Soil Image Segmentation Algorithm under Complex Background

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Abstract. In order to solve the problem of foreground and background segmentation of soil images under complex backgrounds, this paper proposes an image segmentation algorithm that combines colour features and local blur characteristics. First, the collected field soil images are converted from the RED colour space to the HSL colour space and the H component features are extracted. The H component is then converted to the CIELAB colour space. The b* component image is selected as a binary value based on the soil colour characteristics Pre-processing of H component. Then, the image fusion is performed according to the H component features, the b* binarization result, and the H-component local fuzzy variance pre-processing result to obtain a fusion result. Finally, in order to solve the hole problem in the segmentation result, the fusion result is subjected to boundary recognition and maximum boundary extraction, and the obtained maximum boundary region is filled to obtain the final image segmentation result. In order to test the segmentation effect of the proposed algorithm, Otsu is used to perform threshold segmentation on the soil image. The average time consumption of the two algorithms is 2.360 and 4.48. Comparing the time consumption of the two segmentation algorithms and the segmentation effect of the soil image, the experimental results of the proposed algorithm are significantly better than the Otsu segmentation algorithm.

1. Introduction
Image segmentation is the key to image processing until the final comparison image is analysed. The result of image segmentation will directly affect the performance of key image extraction and target classification processes. Diao Zhihua et al. [1] used the super green feature threshold segmentation model to realize the image segmentation of cotton disease leaf mite under complex background, and achieved good results. Perez et al. [2] proposed to use the combination of colour feature factors (G-R) / (G + R) of the RGB model to convert colour images into grayscale images, and realized the separation of soil and plant species. Jiang Haiyang et al. [3] proposed a new multi-domain multi-phase level set method to solve the problem of segmentation of cucumber leaf lesions under complex background. Zhou et al. [4] used colour difference methods R-B and G-R in RGB and HSI colour spaces to detect apples on fruit trees. Han Dianyuan et al. [5] proposed an image segmentation algorithm based on the similarity of multi-colour channels. The algorithm has good robustness to
shades of leaves and spots. Meyer et al. [6] used the super green feature threshold algorithm to identify weeds. D. Stajnko et al. [7] and A. B. Payne et al. [8] used the normalized difference index method (NDI) to separate apple and mango from fruit trees, respectively, and estimated the yield of fruit trees. Zhao [9] and Zeng [10] also used distance transformation theory to extract watershed markers. However, distance transformation could not prevent the subsequent problems caused by over-segmentation. Yu Wangsheng et al. [11] deduced the watershed algorithm based on marker extraction for the over-segmentation of the watershed algorithm in multi-colour image segmentation, which overcomes the problems of inaccurate edge positioning and weak edge extraction of previous algorithms. Researchers have proposed the idea of processing the watershed transform in advance [12-14] to solve the over-segmentation problem. Soille [12] proposed the morphology-based extended minimum transformation (H-minima) algorithm technology. In the process of segmenting an image, noise and a variety of different prior attributes related to the target attribute related prior knowledge are introduced in advance. The number of minimum values to achieve the purpose of controlling the number of divided regions and suppressing over-segmentation.

The image transition area is the area between the target and the background, and the gravy level of the contained pixels is generally between the target and the background. Image segmentation based on transition region extraction has received widespread attention for more than a decade [15, 18]. From the extraction method, the transition area extraction method can be divided into indirect extraction [15, 16] and direct extraction [17, 18]. For the indirect method [15], a univariate linear regression method is adopted to eliminate random fluctuations in the local area, which improves the robustness and positioning accuracy of the transition region determination process. [16] Proposed a transition region extraction method based on the light intensity weighted gradient operator, which greatly improved its ability to adapt to noise. The indirect extraction depends too much on the gravy clipping value and may lead to the shift of the transition area, and even cannot be extracted. For the direct method, [17] proposed a transition zone method based on local entropy, which overcomes the shortage of sensitivity to pepper and salt noise based on the gradient method, but this method has poor noise resistance and high algorithm complexity. Lecture [18] proposed a direct extraction algorithm for transition regions based on local complexity. The filtering effect of local complexity improves the anti-noise performance of the algorithm, and the direct extraction makes the algorithm free from the dependence on the gravy cut value. By analysing the characteristics of its transition region and background region, a transition region extraction algorithm based on local fuzzy variance is studied and used for image segmentation. This method can effectively suppress the influence of noise on the one hand, and has good segmentation performance on the other.

Based on the above research, this paper proposes an image segmentation algorithm that combines colour features and transition areas to achieve effective segmentation of soil image foreground and background under complex backgrounds.

2. Basic theory of image processing

Traditional image segmentation techniques are limited by the speed of the hardware, and are usually processed based on grayscale images. Colour images contain richer information than grayscale images, and the performance of image segmentation based on colour images is higher.

2.1. Colour Space Model

In the HSV colour space, H is the hue to indicate the different colours, S is the saturation, which represents the initial degree of the colour, and V is the brightness, which indicates the relative brightness of the colour. The H variable is linearly transformed into the x, y, z space. The conversion formula is as follows:

\[ X = 0.180423 \times H \]
\[ Y = 0.072169 \times H \]
\[ Z = 0.950227 \times H \]

(1)
The CIELAB colour space is also called L* a* b* colour space, which is composed of 3 coordinate axes of L*, a*, and b*. It is a uniform colour space [19, 20, 21], which will suit all Calculation of light source colour. In the CIELAB colour space, the difference between the two colours can be expressed by the distance between the two points, which is suitable for image segmentation and analysis. Turn x, y, z into the Lab space to mention the b component. The Lab model space is as follows:

\[
L^* = 116 f(Y/Yn) - 16 \\
a^* = 500[f(X/Xn) - f(Y/Yn)] \\
b^* = 200[f(Y/Yn) - f(Z/Zn)]
\]

\[
f(t) = \begin{cases} 
  t^{1/3} & t > \frac{6}{29} \\
  \frac{1}{3} \left( \frac{29}{6} \right) t + \frac{4}{29} & \text{otherwise}
\end{cases}
\]

\[X_n = 0.950456, Y_n = 1.0, Z_n = 1.088754\]

In the colour space, the b* component and the colour features extracted using the H component can be combined to establish an image segmentation model based on the colour features.

2.2. Construction of local fuzzy variance

According to the fuzzy set theory, an image f with L gravy level and size M × N can be regarded as a fuzzy point set matrix [22], as shown in (3):

\[
f = \begin{bmatrix}
  \mu_{i1}(f(1,1)) & \ldots & \mu_{iN}(f(1,N)) \\
  \vdots & \ddots & \vdots \\
  \mu_{M1}(f(M,1)) & \ldots & \mu_{MN}(f(M,N))
\end{bmatrix}
\]

Where \( \mu_{ij}(f(i,j)) \) indicates that the membership degree of the \((i, j)\) fuzzy single-point set in the matrix is \( \mu_{ij} (0 \leq \mu_{ij} \leq 1) \).

Membership can be calculated according to the standard S-type function:

\[
S(f(i,j); a, b, c) = \begin{cases} 
  0 & f(i,j) <= a \\
  2[(f(i,j) - a)/(c-a)]^2 & a < f(i,j) <= b \\
  1 - 2[(f(i,j) - a)/(c-a)]^2 & b < f(i,j) < c \\
  1 & f(i,j) >= c
\end{cases}
\]

Here \( a \) and \( c \) respectively represent the lower and upper bounds of the fuzzy window width in the S function, and the difference between the randomly chosen fuzzy windows varies, and \( b = (a + c) / 2 \) measures the remaining information in probability theory and can measure a fuzzy in fuzzy set theory. The size of the ambiguity in the set. The fuzzy variance of the fuzzy set A is defined as:

\[
V(A) = \frac{1}{n} \sum_{i=1}^{n} [S(\mu_{i}(X_i)) - \frac{1}{n} \sum_{i=1}^{n} S(\mu_{i}(X_i))]^2
\]

In formula (5), \( S() \) is a Shannon function \( S(x) = x \ln x - (1-x) \ln (1-x) \). The fuzzy variance is now generalized to a two-dimensional image as follows:
The fuzzy degree of the whole image can be measured by its fuzzy variance, but the global fuzzy variance does not consider the spatial distribution of a single pixel, and cannot measure the blurriness of a part of the image. Therefore, the global fuzzy variance should be extended to the local fuzzy variance. It is possible to calculate the fuzzy variance of a small neighbourhood $kX\times kX$ in the image to get:

$$V(f(i,j)) = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} [S(\mu_i(f(i,j))) - \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} [S(\mu_i(f(i,j)))]^2$$  \hspace{1cm} (6)

From equations (4) and (5), it can be observed that the distribution of gravy levels in the corresponding distribution area of the target (or background) is more prominent, with relatively small local fuzzy variance, and the gravy level distribution in the transition area is relatively scattered. The local fuzzy variance is large, so the transition area can be extracted.

3. Image segmentation algorithm
In order to effectively segment the foreground and background accurately from a complex background, this paper proposes an image segmentation algorithm that fuses colour features and transition regions. The algorithm flow is shown in Figure 1.

![Figure 1. Flow chart of algorithm.](image)

The algorithm implementation steps are:
(1) The RGB image is converted to HSL space, and the H component is extracted. The H component is linearly transformed to obtain the X, Y, and Z components. The $b^*$ component is extracted according to the $L^*$ $a^*$ $b^*$ formula. The threshold is used to divide the image. The value is 255, the other areas are set to 0, and the binarization process obtains the image Bib.
(2) Using the local fuzzy variance to extract the transition region for the H component, the local fuzzy variance of the dwelling image will be obtained, and the image Bevy will be obtained.

(3) An AND operation is performed on the obtained colour feature segmented BIb and the BIh segmented according to the local fuzzy variance map, and the result is again ANDed with the H component, and morphologically processed to obtain the final segmentation result.

4. Results and analysis
The background of soil images taken in the field is very complicated and there are many influencing factors. As a research object, the effectiveness of the proposed algorithm for segmentation is verified. Part of the collected pictures are shown in Figure 2.

The test picture in Figure 2 is converted from RGB space to HSL space and the H component is extracted, and then the H component is linearly transformed to the L* a* b* space. According to the b* component, the experimental measurement is appropriate. When \( \text{avg} + 13.8 \), there is a better segmentation effect, \( \text{avg} \) is the average of b*. The binary images of the three test images in Figure 2 are represented by BIb, as shown in Figures 3a-c.

The H component is pre-processed using local fuzzy variance to obtain the image Bevy. The results are shown in Figures 3d-f.

In order to reduce the influence of uneven light distribution, the picture in Fig. 3 is converted from RGB colour space to HSV colour space, and the colour attribute component H is used to extract colour features. The binary images of the three test pictures in Fig. 2 are represented by BIh, such as Figure 3g-i.

Observe Figures 3a-i and perform image fusion on the above three image results. When the BIh image is 0 and the local blur variance Bevy is 0, the image is combined with the BIb result. The foreground is set to 255 and the background is set to 0 to obtain the image BIm. The results are shown in Figures 3j-l.

The application of colour features and local blur characteristics has roughly extracted the soil foreground from the background. Due to the influence of light, there are large holes in the soil foreground area. The boundary of the foreground region is obtained by the maximum boundary recognition and extraction, and the BIf is obtained by region filling it. The results are shown in Fig. 3m-o. Bio is obtained by convolution in Fig. 3m-o and Fig. 2, and the results are shown in Fig. 3p-r.
It can be seen from FIG. 3 that according to the results of the algorithm segmentation, the comparison between the actual image foreground and the actual image foreground in FIG. 3p-r shows that the segmented soil foreground area is basically the same as the actual soil foreground area.

Use Otsu (Maximum Inter-Class Variance) algorithm to perform image segmentation on Figure 2. From the comparison of the time consumption of the two algorithms in Table 1, the segmentation results of the two segmentation algorithms can be seen. It is twice that of the Otsu algorithm. From the above analysis, the segmentation method mentioned in this article will perform better, and the segmentation results will be consistent with the foreground of Figure 3. The Otsu segmentation effect is biased, and the results are shown in Figure 4.

**Figure 3.** Segmentation process of three samples.
Figure 4. Otsu algorithm segmentation results.

Table 1. Comparison of time-consuming segmentation results of the samples.

| Otsu algorithm Average time | Algorithm Average time |
|----------------------------|------------------------|
| Sample 1 2.334 2.326 2.421 | Sample 1 2.360 4.469 4.34 |
| Sample 2 2.360 4.469 4.34 | Sample 3 4.648 4.48 |
| Sample 3 2.421 2.360 4.34 |

5. Conclusion
In view of the characteristics of soil images, this paper proposes a soil image segmentation algorithm that combines colour features and local fuzzy variance maps. The algorithm first uses HSL and Lab colour space models to segment the image, and removes most of the background to obtain foreground regions segmented by colour features; Use the local fuzzy variance map to obtain the segmented area; fuse the colour feature area and the local fuzzy variance area and do the maximum boundary recognition, maximum boundary extraction and area filling to achieve the segmentation of the foreground and background of the soil image. This algorithm can accurately segment the soil foreground from the complex background, and it has certain theoretical guidance and practical significance for the research of agricultural soil foreground and background segmentation algorithms.

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