesion images on apple surface and deal with them [13]. Omrani et al. used the support vector regression method to segment the lesion regions from the images of leaves [14]. However, these methods process lesion images after targeted collection of diseased individuals. They cannot do well with the lesion image processing under the status of plant growth in complex environment.

In order to improve the robustness and accuracy of plant image processing, neural network and other machine learning methods have been widely adopted [15,16,17]. BPNN has good nonlinear mapping ability, high self-learning and adaptive ability, which provides the possibility of processing fruit images in orchard with complex background and uneven illumination. Under different environments, the parameters can be adjusted adaptively by neural network self-learning, and the corresponding processing model can be obtained. In apple image processing, Zarifneshtat et al. used artificial neural network to predict the apple bruise volume [18]. SVM is another effective method in image processing. It can effectively solve machine learning problems with small samples and high dimensions. It was also used in the recognition of fruit lesion images. Rumpf et al. used SVM method to detect and classify plant diseases [19]. Ebrahimi et al. used SVM method to separate

images of plant and insect pests, so as to complete the detection of pests [20].

In this paper, a GA-BPNN algorithm is proposed to realize adaptive multi-threshold image binarization. After image binarization processing, an image post-processing method is used to realize the segmentation of green apple image, and the ROI of green apple is extracted. Based on the results of the above process, a soft margin SVM algorithm based on RBF kernel is used to extract the lesion image of green apples. According to the relationship between the centroid of the lesion region and the centroid of the connected domain of ROI, the recognition of the diseased apple is realized. With this method, apple images can be processed in batch and the lesion image database can be consummated automatically.

II. SEGMENTATION ALGORITHM OF GREEN APPLE IMAGES

A. Image Features Analysis of Green Apples in Orchard

In the modern orchard, the growth of typical fruit trees is monitored continuously by fixed camera. The information provides technical basis for the orchard management and decision-making. In this paper, apple experiment were made in Yantai, Shandong Province, China. The images were collected at different positions in the orchard during the day. The collected green apple images often own the following characteristics:

1. The background of image is complex.
2. The illumination is uneven.
3. The lesion images cannot be clearly distinguished from branches.
4. Some apples are partially blocked by the branches and leaves.

B. Image Binarization Processing

The traditional image binaryzation algorithm can only be used in the case that image background and foreground can be relatively obvious separated, and the light conditions are basically unchanged. It is difficult to apply to the ROI extraction issue in this paper. Neural networks are widely used in classification problems. BPNN has good generalization ability, but it also has the disadvantages of slow convergence speed in later period of training and easy to fall into local extremum. In order to solve the shortage of BPNN, genetic algorithm (GA) is used to optimize the weights and thresholds of the neural network in this paper. GA is an algorithm to simulate the phenomenon of gene selection, crossover and mutation in the process of natural selection and genetic evolution. The main operation process of genetic algorithm includes population initialization, individual evaluation according to fitness, selection operation, crossover operation, mutation operation and termination condition judgement.

The GA-BPNN algorithm is used to realize the classification of image foreground and background, and realize adaptive multi threshold image binarization as Fig. 1. In this paper, the accumulated mean square error E is used as the cost function of the neural network.

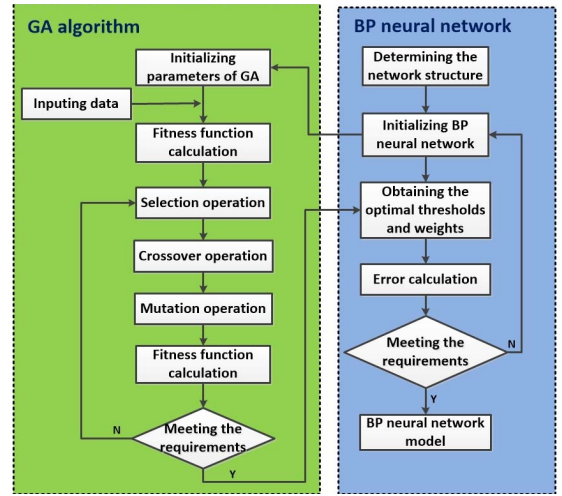


Fig. 1. GA-BPNN algorithm flow chart.

Each individual in the population contains all the weights and thresholds of the BPNN. Initializing parameters of GA is to encode the weights and thresholds of each individual by real numbers. The value of individual fitness is calculated by fitness function. In this paper, the linear function of E is set as the fitness function, because E is the most intuitive function to determine whether the whole network parameters meet expectation. The smaller the E is, the higher the fitness is. In this paper, we use the method of linear transformation, the formula of fitness calculation is as follows:

$$F = 1 - E \quad (1)$$

Where F is the fitness. Because $E \in [0,1]$, $F \in [0,1]$.

The selection operation first sorts individuals based on the fitness, and then calculates the probability of each individual being selected as follows:

$$P_i = \frac{F_i}{F_{sum}} \quad (2)$$

Where F_i is the fitness of the i th individual, and F_{sum} is the sum of all individual fitness.

Then the selection operation is carried out according to the method of roulette. Better individuals of the last generation are more likely to be chosen.

In this paper, a linear combination method is used to realize the crossover operation. Two individuals are selected at one time according to a certain probability P_c , and $P_c = 0.5$ in this paper. The two selected individuals, x and y , are crossed to generate two new individuals x' , y' using the formula as follows:

$$x' = \alpha x + (1 - \alpha)y \quad (3)$$

$$y' = \alpha y + (1 - \alpha)x \quad (4)$$

In this paper, we take the $\alpha = 0.4$.

In this paper, the mutated individuals are selected with the probability $P_m = 0.01$, and the mutation operation is carried out as follows:

$$z = U_{min} + \beta(U_{max} - U_{min}) \quad (5)$$

Where z is a new individual after mutation. $[U_{max}, U_{min}]$ is the scope of individual value, β is a random number between 0 and 1.

The population updates after selection, crossover and mutation operations and calculates a new fitness for each individual. In this article, if the gap of the five consecutive training results less than 0.005, the training will be stopped. The individual with the highest fitness is chosen as the final parameter of the BPNN.

In this paper, the input layer of the single hidden layer neural network has 4 nodes, the hidden layer has 10 nodes, and the output layer has 1 node. the input variable x_i is the selected pixel, and the expected output y_i is labeled with 0-1 binary variable. Pixels whose labels are 0 are background pixels, and pixels whose labels are 1 represent apple pixels. The input layer of the neural network $(x_R, x_G, x_B, 1)$ takes the 3D vector (x_R, x_G, x_B) in RGB color space of the selected pixel as the features, and 1 as a bias. In order to facilitate the image processing, the collected 1020×1980 size images are clipped to 1000×1000 size in this paper. 90 pictures are randomly selected as the image training set, and other 10 pictures as the image test set. The pixel training set is composed of manually collected pixels from image train set. In each picture from image train set, 600 pixels are selected, of which 400 pixels belong to the background, and the remaining 200 pixels belong to the green apple image. This paper carries out five times cross-validation for the pixels in the pixel training set. The accuracy results of cross training is shown in Table I. In the five trainings, the best training accuracy rate reached 97.75%. The parameters obtained from the best training were used as the final parameters of the neural network model in this paper. The trained model is used to process the test image. The original image and the binarization result are shown in Fig. 2.

TABLE I. THE ACCURACY RESULTS OF FIVE TIMES CROSS TRAINING

The number of training	Accuracy(%)
1	96.83
2	97.75
3	97.54
4	96.95
5	97.27

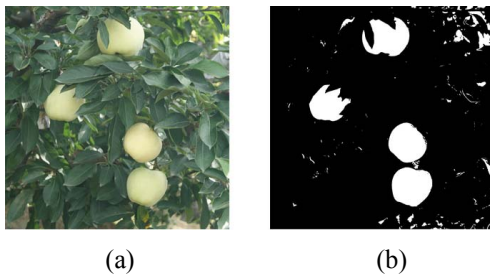


Fig. 2. Binarization processing with GA-BPNN. (a) the original image, (b) Binary image processed by GA-BPNN binarization algorithm.

C. Post-processing of Green Apple Image

Because the noise and a small part of the background are too close to the green apple image in the RGB color space, the binary image processed by GA-BPNN binarization algorithm needs further processing to obtain the ROI of green apples.

In this paper, because the noise and the background region which is recognized as green apple is small relative to the target region, a connected domain processing method is used. Firstly, each connected domain is detected and labeled, and the area of each connected domain is calculated. Then, the threshold of the area of connected domain is set. The domain whose area is lower than the threshold is filtered, and the domain with the area higher than the threshold is reserved, so that the connected domain of the target apple is retained. After that, the median filter is used to remove the salt and pepper noise. There are some background images which are wrongly recognized as apple images and are connected with the binary images of target apple. Therefore, the algorithm of opening operation in image morphology is adopted. The opening operation firstly carries on erosion operation to the image, and then dilation operation is used. In this paper, a regular octagon is used as the structuring element of the opening operation. The inscribed circle diameter of the regular octagon is 10 pixels. The processed result is shown in Fig. 3.

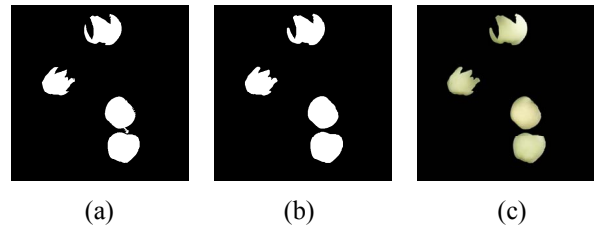


Fig. 3. Post-processing of green apple image. (a) Binary images processed by the connected domain algorithm, (b) Binary images processed by median filtering and morphological processing, (c) the ROI.

III. LESION IMAGE PROCESSING OF GREEN APPLES

Apple skin diseases mainly include ring rot, anthrax, dry rot, water core disease and so on. The main pathogenesis of apple skin diseases is that the lesion start from one point, and gradually spread to the surrounding, eventually formed a certain area lesion on the apple surface. The color of the lesion image is mainly brown to dark brown. It is similar to the branches.

A. Existence Judgment of Diseased Apples

It is the premise of processing the lesion image to judge whether there is a diseased apple in the image. The diseased apple image is shown in Fig. 4(a). The color of the lesion is dark brown, which is significantly different from that of the surrounding normal apple regions. Compared with the normal pimples on the surface of green apple, the area of lesion is much bigger. The result obtained by the above image segmentation method is shown in Fig. 4(b). It can be seen from the figure that irregular hole regions are formed in the binary image.



Fig. 4. Processing result obtained by the above image segmentation method. (a) The original image, (b) binary image processed by the above image segmentation method.

In this paper, a hole area detection method is proposed to detect whether there exists diseased apples in the image by detecting the total area of holes in the preliminary extracted ROI binary image. The flow chart of the proposed algorithm is shown in Fig. 5. The method calculates the total area of lesion holes to determine whether there exists lesions. The effect of the lesion shape to the discrimination can be ignored. It is convenient for further processing of the apple lesion images.

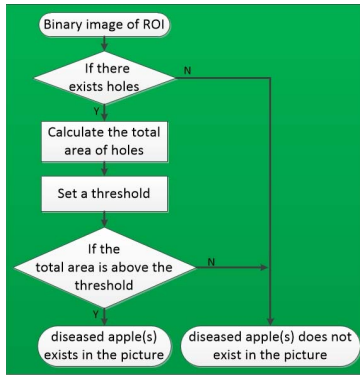


Fig. 5. Flow chart of the hole area detection method.

B. ROI Extraction of Diseased Apple Images

The image of diseased green apple, which is checked out by the hole area detection method, cannot be totally extracted by the proposed segmentation algorithm. In this paper, a hole filling method is used to fill the black holes surrounded by white regions in binary images. After the hole filling algorithm, median filtering and morphological processing methods are needed to process the edge noise of the binary image. The processed image is shown in Fig. 6.

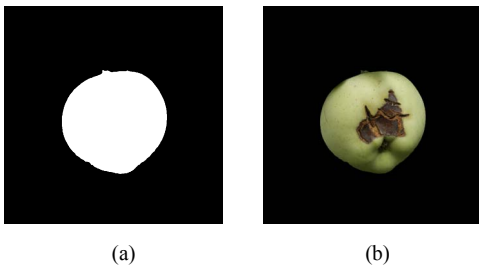


Fig. 6. ROI extraction of diseased apple. (a) Binary image processed by hole filling algorithm and morphological opening operation (b) ROI of the diseased apple.

C. Lesion Image Segmentation Using Soft Margin SVM

It is very difficult to extract lesion images directly from the original images because the color of lesions is brown to black brown, which is similar to the color of apple tree branches. Therefore, the extracted ROI image needs to be further processed to extract the lesion images of green apples. SVM shows unique advantages in solving small sample and high dimensional nonlinear problems. Therefore, this paper uses SVM algorithm to realize the segmentation of lesion images. The SVM model is shown in Fig. 7.

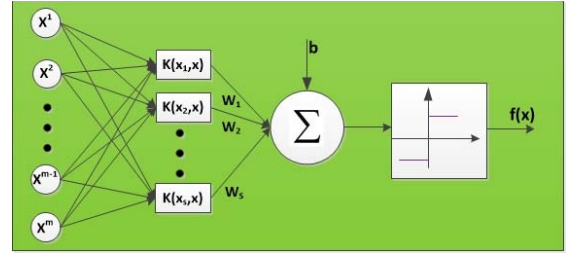


Fig. 7. Diagram of SVM model.

Considering that there may not exist a hyperplane that can divide the samples of different types in case of abnormal samples, the soft margin SVM is used in this paper. The formula of the soft margin SVM model is shown as follows:

$$\min_{w, b, \varepsilon_i} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m \varepsilon_i \quad (6)$$

$$s. t. \quad y_i(w\varphi(x_i) + b) \geq 1 - \varepsilon_i, \quad i = 1, 2, \dots, m, \quad \varepsilon_i \geq 0$$

Where w and b are constraint parameters of the hyperplane, ε_i is the slack variable, C is a constant greater than 0, x_i is the input and y_i is the label of the sample i .

In this paper, RBF kernel function is used as kernel function of the SVM model. The RBF kernel function is also called the Gaussian kernel function. Its expression is shown as follows:

$$k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), \quad \sigma > 0 \quad (7)$$

Where σ is the bandwidth of the Gaussian kernel, and $\sigma = 1$ is set in this paper.

In this paper, six features in RGB and HSI color spaces, are used as inputs of SVM model to learn and classify apple lesion images and normal apple surface images. The HSI color space uses hue, saturation and intensity to describe colors.

In order to reduce the impact of abnormal data points on the experimental results and improve the stability and robustness of the SVM model, this paper uses a soft margin SVM model based on RBF kernel with $C = 0.01$ to train the collected samples. The samples of normal apple pixels are labeled with -1, and the pixels of lesions are labeled with +1. The SVM model obtained by training is used to process Fig. 6(b) directly. The result obtained by SVM processing successfully segment the lesion images. However, there are still a few spots of the normal apple image which are mistakenly recognized as lesion images, and there is also a small amount of noise inside the lesion image. Therefore, the hole filling and morphological opening algorithms are used to process the lesion image. The

segmented lesion image is shown in Fig. 8. In the final segmented lesion image, the main information is retained except for a small amount of the edge information. The effect of noise is eliminated for further image processing.

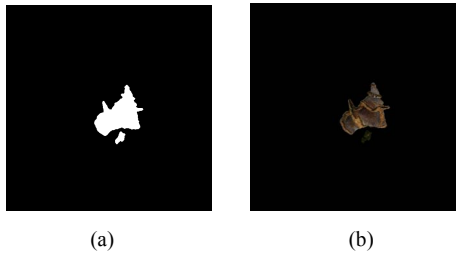


Fig. 8. Lesion image segmentation realized by SVM. (a) Binary image of lesion, (b) lesion image obtained.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

A. Comparison of Binarization Algorithms

In this paper, a GA-BPNN algorithm is proposed to realize adaptive multi-threshold image binarization for the green apple images in orchard. To verify the performance of the proposed method in this paper, three common binarization algorithms are set as contrast experiments, Otsu method, maximum entropy threshold method and iterative threshold method, and the processing results are shown in Fig. 9. It can be seen that the common image binarization algorithms cannot get ideal experimental results in the case of complex background and uneven illumination. Fig. 9(e) is the experimental result obtained by the proposed method in this paper.

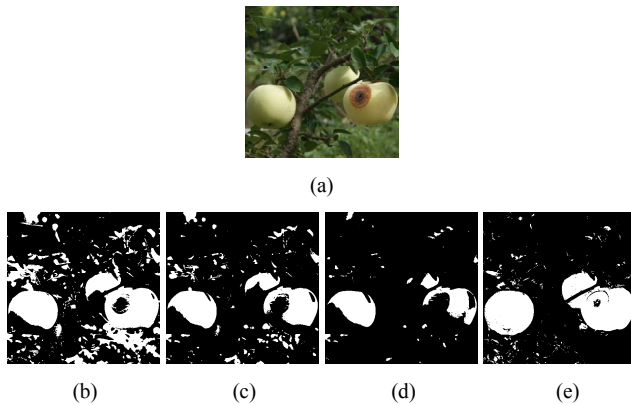


Fig. 9. Comparison of the results of four binaryzation algorithms. (a) The original image, (b) binary image processed by Otsu method, (c) binary image processed by iterative threshold method, (d) binary image processed by maximum entropy threshold method, (e) binary image processed by GA-BPNN method.

To better verify the performance of the proposed method, Table II compares the four binarization algorithms by the recognition accuracy of foreground and background. From the recognition accuracy data in Table II. It can be concluded that the proposed method in this paper can better realize the adaptive multi-threshold binarization under complex background and uneven illumination compared with the other three common binarization algorithms.

TABLE II. ACCURACY OF THE FOUR BINARIZATION ALGORITHMS FOR THE RECOGNITION OF THE FOREGROUND AND BACKGROUND

Binarization algorithms	Recognition accuracy of foreground (%)	Recognition accuracy of background (%)
Otsu Method	68.8	75.3
Iterative Threshold Method	52.4	84.7
Maximum Entropy Threshold Method	41.3	87.5
GA-BPNN Method	92.1	91.4

B. Image Database Establishment and Robustness Analysis of the Algorithm

In this paper, we use the proposed algorithm to process the selected pictures in batch. The image database of diseased apples and lesion images can be set up. The experimental results are shown in Fig. 10. It can be seen from the picture that the lesion image processing algorithm proposed in this paper has good robustness in the case of complex background and uneven illumination, which can well realize the process of different lesion images.



Fig. 10. Establishment of lesion image database. (a) The original apple images; (b) ROI extracted of apple images; (c) lesion image extracted;

C. Diseased Apple Recognition among Multiple Apples

The proposed method in this paper is applied to the recognition of diseased apples in multiple apples. The experimental process and the processing result are shown in Fig. 11. It can be seen that the obstacles in the picture like branches and leaves, do not form holes in the connected domain, so the hole filling algorithm does not fill the area where the obstacles are located. Therefore, obstacles in front of green apples do not affect the further processing of the lesion image. It can be seen from Fig. 11(d) that the lesion extraction method can also be used to extract lesion image from multiple apples.

Locating diseased apples in multiple apples is the precondition for disease control. In order to locate the region of the diseased apple in the multi-apple image, the following method is proposed in this paper. Firstly, the centroid of each connected domain and lesion image is marked in the extracted binary ROI.

Then, connect the centroid of each lesion image to the other centroids of collected domains. Finally, select the connected domain which all the nodes on one connection belong to as the connected domain of the diseased apple. As shown in Fig. 11(f), the apple in the green frame is recognized as the diseased one.

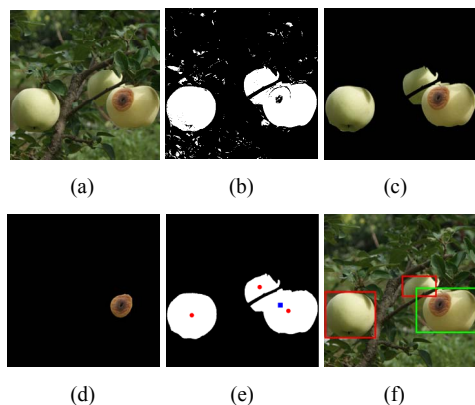


Fig. 11. Lesion image processing in multiple apples. (a) The original image, (b) binary image obtained by the BPNN binaryzation algorithm, (c) ROI image, (d) the image of the lesion region, (e) the centroid of each connected domain and lesion image, (f) recognition of the diseased apple;

V. CONCLUSION

In view of the uneven illumination and complex background in the orchard, an image processing method for the lesion image of green apple is proposed. In this paper, a GA-BPNN is proposed to realize adaptive multi-threshold image binarization. To better finish the processing task of green apple lesion images, image ROI extraction, soft margin SVM algorithm and other algorithms are used in this paper. With these methods, apple images can be processed in batch and the lesion image database can be consummated automatically.

Based on the experimental results, the following conclusions are obtained:

1. The image binarization algorithm achieves adaptive multi-threshold image binarization under uneven illumination and complex background. Compared with other three common image binarization algorithms, it has higher accuracy and better practicability.

2. The method can well realize ROI extraction and lesion image detection of green apple under uneven illumination and complex background in the orchard.

3. This lesion image processing method has strong robustness in the case of different backgrounds and different types of lesions.

4. The method can well process the lesion image with multiple apples and locate the region of the diseased apple.

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