Image Segmentation of Pitaya Disease Based on Genetic Algorithm and Otsu Algorithm

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Abstract: Aiming at the problem of using traditional Otsu algorithm to segment pitaya disease images, this paper proposes the Otsu algorithm combined with genetic algorithm. The maximum variance between classes obtained by Otsu is calculated as the fitness value of the genetic algorithm to improve accuracy and improve efficiency of optimization. The experimental results show that the segmentation accuracy and efficiency of the algorithm in this paper are higher, and it has certain practical value.

1. Introduction
The better economic benefits of dragon fruit have prompted many fruit farmers to start growing dragon fruit in large quantities. However, artificial identification of dragon fruit diseases is very dependent on professional experience, especially in the early stage of the disease, the characteristics of the disease are not obvious, and the differences between different types of diseases are very small. It is difficult for even professionals to judge and identify virus categories in a timely and accurate manner with the naked eye. This will delay the treatment time and cause certain economic losses for the fruit farmers. In order to identify the virus category faster and more accurately, this paper uses image processing technology to segment the diseased parts of the dragon fruit, and realizes fast and accurate virus identification by judging the size and shape of the disease spots on the stems and leaves of the dragon fruit. This is of great significance for reducing the economic losses caused by diseases.

2. Related research
Traditional methods of plant disease identification are based on artificial judgment, which is inefficient and prone to error. With the development of image processing technology, the use of image processing technology can quickly and accurately determine the type of disease, in order to timely prevent and control to reduce economic losses. In recent years, image processing technology has been applied in the field of agriculture. Camargo and Smith [1] successfully separated banana leaf black spot from leaves by using histogram threshold segmentation method with optimal threshold. Baum [2] et al. used Sobel edge detection operator to segment barley plaque, which separated plaque from leaves with...
remarkable effect. Rupali Patil[3] calculates the shielding threshold of the green pixels of the disease image using the method of maximum interspecific variance, eliminates the null RGB pixels and the edge features of the infection, and separates the disease spots from the leaves using k-means clustering. Whitley[4] proposed an adaptive mutation strategy that is inversely proportional to the distance Hamming between a pair of parent strings. The results show that this method effectively maintains gene diversity. Abd-El-Wahed[5] combines genetic algorithm and particle swarm optimization algorithm to solve nonlinear optimization problems with excellent results. A.R. Kavitha, C. Chellamuthu [6] studied a watershed method based on the mean and variance of gray histogram and divided the derived cluster image, which can enhance the overall image quality to some extent.

Image processing technology has been successfully used for disease identification of some crops and fruits, but it does not involve the segmentation and identification of diseases related to dragon fruit. In image processing, the Otsu threshold segmentation algorithm is a very classic segmentation algorithm, but the pitaya disease has a complex shape and is easily affected by factors such as illumination and background, resulting in low recognition efficiency. In this regard, this paper proposes Otsu image threshold segmentation based on genetic algorithm to study dragon fruit disease segmentation.

3. Theoretical basis of related algorithms

3.1. Otsu Arithmetic

Otsu is a method to determine the thresholds for image binary division, which was first proposed in the late 1970s. It divides an image into foreground and background parts according to the gray-scale characteristics of the image. The greater the class variance between background and foreground, the greater the difference between the two parts of the image, and the better the foreground and background are segmented. It can be understood that segmentation works best when the threshold value maximizes the variance between foreground and background classes, which is the result of the Otsu algorithm.

Algorithm principle: For image I, let the gray level of the image be L (usually 256), among them, there are $n_i$ pixels with gray value $i$, so the total number of pixels in the image is the sum of the number of gray values: $N = \sum_{i=0}^{L-1} n_i$, the probability of each gray value appearing in the image is $p_i = \frac{n_i}{N}$, among them: $p_i \geq 0$, $\sum_{i=0}^{L-1} p_i = 1$. The maximum inter-class variance selects the gray value $T$ as the threshold to segment the image, and divides the image into two categories: foreground and background: The pixels with gray levels from 1 to $T$ are $W_1$, the general situation is background. The pixels with gray levels from $T+1$ to $L-1$ is $W_2$, which are the foreground target class. The probability of occurrence of $W_1$ and $W_2$ are $P_{w1}$ and $P_{w2}$ respectively. It can be calculated by formula:

$$P_{w1} = \sum_{i=0}^{T} p_i \quad (1)$$

$$P_{w2} = 1 - P_{w1} \quad (2)$$

The gray values of $W_1$ and $W_2$ are respectively:

$$\mu_{w1} = \sum_{i=0}^{T} i \cdot p_i$$

$$\mu_{w2} = \sum_{i=T+1}^{L-1} i \cdot p_i$$

$$\mu_{w1} = \sum_{i=0}^{T} i \cdot \frac{p_i}{P_{w1}}$$

$$\mu_{w2} = \sum_{i=T+1}^{L-1} i \cdot \frac{p_i}{P_{w2}}$$

$$\mu_{w2} = \sum_{i=T+1}^{L-1} i \cdot \frac{p_i}{1 - P_{w1}}$$
The total gray average of the image is:

\[ \mu = P_{w1}\mu_{w1} + P_{w2}\mu_{w2} \]  

(5)

The following formula is the variance between classes \( W_1 \) and \( W_2 \), that is, the classification category function during image segmentation. This function describes the distance between the two classes:

\[ \sigma^2(T) = P_{w1}(\mu_{w1} - \mu)^2 + P_{w2}(\mu_{w2} - \mu)^2 \]  

(6)

From the above formula, and \( P_{w1} + P_{w2} = 1 \), the following equivalent formula can be obtained:

\[ \sigma^2(T) = P_{w1}P_{w2}(\mu_{w1} - \mu_{w2})^2 \]  

(7)

When the inter-class variance of the foreground and background divided by the threshold \( T \) is larger, the value of \( \sigma^2(T) \) is larger, and the misclassification rate of the background and the target is smaller, and the final image segmentation effect is better. Therefore, when \( \sigma^2(T) \) takes the maximum value, \( T \) is the optimal threshold, namely:

\[ T = \arg \max_{0<T<D-1} \sigma^2(T) \]  

(8)

Otsu threshold segmentation is the best solution to solve the global threshold. It is suitable for most occasions where the global threshold of the image is required, and the calculation is simple and fast. However, this method also has a big defect: the noise interference ability is relatively poor, and if there is a lot of noise in the image, the segmentation effect is poor. For single-threshold segmentation, when the image histogram is double-peaked, the algorithm can get ideal results, but if the histogram is single-peak or close to single-peak, the image segmentation effect is poor.

3.2. Genetic algorithm

The genetic algorithm was proposed by Holland in 1970. By simulating the natural environment, selection, crossover and mutation operations are performed on the population to obtain the next generation population. After several generations of evolution, the final result is obtained. Because of its robustness, implicit parallelism and strong global search capabilities, it is widely used in various fields. The steps of the basic genetic algorithm are selection, crossover, mutation, and inheritance. Both crossover and mutation will cause the population to generate new individuals. The crossover operation is the main method to generate new individuals, which determines the global search ability of the genetic algorithm, while the mutation operation determines the local search ability of the algorithm at the later stage of the iteration. The two complement each other to complete the process of finding the optimal solution.

The specific algorithm is as follows: Firstly, each individual is binary coded as the allele on its chromosome, and the number of the population is initialized as the first-generation population, which is the operation object of the genetic algorithm. Afterwards, each individual is evaluated by the fitness function that has been given, and its fitness value in the current generation is obtained. The selection operator is then used to screen the individuals of the current generation, and the individuals with larger fitness values in the previous generation will be inherited to the next generation with a greater probability, while the individuals with low fitness values will be inherited to the next generation with a small probability. In order to generate more new individuals in the genetic process, crossover operators and mutation operators are set up. Among them, the crossover operator exchanges partial genes of two random paired chromosomes in the population with a certain probability, thereby forming a new individual. The mutation operator selects an individual in the population in a random manner, changes the value of several random gene positions in this individual with a certain probability, and generates a
After the execution is completed, if the specified number of iterations is not reached, continue to perform the genetic operation steps, otherwise the optimal solution will be output.

3.3. Otsu Threshold Segmentation Algorithm Based on Genetic Algorithm
Because genetic algorithm has the advantages of simplicity, robustness and parallelism in solving the optimal value problem, and the process of solving the optimal threshold of the maximum between-class variance algorithm can be equivalent to the process of searching for the optimal solution of the expression, so this article use genetic algorithm to find the best threshold for image segmentation. The main steps of combining genetic algorithm and Otsu algorithm are as follows:

(1) Encoding: Since the gray value range of the image is 0-255, each individual is coded as an 8-bit binary number. The value of an individual gene location is generally generated by judging the random value. When the random value is greater than 0.5, the gene location is assigned 1, and when the random value is less than 0.5, the gene location is assigned 0.

(2) Population initialization: The most important problem in population initialization is how to choose the size of the population. When the selected population size is too small, the problem will easily fall into a local optimal solution, leading to inaccurate results. When the population size is too large, it will increase the calculation amount of the algorithm and reduce the time efficiency of the algorithm. Therefore, the population size in this article is set to 20.

(3) Calculate the fitness value of the individual: take the maximum between-class variance of the Otsu algorithm as the fitness value of the genetic algorithm: \[ \sigma^2(T) = \frac{P_{w1}P_{w2}(\mu_{w1} - \mu_{w2})^2}{}, \] when the value is larger, the adaptability of the individual is better.

(4) Selection operation: The selection method in this article uses roulette, that is, the fitness value of the individual is calculated to obtain the individual cumulative value \[ S_i \], when it is accumulated to the last individual, it is \[ S_n \], and then a random value \( K \) is taken from \([0, S_n]\) in a random manner, and \( K \) is sequentially compared with \( S_i \) until it is less than \( S_i \), that is, the individual corresponding to the second accumulated value is selected, and the first two steps are repeated until obtain a specified number of individuals.

(5) Crossover operation: This article uses single-point crossover, with the crossover probability set to 0.9, select any pair of individuals from the new population, randomly generate a variable \( r \), and compare it with the crossover probability. When the crossover probability is greater than \( r \), the alleles of the pair of individuals are randomly designated to be crossed. If the crossover probability is less than \( r \), the crossover operation of the pair of individuals is cancelled.

(6) Mutation operation: This article uses the basic bit mutation operator to perform mutation operation, set the mutation probability to 0.05, traverse each individual in the new population, and generate a random variable \( m \), which is compared with the mutation probability. When the mutation probability is greater than \( m \), randomly select a gene of the individual and reverse it. If the mutation probability is less than \( m \), then cancel the mutation operation on the individual.

(7) Termination condition: The algorithm terminates when the algorithm evolves to the maximum algebra. At this time, the individual with the best fitness is the best threshold \( T \), otherwise, go to step (3).

(8) Image segmentation: assign the values of pixels with grayscale values less than \( T \) to 0 in the original image, and assign the values of pixels greater than \( T \) to 1, thereby transforming the original grayscale image into a binary image, To complete the segmentation of the target and the background.

4. Experiments and results
This article uses four kinds of dragon fruit disease images to carry out the experiment, mainly including: ulcer virus, mosaic virus, anthrax virus, round spot chlorotic virus. Randomly select one of each category from the given image library for experimentation. The original image is shown in Figure (a), and the segmentation result obtained by the algorithm proposed in this paper is shown in Figure
5. **Summary**

Experimental results show that the segmentation effect of the algorithm proposed in this paper is ideal, and it is faster than traditional segmentation algorithms in terms of computational efficiency. But for the noise in the complex original image, it will cause some interference in the result. Therefore, there is still room for improvement in this research, and we hope that these problems can be overcome in the follow-up research.

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