

Improved Rotation Kernel Transformation Directional Feature for Recognition of Wheat Stripe Rust and Powdery Mildew

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Abstract—To overcome the problem of lacking apparent features, e.g. color or shape, in the process of identifying wheat stripe rust from powdery mildew using computer vision algorithms, a novel directional feature based on Improved Rotation Kernel Transformation (IRKT) is proposed. IRKT can calculate the statistics of the direction distribution of infected leaf images in spatial domain. The statistics calculated from IRKT are insensitive to noise and can lead to a good description of directional distribution of object, which is suitable for the recognition of wheat stripe rust and powdery mildew and provides a novel method to represent other plant disease. As showed in experimental results, the proposed IRKT directional feature is fit for the recognition of wheat stripe rust and powdery mildew, and the accuracy can achieve 97.5%.

Keywords- *Stripe rust and powdery mildew; IRKT directional feature; Directional distribution parameter; Disease recognition*

I. INTRODUCTION

The quality of wheat is not only affected by the environmental factors such as light, soil, temperature, but also related to whether it's infected by plant diseases or insect pests. The powdery mildew and the stripe rust are two common foliar diseases of wheat. The yield loss can be avoided if it can be rapidly discovered and accurately judged which disease the plant has infected and then adopt appropriate measures to control it timely [1]. At present, the digital image processing technology and pattern recognition technology have get involved in the recognition of plant diseases, instead of relying on human experience in the past. And depending on a variety of image processing techniques, most plant diseases can be recognized precisely, which has made a big difference in the realization of comprehensive control of diseases and the automation of agricultural production[2].

In 1987, Meyer used image processing techniques to build the growth mathematical model for crops [3]. But this research didn't give a segmentation method for the leaf under complex conditions, which may lead a failure when the edge was not located accurately. Zayas, et al. extracted a variety of morphological feature parameters of the infected wheat image, with which achieved the recognition of wheat varieties, and the

recognition rate was above 85%[4]. But this method combined multispectral analysis which was costly. Interiorly, lots of scholars have had efforts on plant disease recognition based on computer vision. Cen Zhixin used the statistic feature of image color to recognize infected samples from different periods [5]. However, this method has a precondition that the color features must be obvious. Cheng Pengfei et al. suggested that chroma skewness could be adopted as the characteristic parameter to distinguish spotted disease with angular leaf spot [6]. But this feature doesn't fit for objects of our study. References [7-11] also had important results in terms of crop pest and disease recognition. References [7][8], respectively, proposed new algorithms for testing wheat stripe rust and powdery mildew; [9] detected and discriminated yellow rust disease from nutrient stresses; [10] used hyperspectral sensor systems to distinguish yellow rust, powdery mildew and aphids; in [11] some effective spectral wavelengths, and vegetation indices for crop diseases or pests monitoring were summarized, but these studies used spectral data analysis which made the data collection process complicated, and not suitable to form portable application results. Additionally, a lot of researches have extracted various disease features, for example, junction feature parameters [12] or the statistic of various traditional features [13]. However, these features respectively used the image color histogram and the result of the pixel gray value distribution, which were still not fit for distinguishing wheat powdery mildew and stripe rust. So it's necessary to explore a simpler feature to describe different plant diseases, and identify these diseases precisely in the end.

The extraction of the disease feature, which can decide the final accuracy of the disease recognition, is the most important operations in the process of computer vision-based plant diseases recognition. It can be found that three categories of features are usually used in the image processing-based diseases recognition. They are color features, texture features, and shape features [1][2]. By observing the areas of two diseases, it can be described that the color of the stripe rust and the powdery mildew are too similar to distinguish from each other, but they can differ in the texture of the lesions. On wheat's leaves, the spots of stripe rust are distributed vertically,

and the spots' directions are consistently. On the contrary, the spots of the powdery mildew are scattered, and have no obvious direction. Depending on these characteristics, this research extracts the directional features of wheat's disease spots as a kind of features to identify the stripe rust and the powdery mildew. At present, the most common methods to extract image directional features are histogram of oriented gradients (HOG)[14], edge orientation histograms(EOH)[15] and so on. The HOG method calculates the statistics of image local areas' gradients according to directions to form a feature; EOH method first calculates the image gradient and extracts the edge, then gets the directions of the edge which are divided into several bins, and calculates the statistics of a certain direction's edge strength, and ultimately get the image's EOH features. However, the HOG feature and the EOH feature are dependent on the image gradient, so they are sensitive to noise. In [16], the paper proposed a method of improved rotation kernel transformation (IRKT) to extract the directional statistics information of a noisy image. This method used directional kernels rather than the gradient to count the image's direction information, which has strong anti-noise performance, and better edge extraction. The statistical direction information calculated by IRKT method can better reflect the directional distribution of target noisy image. Currently, there is no research use IRKT as a characterization to get involved in image recognition.

According to the above, an IRKT-based directional feature is proposed, and this feature is used to recognize the wheat's stripe rust and powdery mildew diseases. The paper is organized as follows: Section II briefly introduces the diseases recognition process; Section III introduces the feature extraction method based on IRKT directional feature and its application in disease recognition; Section IV analyses the results of experiments; Section V summarizes the work done in this study.

II. PROCESS OF DISEASES RECOGNITION

The overall process of diseases recognition is as shown in Fig.1. Using image processing techniques, we segment the wheat's leaf spots, and extract the features, then recognize diseases. This research process has been widely used in the detection and recognition of crop diseases [1].

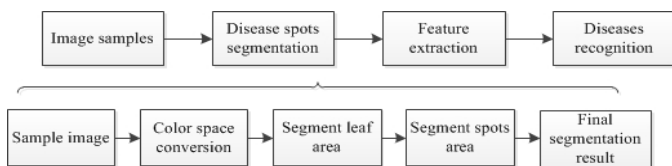


Figure 1. The flowchart of diseases recognition

As experimental material, the infected plants were taken from Beijing Xiaotangshan Precision Agriculture Experimental Base, and the images were acquired during the early grain filling in 2012. The wheat stripe rust infected plants were induced by artificial inoculation, and the wheat powdery mildew infected plants occur naturally. In order to eliminate the error caused by instability of natural light, the images of

infected leaves are collected indoor. Fig.2 shows some sample images of infected wheat leaves.

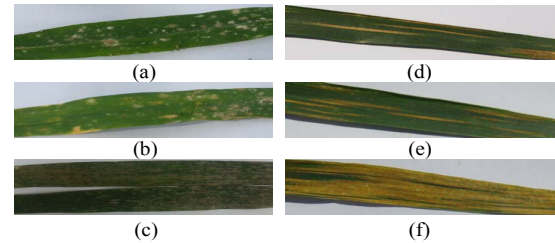


Figure 2. Some sample images of wheat leaf diseases. (a)-(c) show the powdery mildew spots images, (d)-(f) show the stripe rust spots image

The main purpose of infected leaf image segmentation is to divide the image into the lesion area and the non-lesion area, so that the lesion area can be extracted from the image. The image segmentation directly impact on the success of the later disease recognition. In general, the color difference between the leaf and lesions is obvious, and this difference may be reflected in the change of the image's gray level. In [17], the color space was converted from RGB color space to YCbCr space to achieve the corn leaf lesion segmentation. Reference [18] compared the histograms of the different channels of the RGB color space, and combined with bimodal method to select a channel as segmentation criteria to solve the problem of RGB value's uncertainty in different brightness images. HSV and YCbCr color spaces share the similar composite principle with human visual perception process, which is conducive to segment the lesion area. Therefore, this paper uses the method that converts RGB, HSV and YCbCr color spaces and compares their grayscale leaf images and histograms in different color channels to achieve lesion area's segmentation results. The method of disease spots segmentation is shown in Fig.1. Firstly, choose the right color channel and separate the leaf area from the background of sample image. Secondly, use the same method as above to separate the lesion area from the leaf area. Finally, use the Otsu algorithm to segment the image under different color channels, and obtain the final lesions area's segmentation results. Fig.3 shows some disease spots' segmentation results, where (a)(d) are binary images of leaf lesion area, (b) is the binary image of powdery mildew lesions area, (e) is the binary image of stripe rust lesions area, (c)(f) are lesions area segmentation results of powdery mildew and stripe rust eventually. From the simulation results, it can be proved that the use of color spaces conversion and Otsu method in this paper can quickly and accurately segment the lesion area.

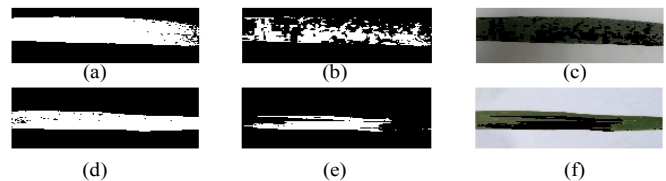


Figure 3. (a) (d) are binary images of leaf lesion area, (b) is the binary image of powdery mildew lesions area, (e) is the binary image of stripe rust lesions area, (c) (f) are lesions area segmentations of powdery mildew and stripe rust eventually

After the segmentation of disease spots, the next step is the feature extraction and recognition of different diseases. Feature extraction is a crucial step, which is related to the final judgment of the recognition accuracy. The powdery mildew spots and the stripe rust spots on wheat leaves is difficult to distinguish in color, so the traditional method based on color features can not achieve the desired effect of disease recognition. Therefore, in this paper, IRKT will be used as a directional feature of disease spots and be extracted to identify diseases.

III. IRKT DIRECTIONAL FEATURE EXTRACTION AND DISEASE RECOGNITION

Currently, the most commonly used features in recognition of crop diseases are shape, color and texture features. Feature selection and extraction is an important prerequisite to support the subsequent recognition. In 1990, Lee and Rhodes proposed the technique of rotation of rotating kernel transformation (RKT), which uses several directional kernels to convolve with image, and selects the maximum value of the convolution results as the filtering result to enhance image[19]. Based on above work, [16] proposed the technique of improved rotating kernel transformation (IRKT) which redefined the kernel's expression of different directions, and used this method to achieve edge detection and directions statistics of noisy image. According to the characteristics of wheat stripe rust and powdery mildew spots, an IRKT based directional feature is propose in this paper, which is then extracted for identifying the stripe rust and powdery mildew, to improve the effect of disease recognition.

A. IRKT Directional Feature

In this paper, the image's edge region is determined by several directional kernels. Calculate the statistic of each edge point's direction, and obtain the number of specified directional vectors as IRKT directional feature. The specific process of this method is as follows. For an image I , The direction number needing to count is known as $Ndir$; K is the size of Kernel, here $K = (Ndir+2)/2$. In order to explain the process, we make $Ndir = 8$ as the example. The corresponding kernels are shown in Fig.4.

Step1: generate the multi-directional kernels according to the $Ndir$. Each kernel is defined as k_i ($i = 1, 2, \dots, 8$) and shown in Fig.4;

Step2: execute convolutions to I with k_i ($i = 1, 2, \dots, 8$) and get eight matrixes M_i ($i = 1, 2, \dots, 8$) which have the same size with I . So each pixel of I corresponds eight values M_i ($i = 1, 2, \dots, Ndir$) in the eight matrixes;

$$M_i = k_i * I \quad i = 1, 2, \dots, Ndir \quad (1)$$

Step3: calculate the standard variation $\sigma(x,y)$ of the eight values $M_i(x,y)$ ($i = 1, 2, \dots, Ndir$). If the $\sigma(x,y)$ is smaller than a threshold T_σ defined in equation (2), the corresponding pixel $I(x,y)$ will be defined as the pixel in the flat area or noise and not be counted, the corresponding eight values $M_i(x,y)$ will be set to zero. The reason for this step is that the pixels of flat

areas or noise have no direction and the standard variation of the convolution results of kernels is small. Actually, the procedure defines the edge very well, as shown in (3).

$$I_{edge}(x,y) = \begin{cases} 1 & \sigma(x,y) > T_\sigma \\ 0 & \sigma(x,y) \leq T_\sigma \end{cases} \quad (2)$$

$$T_\sigma = \frac{\max(\sigma_p) + \min(\sigma_p)}{2} \quad (3)$$

Step4: select the largest value among the eight values $M_i(x,y)$ and count the number of selected of i as the frequency of each direction kernel, which generates a 8 dimensional vector known as Val and represents the frequency of each direction. And the vector Val is known as IRKT directional feature.

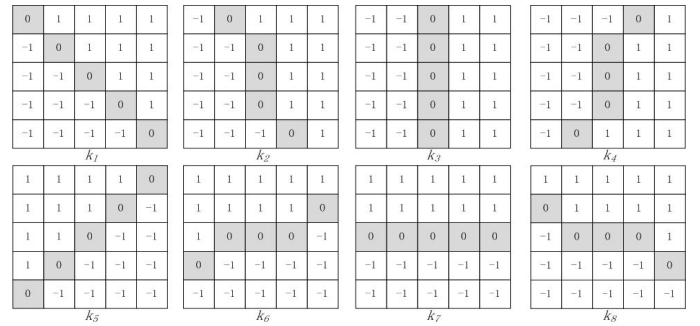


Figure 4. The directional kernels using to count the number of each direction in the image

IRKT directional feature extraction algorithm uses kernels rather than gradient information to define the directional feature. Therefore, it is not sensitive to noise and more intensive edge information comparing with classic feature extraction algorithms, such as HOG, EOH, etc. Moreover, using the IRKT method can obtain statistics of $Ndir$ directions, and ultimately better describe the object's directional distribution. Therefore, IRKT directional feature can be used as a kind of disease spots feature and get involved in disease recognition.

In order to verify the validity of this feature, extract the IRKT directional feature of images (a)-(d) in Fig.5, and draw the histogram of each direction. Fig.5.(e)-(h) describe that using IRKT method can indicate the image's directional feature, and its use as a feature can reflect the spatial directional distribution of the image. Specifically, in Fig.5.(a)(b), the gray areas are distributed in horizontal and vertical directions, which corresponds to the directional histograms (e)(f) respectively that showing the concentrated distribution in two different directions; the gray area in Fig.5.(d) are distributed in both horizontal and vertical directions, and the corresponding directional histogram Fig.5.(h) also reflects concentration in these two directions. So it can be proved that IRKT can be used as an effective directional feature which can be applied to identify the wheat stripe rust and powdery mildew diseases.

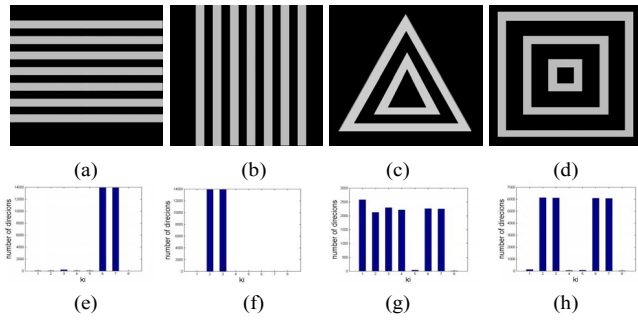


Figure 5. (a)-(d) show four images with different directions. (e)-(h) shows the directions frequency statistics of (a)-(d) using the proposed IRKT feature

B. Calculation of Directional Distribution Parameter and Disease Recognition

Although the analysis of directional histograms of the stripe rust and powdery mildew images can initially obtain disease spots' directional features, in order to identify the two diseases more intuitively, a directional distribution parameter is proposed to replace the vector of IRKT directional feature. The standard deviation of samples can reflect the degree of deviation from the mean. Specifically, the larger the standard deviation is, the more obvious the volatility of sample values is, which applied in directional vector means the sample features are more focused on a certain direction, and vice versa. Therefore, this paper applies the standard deviation of IRKT directional features as the directional distribution parameter to describe the dispersion of disease in different directions. Calculate the standard deviation of directional histograms by using the feature vectors obtained in the previous section, and it is used to represent the degree of edge directional dispersion. This standard deviation is defined as the sample's directional distribution parameter under the IRKT directional feature. The specific calculating process is as follows. First calculate the mean value of IRKT directional feature vector according to (4):

$$m = \frac{1}{Ndir} \sum_{i=1}^{Ndir} Val(k_i) \quad i = 1, 2, \dots, Ndir \quad (4)$$

Where m is defined as the mean value of IRKT directional feature vector; The direction number needing to count is known as $Ndir$; the statistic on direction k_i is defined as $Val(k_i)$. Then get the standard deviation σ of the direction histogram as in (5):

$$\sigma = \sqrt{\frac{\sum_{i=1}^{Ndir} (m - Val(k_i))^2}{Ndir}} \quad i = 1, 2, \dots, Ndir \quad (5)$$

Where σ is the directional distribution parameter value of sample.

In general, the distribution of stripe rust spots on wheat leaf is consistent in one certain direction but the powdery mildew

spots are distributed divergently. So by comparing directional distribution parameters of the two diseases spots, i.e. the standard deviations of the IRKT directional histograms, then the stripe rust and the powdery mildew diseases can be identified.

This article uses the Otsu method [20] to calculate the disease spots classification threshold T . The above steps first calculated the disease spots' directional distribution parameters, and then use the Otsu method to calculate the threshold T . By analyzing the distribution of disease spots' direction, it can be known if the directional distribution parameter value is bigger, the probability of stripe rust is greater; if directional distribution parameter value is smaller, it maybe more likely been defined as powdery mildew. Therefore, the directional distribution parameter which is less than the threshold T can be identified as powdery mildew disease spots. Otherwise it can be identified as stripe rust spots. It can be described as follows:

$$\begin{aligned} \sigma &\geq T && \text{judged as stripe rust} \\ \sigma &< T && \text{judged as powdery mildew} \end{aligned}$$

IV. EXPERIMENTS AND ANALYSIS

In this Section, we first get the IRKT and EOH directional features of standard noise images, and compare their directional histograms, to analyze the anti-noise property of IRKT as a feature. Then according to the disease recognition process, 200 sample images get involved in IRKT directional feature based disease recognition, and the final recognition results are compared with the EOH based recognition results.

A. Noisy Image Comparison Experiment

In order to verify the anti-noise property of IRKT as a directional feature, the IRKT directional feature and the EOH directional feature are extracted for noise images in Fig.6.(a)-(e), and the statistics of their directional information are calculated, respectively. The results are shown as follows. Fig.6.(f)-(j) show the histograms of EOH directional features for images(a)-(e) respectively. It can be known from the statistical results that the distribution of the noise images' directional features can not directly explain the directional trend of the image edges (e.g. Fig.6.(g) shows the directional information statistics of image (b) and it is distributed in three directional kernels, which is incompatible with the actual directional trend of image(b)). So the results using EOH feature are easy influenced by noise. Fig.6.(k)-(o) show the histograms of IRKT directional features for images(a)-(e) respectively. The histogram can roughly show the directional trend of the corresponding noise image (e.g. The statistical distributions shown in Fig.6.(k),(l) are consistent with the gray area's directional trends of image (a),(b), respectively). And comparing with noiseless images (shown as Fig.5.(a)-(d)), the results of noise images shown as Fig.6.(k)-(n) are basically the same as the noiseless results shown in Fig.5.(e)-(h). From the above, it can be proved that compared with EOH feature, the IRKT feature can better describe the noise image's directional information.

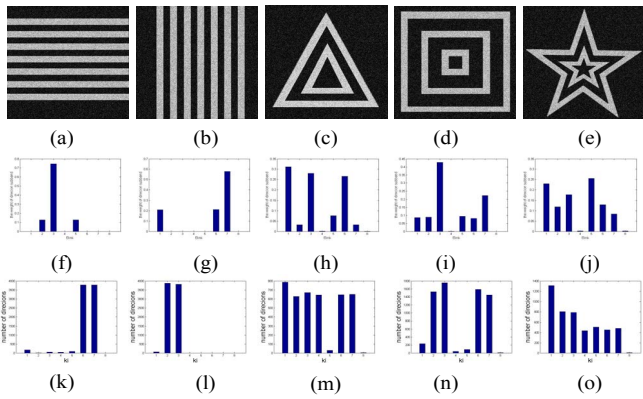


Figure 6. (a)-(e) show five noise images with different directions. (f)-(j),(k)-(o) are directions frequency statistics of (a)-(e) using EOH and IRKT, respectively

B. Wheat Stripe Rust and Powdery Mildew Recognition Experiment

In this paper, the true classes of samples are identified manually, and these visually results are used as true values to evaluate the recognition method. Firstly, obtain the stripe rust and the powdery mildew leaf samples 100 for each, and segment their disease spots area. Secondly, extract the IRKT directional feature of each segmentation result, and calculate its directional distribution parameter. Finally, use Otsu method to obtain the results' threshold and then acquire recognition results. Fig.7 shows partial results of disease spots segmentation and IRKT directional histogram. Fig.7.(a),(b) show the segmentation results of stripe rust, and (c),(d) show the results of powdery mildew spots segmentation. Fig.7.(e)-(h) are IRKT directional feature's histograms for corresponding disease spots area in (a)-(d). From the results shown in Fig.(e)(f), it can be known that the distribution of stripe rust spots is fluctuant in different directions, and has obvious consistency in a certain direction, indicating that the disease spots have high-frequency distribution in corresponding direction. In contrast, as is shown in Fig.7.(g)(h), the distribution of powdery mildew spots has less fluctuation in the directions, and there is no obvious directional distribution trend, showing that the spots are dispersed in direction.

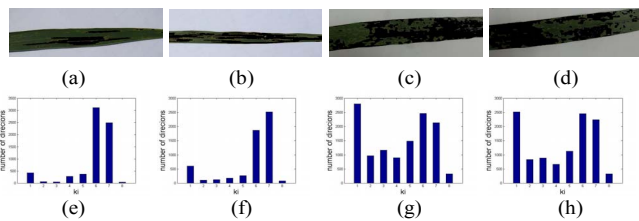


Figure 7. (a)-(d) are segmentation results of wheat stripe rust and powdery mildew leaf lesion, (e)-(h) are directions frequency statistics of corresponding lesions

After extracting the features of disease spots with proposed method and calculating the histograms, the directional distribution parameter can be obtained for each sample. The directional distribution parameters of 200 sample images are

depicted in a two-dimensional coordinate system, where the abscissa represents the directional distribution parameter value; the ordinate represents the serial number of samples. As is shown in Fig.8, in the coordinate, the green dots indicate stripe rust samples, and the red dots indicate powdery mildew samples. The directional distribution parameter values then been projected down to the one-dimensional space and the samples are accumulated into histogram in equal interval. To prove the effectiveness and practicality of the proposed method, it is compared with the EOH feature based disease recognition results. Fig.8.(left) shows the samples distribution obtained by our method, and Fig.8.(right) shows the EOH feature based samples distribution.

Referring to the true value, we first calculate the number of correct recognition number using two different methods; then calculate the accuracy; finally use this rate as the accuracy assessment value to evaluate the validity of two methods in the recognition of the wheat stripe rust and powdery mildew. Where, the accuracy can be calculated as the ratio of the actual sum of samples correctly identified number and the number of samples of two types of disease. Table 1 analyses the final results between IRKT feature based and EOH feature based disease recognition, comparing through their sample number, the correct recognition number and accuracy to test each method's effect.

By analyzing the distribution results shown in Fig.8, it can be deduced that the directional distribution parameter values of stripe rust and powdery mildew which are calculated by EOH feature based method are too close (shown in Fig.8.(right)), especially the distribution of stripe rust dots are not concentrated. Moreover, its directional distribution parameter statistical histograms of stripe rust and powdery mildew have cross-region and maybe hard to find the correct threshold to distinguish the diseases. However, the directional distribution parameter values of stripe rust and powdery mildew calculated by the IRKT feature based method are distributed more intensively (shown in Fig.8.(left)). And it has an obvious boundary between the statistical histograms of two diseases, which is easier to find an appropriate threshold to identify them. It can be derived from the results in Table 1 that for 200 image samples (100 for each disease), the accuracy of the proposed method can reach 97.5%, and the EOH feature based method has only 95% accuracy to identify the stripe rust, indicating that the proposed method of IRKT directional feature is applicable for wheat stripe rust and powdery mildew recognition and has better effect.

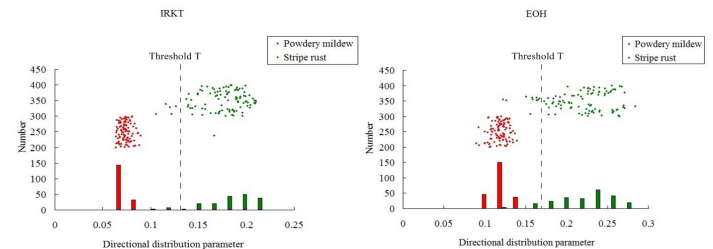


Figure 8. Comparison of sample images' distribution based on IRKT feature and EOH feature respectively

TABLE I. COMPARISON OF DISEASES RECOGNITION RESULTS BY EXTRACTING IRKT FEATURE AND EOH FEATURE RESPECTIVELY

Directional Feature	Disease name	Sample number	Correct recognition number	Accuracy (%)
IRKT	Stripe rust	100	95	97.5
	Powdery mildew	100	100	100
EOH	Stripe rust	100	90	95
	Powdery mildew	100	100	100

V. CONCLUSIONS

In this paper, a new directional feature based on IRKT is described, and it is applied to the recognition of wheat stripe rust and powdery mildew. IRKT is treated as a feature to extract the directional feature of wheat leaf lesions, which the segmentation results of the wheat leaf lesions are obtained by color space conversion and Otsu method. We have discussed the feasibility and effectiveness of IRKT as a feature description in the experiments and got the final recognition results of diseases. Experiments results show that IRKT as a directional feature is not sensitive to image noise, and it can obtain better description of direction features, and it's applicable to the recognition of wheat stripe rust and powdery mildew. Therefore, IRKT as a directional feature provides a new idea for crop recognition and detection based on computer vision.

ACKNOWLEDGMENT

The work is supported by the National Natural Science Foundation (41301476, 61272237); the National Science and Technology Program for the Rural Development during the 12th Five-year Plan of China (863 Program); The Key Technology of Farmland Habitat Perception (2013AA10230207); 2014 Annual Study of Beijing Science and Technology Activities Merit Funded Projects.

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