Variety identification of corn seed based on Bregman Split method

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Abstract: Corn seed purity is closely related to corn yield, so seed selection plays an important role in improving grain yield product. The automatic seed selection procedure based on the machine vision is usually divided into three steps: image segmentation, feature extraction and classification. Variational model for image segmentation and corresponding numerical technique of Split Bregman method were introduced into the identification procedure, which had advantages of feature extraction such as high accuracy and closed continuous border. In addition, the adaptive wavelet collocation method was employed to solve the optimality conditions in Bregman split method. Based on the improved method, the corn geometric features can be extracted more precisely. Nongda108 and Ludan981 were taken as examples to test the new method. Based on a classifier designed with SVM, results showed the identification accuracy of Nongda108 and Ludan981 were 97.3% and 98%, respectively, better than 95% in previous research.

Key words: image recognition, feature extraction, models, Bregman split method, multi-levels wavelet interpolation operator
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0 Introduction

It is well known that grain seed purity is close related to the grain output[1-2]. Seed identification can be both a science and an art. Some seed scientists use “seed keys” to identify seeds[3-4], others visualization, and most use both depending upon what experience they have in the field and what they are trying to identify. Unfortunately, only the most common agricultural and weed seeds have been described, drawn, or photographed. And so it is hard to identify the less common seeds by this method. For any seeds, there are some important characteristics need to be identified, such as size, shape, texture, color[5-7]. When it comes to size, both the overall size of the seed and the size of each of the seed's individual parts[8]should be considered. Corn identification needs such a large amount of time and effort that it’s necessary to develop the automatic identification of corn seed based on machine vision. In general, the automatic identification procedure includes image acquisition and segmentation[9], seed geometric and color features extraction, seeds classification. Obviously, the corn seed identification precision is up to the image segmentation precision.

In fact, segmentation and object extraction is one of most important tasks in image processing and computer vision[10]. Many of the most general and effective segmentation methods can be written as variational based models such as fuzzy connectedness, watershed algorithm[11], Bayesian methods[12], Otsu’s method[13]. This category of variational models has been proved to be very effective in many applications, especially in the processing and analysis of medical images[14]. While there are many disparate approaches to image segmentation, this paper will focus on recently proposed methods which can be cast in the form of totally convex optimization problems and the corresponding numerical method-split Bregman method[15]. Combined with the classifier based on support vector machine (SVM)[16], a novel corn seed

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varieties intelligent identification system will be constructed.

1 The split Bregman method on the globally convex segmentation

1.1 Convex methods for image segmentation

The gloval convex segmentation (GCS) method , first proposed by Chan et al.[17], eliminate difficulties associated with those non-convex models by proposing an approach to segmentation based on convex energies. The GCS formulation based on the gradient flow can be described as follows:

$$\frac{\partial u}{\partial t}=\nabla\frac{\nabla u}{|\nabla u|}-\mu[(c_1-f)^2-(c_2-f)^2] \quad (1)$$

Where u is the level set function, μ is a constant variable, t is the time parameter, f is the image intensity, c_1 and c_2 represent the mean intensity inside and outside of the segmented region, respectively[18]. The strength of the regularization can be controlled by the parameter. This simplified flow represents the gradient descent for minimizing the energy

$$E(u)=|\nabla u|_1+\mu<u,r> \quad (2)$$

where $r=(c_1-f)^2-(c_2-f)^2$. To make the global minima well defined, we must constrain the solution to lie in the interval [0,1]. This results in the optimization problem:

$$\min_{0\leqslant u\leqslant 1}|\nabla u|_1+<u,r> \quad (3)$$

Once this optimization problem is solved, the segmented region can be found by thresholding the level set function to get

$$\Omega=\{x;u(x)>\alpha\} \quad (4)$$

for some $\alpha\in(0,1)$.

1.2 Split Bregman method on GCS

In fact, it's difficult to get the minimize of the model (2). Goldstein and Osher [15] proposed to enforce the inequality constraint using an exact penalty function. Then, the convexified segmentation can be reduced to a sequence of problems of the form

$$\min_{0\leqslant u\leqslant 1}|\nabla u|_g+\mu<u,r> \quad (5)$$

where $r=(c_1-f)^2-(c_2-f)^2$. In order to apply the Split Bregman method, the auxiliary variable d was introduced, that is, $\vec{d}$ can be employed to take the place of ∇u .To weakly enforce the resulting equality constraint, a quadratic penalty function was added, the following unconstrained problem can be got:

$$(u^*,\vec{d}^*)=\arg\min_{0\leqslant u\leqslant 1,\vec{d}}|\vec{d}|_g+\mu<u,r>+\frac{\lambda}{2}\left\|\vec{d}-\nabla u\right\| \quad (6)$$

In order to strictly enforce the constraint $\vec{d}-\nabla u$, Bregman iteration can be applied to the problem. The resulting sequence of the optimization problme is

$$(u^{k+1},\vec{d}^{k+1})=\arg\min_{0\leqslant u\leqslant 1,\vec{d}}|\vec{d}|_g+\mu<u,r>+\frac{\lambda}{2}\left\|\vec{d}-\nabla u-\vec{b}_k\right\|^2 \quad (7)$$

$$\vec{b}^{k+1}=\vec{b}^k+\nabla u^k-\vec{d}^k \quad (8)$$

To the Optimization problem in Eq.(7), the optimization condition can be described as

$$\Delta u=\frac{\mu}{\lambda}r+\nabla\cdot(\vec{d}-\vec{b})$$

If the solution to this equation lies in the interval [0,1] then this global minimizer coincides with the minimizer of the constrained problem. If the solution lies outside of this interval, then the energy is strictly monotonic inside [0,1], and the minimizer lies at the endpoint closest to the unconstrained minimizer. We have the following element-wise minimization formula:

$$\alpha_{i,j}=d^x_{i-1,j}-d^x_{i,j}-b^x_{i-1,j}+b^x_{i,j}+d^y_{i,j-1}-d^y_{i,j}-b^y_{i,j-1}+b^y_{i,j}$$

$$\beta_{i,j}=\frac{1}{4}(u_{i-1,j}+u_{i+1,j}+u_{i1,j-1}+u_{i,j+1}-\frac{\mu}{\lambda}\alpha_{i,j})$$

$$u_{i,j}=\max\{\min\{\beta_{i,j},1\},0\}$$

Minimization with respect to $\vec{d}$ is performed using the following formula:

$$\vec{d}^{k+1}=shrink_g(\vec{b}^k+\nabla u^{k+1},\lambda)$$

1.3 Maize image segmentation experiment

In order to examine the effectiveness of the split Bregman method on the globally convex segmentation, it was applied to segment the maize image, as shown in Fig.1. The purpose of method is to find the maize shape, the exact edge and the color information. The segmentation results were shown in Fig.2~3.

Fig.1 Original maize image

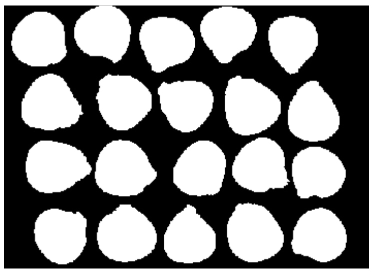

Fig.2 Segmentation with the Split Bregman method

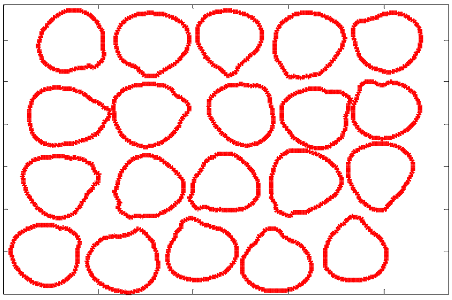

Fig.3 Contour of the maize image with split Bregman method

Compared with the watershed method shown in Fig.4, the segmentation result with split Bregman method was more accurate and had closed continuous border, which would be helpful in measuring the geometric feature of the maize images. But we can't get the different regions with different color. If we can get them, the more features of the maize image can be obtained, which are helpful in identification of the maize seeds.

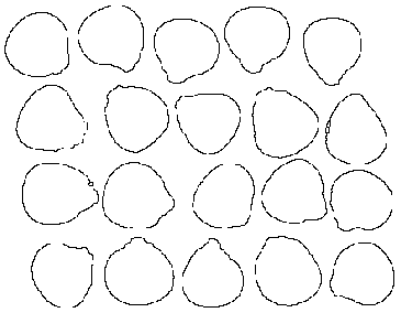

Fig.4 Watershed method

2 Modified split Bregman method based on the morphological reconstruction

Morphological reconstruction is a useful but little-known method for extracting meaningful information about shapes in an image. The shapes could be just about anything: letters in a scanned text document, fluorescently stained cell nuclei, or galaxies in a far-infrared telescope image. We can use morphological reconstruction to extract marked objects, find bright regions surrounded by dark pixels, detect or remove objects touching the image border, detect or fill in object holes, filter out spurious high or low points, and perform many other operations.

Essentially a generalization of flood-filling, morphological reconstruction processes to an image, which can be called the marker, based on the characteristics of another image, called the mask. The high points, or peaks, in the marker image specify where processing begins. The peaks spread out, or dilate, while being forced to fit within the mask image. The spreading processing continues until the image values stop changing.

If $\boldsymbol{G}$ is the mask and $\boldsymbol{F}$ is the marker, the reconstruction of $\boldsymbol{G}$ from $\boldsymbol{F}$, denoted by $\boldsymbol{R_G}$ ($\boldsymbol{F}$), is defined by the following iterative procedure:

1) Initialize h_1 to be the marker image, F.

2)Create the structuring element: $B = \text{ones}(3)$.

3) Repeat:

$$h_{k+1} = (h_k \oplus B) \cap G$$

until $h_{k+1}=h_k$.

4)$R_G(F)=h_{k+1}$

Fig.5~6 illustrate the preceding iterative procedure. Although this iterative formulation is useful conceptually, much faster computational algorithms exist.

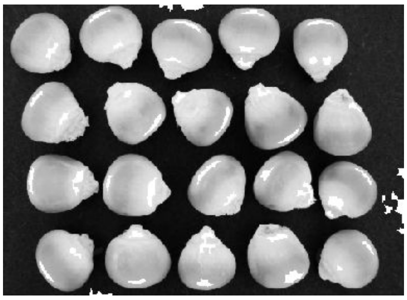

Fig.5 Modified regional maxima

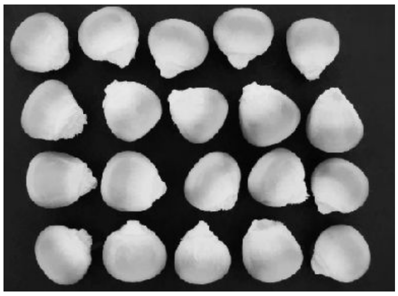

Fig.6 Opening-closing by reconstruction

After the morphological reconstruction, we can segment the maize images with the split Bregman method, the result was shown in Fig.7. It's easy to observe that the modified method can identify the different color regions exactly.

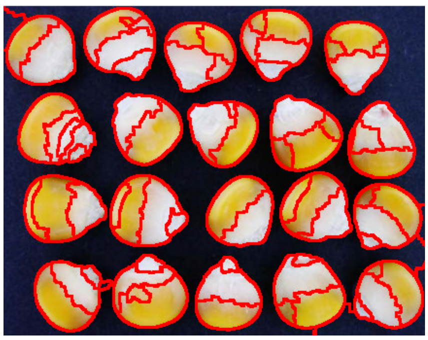

Fig.7 Modified split Bregman method combing with morphological reconstruction

3 Multi-Object feature extraction

In order to quantitatively describe the color information of maize seeds, six color features were defined as the mean values of Red, Green, Blue color, the mean value of the Hue, Saturation, Intensity. Combining with the geometric features measured with the segmentation results. Table 1 shows parts of the geometric feature parameters of two varieties of maize seeds, Nongda 108 and Ludan 981. Table 2 shows the color features.

Table 1 Geometric feature parameter of maize seeds

Geometric feature	Nongda 108	Ludan 981
Contour points amount	834	756
Circumference	952	878
Area	60 034	48 061
Length of long-axis	336	287
length of minor-axis	256	241
Maximum inscribed circle radius	162	134
Minimum inscribed circle radius	121	112
Largest span	321	243
Equivalent diameter	276	241

Table 2 Mean value of color feature parameter for maize seeds

Color feature	Nongda 108 mean value	Ludan 981 mean value
R	227	218
G	195	181
B	127	132
H	0.88	0.66
S	0.15	0.036
I	182	176

4 Corn seeds identification with SVM

Support Vector Machine (SVM) is a classification and regression prediction tool that uses machine learning theory to maximize predictive accuracy while automatically avoiding over-fit to the data. SVM can be defined as systems which use hypothesis space of a linear functions in a high dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory.

Here we present the QP formulation for SVM classification. This is a simple representation only.

SV classification:

$$\min_{f,\xi_i} \|f\|_K^2 + C\sum_{i=1}^{l}\xi_i \quad y_i f(x_i) \geqslant 1-\xi_i, \text{ for all i} \quad \xi_i \geqslant 0$$

SVM classification, dual formulation:

$$\min_{\alpha_i} \sum_{i=1}^{l}\alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\alpha_i\alpha_j y_i y_j K(x_i, x_j)\ 0 \leqslant \alpha_i \leqslant C,$$

for all i:

$$\sum_{i=1}^{l}\alpha_i y_i = 0$$

Variables ξ_i are called slack variables and they measure the error made at point (x_i,y_i). Training SVM becomes quite challenging when the number of training points is large. A number of methods for fast SVM training have been proposed.

Applying the feature parameters extracted in section 3, we can construct a classfier of corn seeds identification based on the SVM theory. Using the varieties identification classifier, the test of single variety identification and mixed varieties identification are done to 2 varieties maize seeds such as Nongda108 and Ludan981. The identification accuracy of Nongda108 and Ludan981by the method were 97.3 and 98%, respectively, showing that the identification accuracy was improved than that by Shi[19], in which the identification accuracy of Nongda108 and Ludan981 were about 95%, respectively.

5 Conclusions

The variational models for image segmentation and the corresponding split Bregman method were first employed to identify the corn seed variety in this paper, and the result showed the methods had advantages of high accuracy and closed continuous border. In fact, the reason that the method can improve the seeds identification precision is that image segementation results are more precise. Future research will focus on accelerating the Split Bregman scheme in the case of fidelity parameters, allowing for faster coarse segmentation of large images, and faster evolution of the GAC contour.

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基于分裂 Bregman 算法的玉米种子品种识别

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摘要：玉米品种的纯度和玉米产量密切相关，因此玉米品种的筛选对提高粮食产量具有非常重要的作用。基于机器视觉的自动品种筛选技术通常分为图像分割、特征获取和分类等三步。图像分割的精度直接决定了种子识别准确度。在众多的图像分割技术中，本研究尝试将图像分割变分模型及其对应的数值求解方法-分裂 Bregman 算法应用于玉米种子自动识别中。该方法具有精度高，分割边界封闭连续等有利于玉米特征提取的优点。此外，本文还将自适应小波配置法用于求解分裂 Bregman 算法中的最优条件，得到一种更为精确高效的分裂 Bregman 算法。进而结合改进分裂 Bregman 算法得到的不同玉米品种特征和支持向量机技术得到了一种新的玉米品种分类器。采用该方法对玉米品种农大 108 和鲁丹 981 进行实验，识别精度分别达到 97.3%和 98%，相对于由其他分割方法得到的分类结果精度（95%）要高。

关键词：图像识别，特征提取，模型，分裂 Bregman 算法，多层小波插值算子