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An Algorithm for Segmenting Pest from Crop Pest Image with Complicated Background ⋆

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Abstract

To deal with the problem of segmenting pest from crop pest image with complicated background, a segmentation algorithm based on region merging by using joint color- texture histogram is proposed in this paper. The region merging algorithm by maximal similarity (MSRM) with color histogram has been applied successfully in color image segmentation with simple background, but in some specific scenes, such as segmenting pest from crop pest image with complicated background, the MSRM algorithm cannot get very good results caused by it only using color histogram information. To address this issue, in this paper, instead of only using color histogram information to measure the similarity of different regions in region merging process, we propose a novel method combines color histogram with texture histogram information to measure the similarity of different regions and guide the region merging for robust segmenting the crop pest image with complicated background. Experimental results show that the proposed algorithm can accurately extract the pest from crop pest image with complicated background, which can provide the foundation for recognizing the crop pest.

Keywords: Image Segmentation; Crop Pests; Color Histogram; Local Binary Pattern; Region Merging

1 Introduction

The occurrence of crop pests can seriously affect the yield and quality of crop. Therefore, control measures must be taken to reduce its hazards to agricultural production. Traditionally, farmers approach experts to seek their advice regarding the treatment of pest and suggestions for control, sometimes they have to go long distance to contact experts. Moreover, experts recognition methods of pests are mainly based on pests original features, and technicians with magnifying

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glass, microscope, or directly with the naked eyes. Obviously, seeking the expert advice is not only very expensive and time consuming but also only a small amount of species of pests can be recognized. Due to this, there is an urgent need for systems that can help crop producers and farmers, particularly in remote areas, to recognize the crop pest by means of analyses of digital images of crop pest images.

Image segmentation is a key step in computer vision and image processing. In particular, it is an essential process for many applications. Both object recognition and feature extractions depend on the image segmentation directly. The color and texture features in a natural image are so complex that the fully automatic segmentation of the object from the background is still a challenging problem. Therefore, various image segmentation methods incorporating user interactions have been developed [1-7].

The accurate segmentation of pest from crop pest image is the first step in intelligent recognition system of crop pest based on image processing. Although many scholars has already applied mathematics morphology to the agricultural crop disease image segmentation and have made some success under various cases, it remains a challenging problem due to complicated background. Huang et al.[14] propose a segmentation method that morphological template to filter color image is used, and have been applied for colorized digital image segmentation of vermin in cropper foodstuff. The results show that this segmentation method can obtain good effect. Xue et al.[15]firstly adopt mathematical morphology to segment image in three two-dimensional color subspaces, then compute two-dimensional histogram, and watershed algorithm is implemented respectively for the three two-dimensional histograms, final image segmentation is obtained by region splitting-merging process. This method is faster and less memory than the method applied in three dimensional spaces has good segmentation result. In [13] Joe et al .have developed an adaptive image segmentation algorithm based on the local pixels intensities and unsupervised thresholding algorithm to obtain good effect. Unfortunately, the images captured from field environment are often with complicated background, such as soil, dry leaves and stalk. Therefore, automatic segmenting pest from crop pest image is impossible. So we turn to interactive image segmentation methods. Among interactive image segmentation methods, a preferable segmentation method based on the initial segmentation of mean shift was considered by means of the maximal similarity based region merging [6] in color image segmentation. The key idea in the region merging algorithm is how to determine the similarity between the object regions so that the most similar regions can be firstly merged with some logic controls. Currently, the color histogram [16], which could be viewed as the discrete probability density function (PDF) of the object region, is a widely used form of regional representation to measure the similarity of the different regions in a nature image, and it is very robust in representing the object appearance. However, color histogram can only describe the global color distribution, but ignore the description of texture feature. Considering the characters of our research object, in this paper, the region merging segmentation algorithm using joint color-texture histogram is proposed. In this paper, local binary pattern [11] operator is adopted as the texture feature descriptor due to its fast computation and rotation invariance, and then the LBP histogram of a local circular window and color histogram are incorporated to measure the similarity of the different regions and then guide region merging process.

2 Materials and Methods

2.1 Images for experiment

The crop pest images used in this study were obtained from Anhui Academy of Agricultural Sciences, China. Each image showed different pest with complicated background. Fig. 1(a) shows rice case worm, Fig. 1(b) shows Chinese rice grasshopper, Fig. 1(c) shows cabbage butterfly, and Fig.1(d) shows brown plant hopper.

Fig. 1: Crop pest images: (a) rice case worm, b) Chinese rice grasshopper, (c) cabbage butterfly, (d) brown plant hopper.

2.2 Maximal similarity based region merging

Experiments show that region merging based approaches perform well for image segmentation [6]. To merge homogeneous regions, an initial segmentation which partitions the image into homogeneous regions is carried out. In MSMR algorithm, the mean shift method [8] was adopted for the initial segmentation Fig. 2(a) shows original image, the flower is the object to be segment. Fig. 2(b) shows an example of the mean shift initial segmentation with the object boundaries. Fig. 2(c) shows an example of the interactive information input by the user, where the green lines are the object markers and the blue lines are the background markers. Fig. 2(d) shows segmenting result.

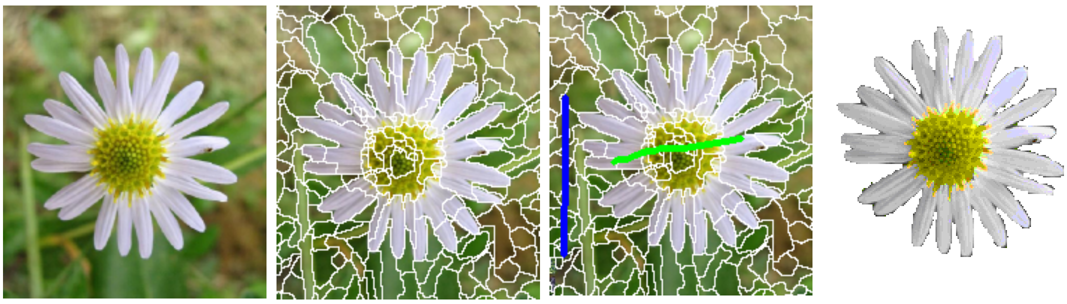

Fig. 2: Region merging method: (a) original image, (b) initial mean shift segmentation, (c) the interactive information input by the user, (d) the segmenting results.

In the MSRM algorithm, the users will mark some regions as object and background regions. The key issue in the region merging algorithm is the merge order, in this method, color histogram is used o determine the similarity between the unmarked regions and the marked ones, and the most similar regions can be firstly merged. Color histogram is an estimating mode of point sample distribution, is a widely used form to measure the similarity of the different regions in a nature image because of its robustness to scaling and rotation [9, 10]. Although color histograms can describe the global color distribution, it ignores the texture feature in the natural images. Since the texture features introduce new information that the color histogram does not convey, combining the joint color histogram with texture histogram to measure of similarity is more reliable than only color histogram.

2.3 Local binary pattern

The local binary pattern (LBP) [11, 12] technique is very effective to describe the image texture features. LBP has many advantages such as fast computation and rotation invariance, which facilitates the wide usage in the fields of texture analysis, image retrieval, and image segmentation.

The original LBP operator, first introduced by Ojala et al. [17] ,is defined as follows:

$$LBP_{P,R}(x,y) = \sum_{p=1}^{P-1} S(i_n - i_c)2^p \tag{1}$$

where i_c corresponds to the gray value of the center pixel(x, y),$i_n$is the gray value of a local neighborhood pixel on a circle with radius R, and P is the number of neighboring pixels around the center one. The function $s(x)$is defined as follows:

$$f(x) = \begin{cases} 1 & \text{when } x \geqslant 0, \\ 0 & \text{when } x < 0. \end{cases} \tag{2}$$

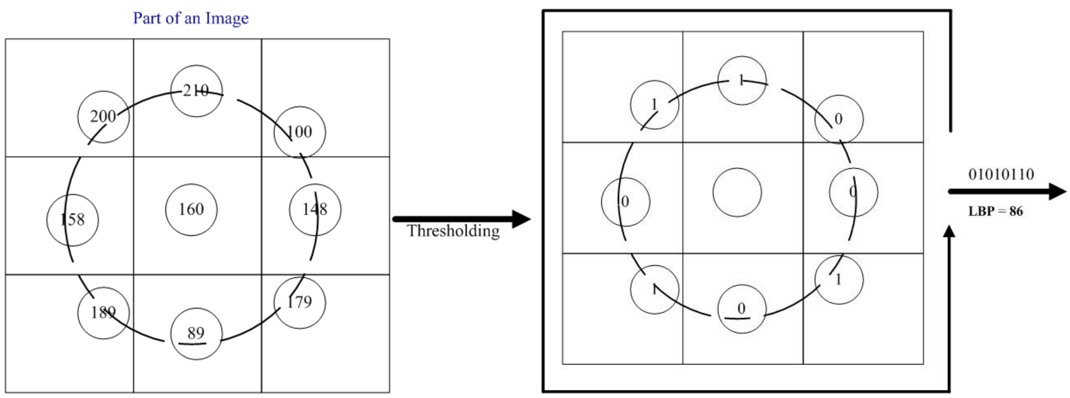

Fig. 3: An example of the basic LBP8, 1 operator.

Figure 3 is an example of the basic LBP8,1 (P=8, R=1).

The texture model derived by (1) has only gray-scale invariance. The gray-scale and rotation invariant LBP texture is obtained by

$$LBP^{u2}_{P,R}(x,y) = \begin{cases} I(LBP_{P,R}(x,y)) & \text{if } U(LBP_{P,R}) \geqslant 2, I(z) \in \{1, 2, \ldots, (P-1)P+2\} \\ (P-1)P+2 & \text{otherwise} \end{cases} \tag{3}$$

where $U(LBP_{P,R}) = |s(i_{p-1} - i_c) - s(i_0 - i_c)| + \sum_{p=1}^{P-1} |s(i_{p-1} - i_c) - s(i_p - i_c)|$

The superscript u2 means that the rotation invariant uniform patterns have a U value of at most 2. If $U(x)$ is smaller than 2, the current pixel will be labeled by an index function $I(z)$, otherwise,$(P-1)P+3$ is assigned.

After labeling an image with an LBP operator, a histogram of the image can be defined as

$$H_i = \sum_{x,y} F(LBP^{u2}_{P,R}(x,y), i), i = 1, 2, \ldots, (P-1)P+3, F(u,v) = \begin{cases} 1 & u = v, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Where i is the number of different labels produced by the LBP operator.

The original images are divided into M non-overlapping $R_0, R_1, \ldots, R_M$ regions (as shown in Figure. 1(b)) by the initial segmentation of mean shift [8], and LBP histograms extracted from each sub-region are then concatenated into a single, spatially enhanced feature histogram. The LBP histogram is defined as:

$$H_{i,j} = \sum_{x,y} F(LBP^{u2}_{P,R}(x,y), i)((x,y)) \in R_j). \tag{5}$$

Where $i = 1, 2, \ldots, (P-1)P+3, j = 0, 1, \ldots, M$. The goal of our segmentation is to merge similar regions in an image and further achieve homogeneous regions according to measuring the similarity of the regions. Therefore, for regions 1 and 2, the similarity measure $T-Hist(H_{i,1}, H_{i,2})$ of two LBP histograms and $C-Hist(H_{i,1}, H_{i,2})$ of two color histograms are defined as below:

$$T\_Hist(H_{i,1}, H_{i,2}) = \sum_{i=1}^{L-1} \sqrt{H_{i,1} H^{`}_{i,2}}. \tag{6}$$

$$C\_Hist(H_{i,1}, H_{i,2}) = \sum_{i=1}^{n} \sqrt{Hist_{i,1} Hist^{`}_{i,2}}. \tag{7}$$

2.4 The maximal similarity based region merging algorithm with joint color-texture histogram

As discussed above, the color channels and the LBP patterns extracted by Eq. (3) can be integrated as joint color-texture histogram to jointly represent each sub-region. The maximal similarity function is rewritten below:

$$Sim(S,M) = (1-\lambda) * T\_Hist(H_{i,S}, H_{i,M}) + \lambda * C\_Hist(H_{i,S}, H_{i,M}). \tag{8}$$

where λ is an adjustable parameter.

The whole segmentation algorithm is summarized as follows.

The maximal similarity based region merging algorithm with joint color-texture histogram

Input: the initial mean shift segmentation result

Output: object result

While there is region merging in last loop

Stage1. Merging non-marker regions in Φ with marker background regions in Ω_B.

(1) Calculate the color and LBP histogram, as well as their corresponding similarities between different regions using Eq. (6) and Eq. (7), respectively;

(2) For each region Ω_B, and its adjacent region $\{\Omega_{B_i}\}, i = 1, 2, ..., R$;

(3) For each region Ω_B, and its adjacent region $\{\Omega_{A_j}\}, j = 1, 2, ..., M$, where $\{\Omega_{A_j}\} \in \Phi$;

(4) Calculate the maximal similarity using Eq. (8), and Ω_{B_i} and $\Omega_{A_j}$are merged if $Sim(\Omega_{B_i}, \Omega_{A_j}) = max_{j=1,2,...,M} Sim(\Omega_{B_i}, \Omega_{A_j})$, otherwise not;

(5) Update Φ and Ω_B;

(6) if $\Omega_B \in \Phi$, end the first step. Otherwise, return to stage1 step2.

Stage2. Merging non-marker regions in Φ.

(1) For each region $\{\Omega_{N_i}\}$, and its adjacent region $\{\Omega_{N_q} \in \Phi\}, j = 1, 2, ..., M$;

(2) For each region $\{\Omega_{N_q}\}$, and its adjacent region $\{\Omega_{N_p} \in \Phi\}, p = 1, 2, ..., r$, where $\{\Omega_{N_p} \in \Phi\}$;

(3) Calculate the maximal similarity using Eq. (8), and Ω_{B_q} and $\Omega_{A_p}$are merged if $Sim(\Omega_{B_q}, \Omega_{A_p}) = max_{p=1,2,...,r} Sim(\Omega_{B_q}, \Omega_{A_p})$, otherwise not;

(4) Update Φ;

(5) if $\Phi \in \emptyset$, end the second step. Otherwise, return to stage2 step1.

End

3 Experiment Results

To verify the feasibility and effectiveness of the proposed algorithm, we use the images as shown in chapter2.1 to carry out our experiments. The image format used is BMP, 24bits. Images of initial segmentation and the input markers with rice case worm, cabbage butterfly, Chinese rice grasshopper, and brown plant hopper are shown in Fig. 4(a). The segmentations by MSRM and our proposed algorithm are shown in Fig. 4(b) and Fig. 4(c), respectively. In Fig. 4(b), blue square illustrates the worse segmentation by MSRM algorithm.

From above , we can found that both the MRSM algorithm and our proposed method can segment pest from crop pest image, but Fig. 4(c) shows better segmentation by our proposed algorithm compared with that in Fig. 4(b), In Fig. 4(c) some pest regions are merged with some background regions, especially for the image of brown plant hopper. The experimental results demonstrate that the MSRM algorithm cannot get very good results caused by it only using color histogram information, and our proposed method is more accurate and reliable.

4 Conclusions

In this paper, we propose a novel region merging approach for segmenting pest from crop pest image with complicated background based on the maximal similarity involving color and texture

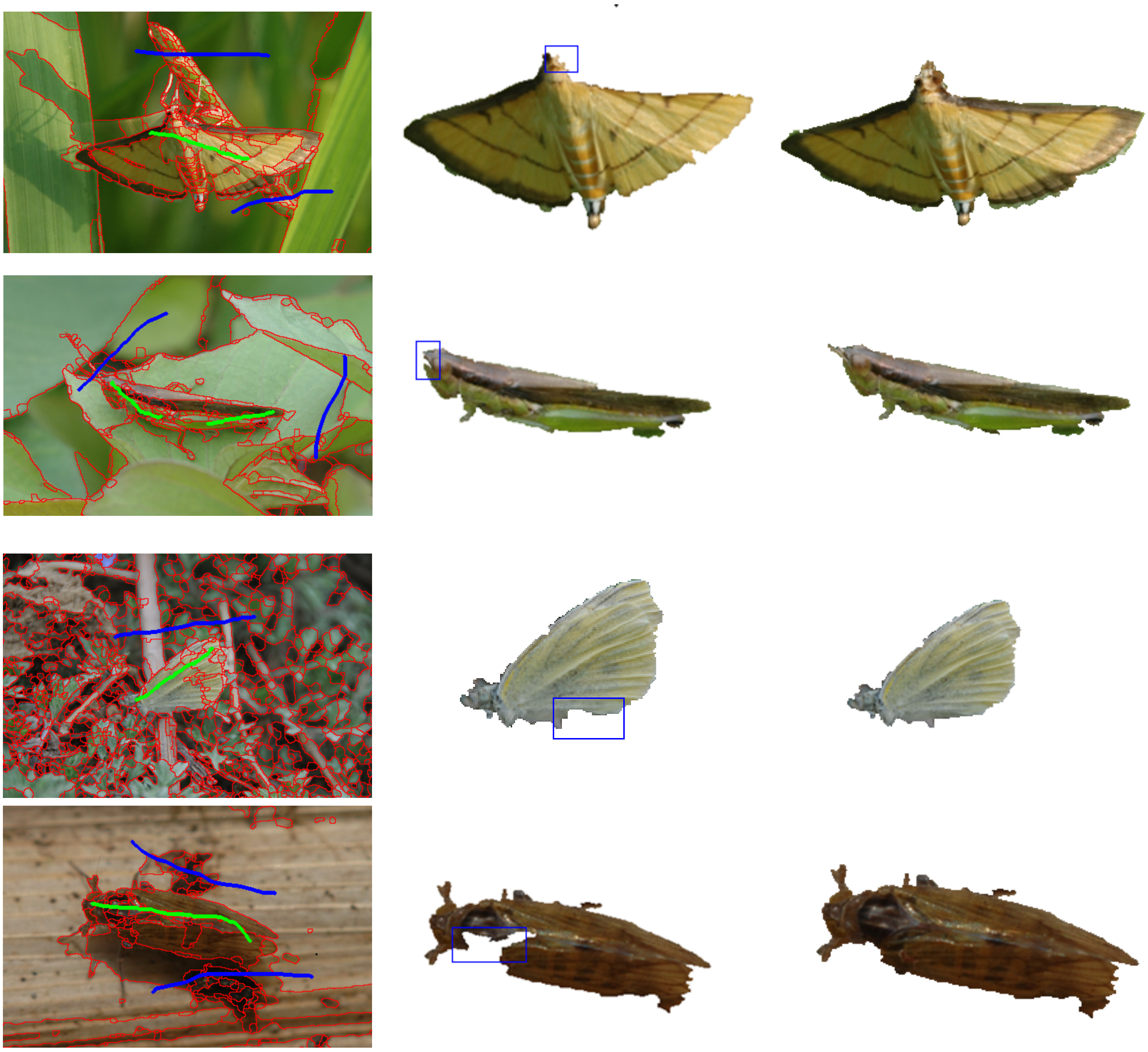

Fig. 4: Comparisons between MSRM and our method. (a) First column: initial segmentation and the input markers; (b) second column: segmentation by MSRM; (c) third column: segmentation by the proposed method.

information. The proposed method incorporates both color histogram and LBP texture histogram information to measure the similarity of different regions and thus to guide the region merging process. The experimental results show that the pest can be effectively extracted. Comparing with MSRM method, our proposed method is more robust and accurate than MSRM algorithm that involves only color similarity for pest image segmenting with complicated background.

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