Research on Rapeseed Counting Based on Machine Vision

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Abstract. Thousand-kernel weight is an important agronomic parameter of rapeseed. In order to quickly realize the grain count, shorten the measurement cycle of the thousand-grain weight, in this paper, we propose a grain counting method based on image detection, by testing 300 rapeseed images, and the results showed that the detection rate reached 89.33%.

Keywords: rapeseeds, the thousand-kernel weight, grain count, machine vision

1. Introduction

As we all know, the thousand-kernel weight of rapeseed is very important for breeding, quality evolution, yield estimation [1-3]. Rape is one of the main crops in Guizhou, so how to realize the rapid detection of the thousand-kernel weight of rapeseed is very important to lay a solid foundation for seed engineering. Manual counting methods are far from meeting the requirements; therefore, we replace manual counting with image processing methods.

Grain segmentation and feature point detection are the two core technologies for grain counting [4], this is determined by the spatial arrangement of the grains. The essence of grain segmentation is noise elimination; Therefore, an excellent denoising algorithm is essential to accurately extract the target region. For the seed kernel image, shadows are one of the most common noises. Since the shadow-oriented exploration of denoising methods is one of the very important ideas in the research process, the difference of our research is that we count the grayscale based on the rotated region to overcome the weakness of the vertical projection method in some cases. For feature point detection, the key content is the detection of corner points and holes for regions. The primary factor is that kernel count is closely related to the number of holes and corners. For the detection of corner points, our research is to judge whether the line paragraph points are inside or outside the target contour. For the
detection of holes, our research will mainly focus on the difference between the filled image and the original image. Please refer to the second section for the specific method.

2. Our methodology
Because our rapeseed grain images were gathered under uneven lighting conditions, shadows of rapeseed grains always exist in an image, sometimes there are little bit sundries among grains. For our research, shadow and sundries are viewed as noise due to them directly affect grains segmentation, so we need to use some de-noising methods to remove noise in an image.

2.1. Image processing

Choice of pressing image: In order to obtain an optimal prepressing image, we analyzed the RGB components of sample images. Finally, we chose R component as the preprocessed image.

Contrast enhancement: As we all know, contrast enhancement of background and target can benefit image segmentation. For this reason, we chose Fast Fourier transform to improve image contrast.

Shadow denoising: Nowadays, the application of denoising based on a sliding window grayscale statistics is very popular, for instance, skeleton extraction, ROI region extraction, target location, etc. However, the sliding window in these methods often only moves to a single direction, generally, only in the vertical direction or horizontal direction. The way of sliding scan to denoise based on grayscale statistics in an image is quite weak when it faces conditions like a sliding window of 1# or 3# in fig.1. The primary factor is that its denoising way only relies on the average and standard deviation of grayscale in a sliding window and one single scan direction is lethal if the processing area in a sliding window is all noise like shadow or targets like grains. In other words, a large proportion of noise would view as targets to be maintained like 1# condition in fig.1, by contrast, most targets would view as noise to be removed like 3# condition in fig.1. For this problem, we proposed a rotation-based denoising method and its core algorithm as follows.

Algorithm 1 Denoising method of the rotation-based scan.

In fig.2. E, F, G, H, T is one any moving point on the image border and rotates clockwise. Their moving step is d, we set d=10 pixel, and E≠F≠G≠H≠T. S represents the green polygon area, S rotates one clockwise to exit the algorithm. All the time EH and FG are symmetrical about the rotation axis R, and EH//FG//R, k is the slope of R, image longitudinal axis of symmetry as the first R for each image processing, O is the origin of coordinates. M, N is width and height respectively for the image. Before the algorithm to start, point (0, N/2−1) is assigned to T.

The input is a contrast-enhanced R component image inImg. The output is a denoised image oImg.

1. In inImg, according to R and d to initialize E, F, G, H.

2. Calculate \( k = \frac{y_t}{x_t} \) when \( x_t \neq 0 \) and \( k = \infty \) when \( x_t = 0 \). where \( y_t, x_t \) are the abscissa and ordinate of T respectively.
3. Calculate feasible region $S$. Since $R \parallel EH \parallel FG$, then s.t $S=\left\{ \begin{array}{l}
\frac{-N}{2} < x < \frac{N}{2} \\
\frac{-M}{2} < y < \frac{M}{2} \\
y - kx - B_{EH} \geq 0 \\
y - kx - B_{FG} \leq 0
\end{array} \right.$ when $T$ is in the second or third quadrants. Same goes for s.t $S=\left\{ \begin{array}{l}
\frac{-N}{2} < x < \frac{N}{2} \\
\frac{-M}{2} < y < \frac{M}{2} \\
y - kx - B_{EH} \leq 0 \\
y - kx - B_{FG} \geq 0
\end{array} \right.$ when $T$ is in the first or fourth quadrants. Where $B_{EH} = y_E - kx_E, B_{FG} = y_F - kx_F$. when $k \to \infty, S=\left\{ \begin{array}{l}
\frac{-M}{2} < y < \frac{M}{2} \\
\frac{-d}{2} < x < \frac{d}{2}
\end{array} \right.$

4. Calculate the mean $m$ and the standard deviation $dev$ of grayscale in $S$.
5. Set threshold value $Th=m-\beta \times dev$. Generally, where $\beta \in (0,1)$.
6. Search area $S$, if one-point intensity $I > Th$, then $I=0$ else $I=1$.
7. $R$ moves one $d$, and update $R$. Repeat from step 0 to step 5.
8. Until $S$ rotates clockwise for a full circle, and copy $inImg$ to $otImg$.
9. Return $otImg$.

**Fig.1** Denoising based on a sliding window grayscale statistic

**Fig.2** Denoising method of rotation-based scan

2.2. *Detection for corner points and holes*
Amounts for corner points and holes are very important to calculate the number of rapeseed grains. We divided the corner point into two categories, one is the inner corner point and the other is the outer corner point. We proposed a corner detection method, as shown in fig.3, the core algorithm is as follows.

**Algorithm 2** Detection of corner points and holes
Input is a binary image; output is a set that contains corner points and holes.

1. Define the matrix $F$. Init $G ← F$. $G$ is the input.
2. Fill image $F$ with the seed fill algorithm.
3. With connected components labeling algorithm to label $G$ and $F$ respectively (We set the same non-zero area with the same tag in $G$ and $F$).
4. Calculate the outer contour $C_{i}^{\text{ot}}$ of all regions in $F$. $i$ is the index of regions, $i \in (1, N)$. $N$ is the number of areas in $G$ or $F$.
5. Define the zero matrix $M$ $-$ $G$. $M$ is the input.
6. Define the tuple $(G_{k}, H_{k})$ with $G_{k}$ and $H_{k}$ denoting the contour of $i$-th non-zero regions (also call holes in $G$); Let $N_{k}$ denote the number of $C_{k}$; $N$ is the total number of holes. $i$ is the index of regions. For $G$, $N_{k}$ is the number of holes in the $i$-th connected region.
7. Calculate the centroid $(\bar{x}_{i}, \bar{y}_{i})$ of $i$-th holes. where $(x_{k}, y_{k}) \in C_{k}$. For instance, $(\bar{x}_{i}, \bar{y}_{i})$ is $O$ in fig.3.
8. Sooth $D$ with moving average method, next detect peak (refer in fig.3) value based on slope $k$ sign change. Where $k = \frac{d_{i}x_{i+1} - d_{i}x_{i}}{x_{i+1} - x_{i}}$. Let $N_{i}^{m}$ denote the number of peaks (peak is the inner point, refer in fig.3, in particular, e and f have no inner corner and hole). $i_{h} \leftarrow i_{h} + 1$. Repeat 5-7, calculate all $N_{i}^{m}$.
9. Define the tuple $G_{k} = (i, H_{k}, l_{k})$. If $k \neq l$, $k \leftarrow l$, then $H_{k} \leftarrow H_{k} = 1$, $l_{k} \leftarrow l_{k} + 1$, $P_{k} \leftarrow P_{k} + P_{l}$. Where $l_{k}$ is the gray level of $C_{k}, H_{k}$ is the number of holes in the $i$-th connected region in $G$, $P_{k}$ is the number of inner corner points in the $i$-th connected region in $G$; $k, l \in [1, N_{k}]. i$ is the index of regions in $G, i_{h} \leftarrow 1$.
10. In $F$, for each $C_{i}^{\text{ot}}$, randomly select $A$ and $B$ on the contour $C_{i}^{\text{ot}}$ (refer d in fig.3). $A, B$ rotate one circle clockwise, record $A_{g}, B_{g}, \forall A_{g} = B_{g - 1} = 2, 3, \ldots$; the arc length $A_{g} B_{g}$ is $l_{AB} = 40$. Let $(x_{AB}, y_{AB}), (x_{BG}, y_{BG})$ denote $A_{g}, B_{g}$ respectively.
11. $k_{i} = \frac{y_{g} - y_{B}}{x_{g} - x_{B}}$ $(x_{m}, y_{m})$ is one moving point on the line $A_{g} B_{g}$, $x_{m} = \min(x_{AB}, x_{BG}) x_{m} \leftarrow x_{m} + 1$, $y_{m} = k_{i} x_{m} + b$. $b = y_{AB} - k_{i} x_{AB}$. Set $P_{A_{g} B_{g}} = \{m \in [1, 1, |x_{B} - x_{A}| + 1]\}$ $(x_{m}, y_{m})$, $i \notin [1, \frac{T}{|x_{A}|}, T = \text{size}(C_{i}^{\text{ot}}))$. Where the line $A_{g} B_{g}$ is a detection line for outer corners.
12. Search $P_A,B_i$, if $(x_m,y_m)$ is outside $C_i^{ot}N_i^{ot} \leftarrow N_i^{ot} + 1. \boldsymbol{N_i^{ot}}$ is the number of outer corner points for $C_i^{ot}. i \leftarrow i+1. \text{Repeat 11.}$

13. Define the tuple $N_i = (i, l_i^{ot}, N_i^{ot})$, $i=1,2,3,4,...,N. l_i^{ot}$ is the gray level of $C_i^{ot}. i \leftarrow i+1, \text{repeat 9-11.}$

14. Define tuple $S(i, P_i, H_i), P_i \leftarrow (G_i \rightarrow P_i^{in} + N_i \rightarrow N_i^{ot}), H_i \leftarrow (G_i \rightarrow H_i^{in})$. where $i=1,2,3,...N_h;i=1,2,3,...N;H_i$ is the number of $i$-th holes; set $Y=\{1 \leq k \leq N|S_1, S_2, S_3, ..., S_k\}$.

15. Return $Y$.

![Algorithm of corner points and holes](image)

**Fig.3** Algorithm of corner points and holes

### 2.3. Calculate the count of rapeseed grains

According to the spatial arrangement characteristics of rapeseeds, the number of holes and corners among the kernels is closely associated with the count of rapeseed grains. The number of grains $N$, the number of holes $H_i$, and the number of corner points $P_i$ make the formula (1) true.

$$N = \sum^n_{i=1}(\frac{P_i}{2} - H_i + 1)$$

In the formula (1), $n$ is the total number of connected regions in an image. The same goes for, replace $P_i$ and $H_i$ in formula (1) with elements in set $Y$, we can get the formula (2).

$$N = \sum^n_{i=1}(\frac{Y \rightarrow S_i \rightarrow P_i}{2} - Y \rightarrow S_i \rightarrow H_i + 1)$$

### 3. Test

Our algorithm code is written in C++ and OpenCV3.4.3, and the development environment is Visual Studio 2013. Test platform configuration is as a processor Intel (TM)i5-82500U CPU @1.80GHz, RAM is 8.00GB, the operating system is Windows 10 and type is 64bit. We randomly selected 300 images to test. The image size is uniformly 640×480.

#### 3.1. Algorithm 1 test
Algorithm denoising performance is generally good, and shapes of most regions are close to the grain shape, as is shown in fig.4. a is the original image, b is the processing result of algorithm 1, c is the processing result of the vertical projection method (which sliding window size is 40×640).

We compared the difference of results for algorithm 1 and the vertical projection method. As is shown the red dotted oval circles in fig.4. Compared with vertical projection denoising, we can get a conclusion that Algorithm 1 denoising can restore grain shape better, for shadows, Algorithm 1 is more sensitive to recognition and positioning.

For some samples, as is shown by the blue dotted ellipses in fig.4, we observed the image segmentation area and found that the area of shadow adjacent grain is still retained. We surmised the most likely cause is that the pixels in this region are quite similar to the target pixel. In addition, fewer grains are incomplete or with an inner hole, the main reason is that there are some spots on the surface of the grain. For these problems, with follow-up studies, we need to take some measures to resolve them.

![Fig.4 Comparison of algorithm 1 and vertical projection method](image)

3.2. Algorithm 2 test

As shown in Fig.5, the green line regions are the corner points positions. The red circular regions are inner corner points and holes regions. The red lines are detection lines. The results show that algorithm 2 is able to detect corners and holes among grains, which can provide reliable parameters for subsequent grain counting.
3.3. **Reliability evaluation of counting method**

In order to evaluate the reliability of the grain counting method in this paper, we analyzed the results of 300 rapeseed images. Finding that there are 268 images with the correct grain count and the correct rate is reached 89.33%, which shows that it has certain robustness. We also analyzed the samples that detected errors, whose main reason is that the algorithm fails to adapt well to the situation of impure grain appearance. Our follow-up research needs to improve the algorithm detection mechanism.

4. **Conclusion**

The image counting method of rapeseed grains makes it possible to quickly detect the thousand-kernel weight of the grains. At the same time, it also provides technical support for breeding evaluation, yield estimation, and quality evaluation.

In general, the counting method that we researched is able to detect most samples correctly. We proposed the algorithm 1 guarantees the validity of the feature parameters detected by Algorithm 2 that provides reliable data for grain counting. For the variety of grain skin colors, further research is still needed.

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