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Structure tensor based analysis of touching grain kernels for visual grading

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Abstract. Automatic visual grading of seed lots with a high density of touching grain kernels is a challenging problem. The structure tensor is a simple and robust descriptor that was developed to analyze textures orientation. Contrarily to segmentation methods which rely on an object based modelling of images, the structure tensor views the sample at a macroscopic scale, like a continuum. Thanks to this tool, it is possible to extract useful information on the orientation of grain kernels even in a bulk. Knowing the rough orientation of a grain kernel could provide an initialization for segmentation techniques. The comparative results with ground truth orientations on four different grain kernels demonstrate the ability of the structure tensor to detect the seed orientations.

Keywords: structure tensor, orientation field, visual grading, image analysis

1 Introduction

In agriculture, the global grain harvest reached several billion tons each year. Seed producers exchange their crops at a price determined by the quality of their production. This assessment, called grading, is performed for each set on a representative sample. The difficulty of this assessment is to fully characterize the sample. To do so, it is necessary to qualify each of its elements. Historically, this has been performed manually by an operator. This method is exposed to various problems and the results can vary from one operator to another.

Due to the huge amount of data contained in large images, automatic procedures are indeed essential to assess grain kernel shape properties such as size, orientation, aspect ratio, ... The lack of robust, fast and universal procedures to provide such a geometric description in the case of touching grain kernels is one of the obstacles to exploit the full potential of images.

The visual grading of grain kernels has been widely discussed during the last ten years. A number of studies have been conducted to classify grain based on physical attributes. Some classification studies are done on images with separated grain kernels [1, 2]. Other studies have been conducted on the grain segmentation with low density of touching grain kernels [3–6]. Segmentation processes that deal with touching grain kernels, with low or high densities, under the constraint of no seeds overlapping, have been lately proposed in [7] and [8].

The structure tensor is an interesting preprocessing tool which could improve these segmentation methods in the case of high density of touching grain kernels. In the presented experiments, the considered seed samples are placed in bulk, without any arrangement. They are spread over a tray in such way that there is nearly no overlapping between the objects to avoid occlusion.

The structure tensor appeared in the field of image processing in the late 80's [9] for the problem of interest point detection. It was then justified theoretically and popularized in different contexts such as interest point detection [9], [10], texture analysis [11], representation of flow-like images [12], optical flow problems [13] and anisotropic or coherence enhancing diffusion [14]. The results of this paper demonstrate that the structure tensor provides a fast, robust and precise enough tool to retrieve grain kernel orientations. The proposed method has the advantage to be fast and invariant under contrast changes.

In Section 2, the definition of the structure tensor is recalled and some implementation information is provided. Section 3 proposes a way to choose the correct algorithm parameters. Section 4 demonstrates the interest of using the structure tensor on real images with low and high density of touching grain kernels. Its output is compared to the ground-truth orientations obtained by a human operator. These comparisons show that the structure tensor provides a good orientation estimation which could be used in segmentation approaches.

2 Structure tensor

The structure tensor of an image u is defined as follows

$$T := G_\rho \star (\nabla u_\sigma \nabla u_\sigma^T), \quad (1)$$

where $u_\sigma = G_\sigma \star u$, u denotes a gray-level image G_σ and G_ρ are Gaussian filters with standard deviation $\sigma \geq 0$ and $\rho \geq 0$, which control the amount of pre- and post-smoothing. The parameter σ is called the inner scale, the parameter ρ the outer scale. For a color image, the structure tensor is computed as the sum of the structure tensors for each channel.

In practice, the discrete gradient operator ∇ is defined by $\nabla = (\partial_1, \partial_2)^T$. In all reported experiments, the partial differential operators ∂_i are defined as convolutions with discrete kernels. From an asymptotic point of view any kernel leading to a consistent discretization should provide good results. However, the kernel design turns out to be crucial to provide good orientation and anisotropy estimates. Key properties of discrete kernels are [15]: i) rotation invariance, ensuring a reliable orientation estimation, ii) separability, ensuring faster computations and iii) no shift, implying the use of centered finite differences. Following these criteria, the authors of [15] suggested to use the following operations:

$$\partial_x u = \frac{1}{32} \begin{pmatrix} -3 & 0 & 3 \\ -10 & 0 & 10 \\ -3 & 0 & 3 \end{pmatrix} \star u \quad \text{and} \quad \partial_y u = \frac{1}{32} \begin{pmatrix} -3 & -10 & -3 \\ 0 & 0 & 0 \\ 3 & 10 & 3 \end{pmatrix} \star u.$$

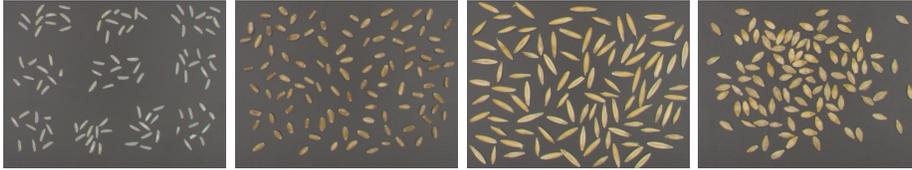


Fig. 1. Seeds used to extract the geometric statistics presented in Table 1. Top line, rice and wheat seeds. Bottom line, two types of barley seeds.



Fig. 2. Mean maps of the shapes: from left to right, rice, wheat, first and second type of barley grain kernels, from top to bottom, with or without a green ellipse.

The gradient is computed in the space domain, while the convolution with G_σ or G_ρ are based on fast Fourier transforms. The overall computational complexity for an image with n pixels is therefore $\mathcal{O}(n \log(n))$. In practice, the structure tensor can be computed in near real-time. In each pixel, the orientation is given by the direction of the eigenvector associated with the highest eigenvalue of the structure tensor.

3 Postsmoothing parameter estimation

As seen in the previous section, there are two parameters σ the inner scale and ρ the outer scale for the structure tensor. The experiments show that $\sigma = 0$ is sufficient, due to the quality of the acquisitions, and ρ is linked to the shape of the grain kernel.

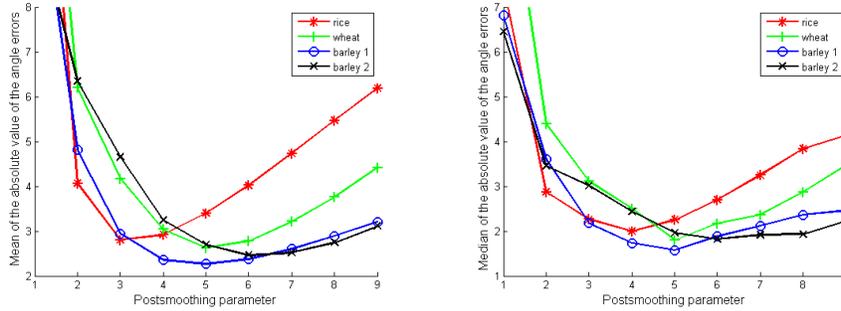
Figure 1 presents isolated rice, wheat and barley seeds. The images are binarized and statistics on the features of isolated seeds are computed. Table 1 presents these statistics which will be helpful for the parameter selection in the algorithm. The major axis length (respectively minor axis length) is the scalar specifying the length in pixels of the major axis (respectively minor axis) of the ellipse that has the same normalized second central moments as the grain kernel.

Figure 2 presents the mean maps of the isolated seed shapes. A green ellipse is plotted on it to illustrate the interest of using an ellipse to estimate the statistics in Table 1. The mean shape maps are obtained by performing a partial Procrustes superimposition of the isolated seed shapes. The grain kernel shape and their three symmetries (two axial and one central) are optimally translated and rotated before performing the superimposition.

Comparisons with ground truth orientation were performed in order to determine the parameter ρ . The samples for these experiments are presented in

Table 1. Geometric statistics on the grain kernels presented in Figure 1.

Rice seeds, Figure 1 (top left)					
Features	Minimum	Maximum	Mean	Median	Standard deviation
Major axis length	23	51	43	44	6
Minor axis length	10	15	13	13	1
Wheat seeds, Figure 1 (top right)					
Features	Minimum	Maximum	Mean	Median	Standard deviation
Major axis length	34	54	43	42	4
Minor axis length	11	24	18	18	3
Barley seeds, first type, Figure 1 (bottom left)					
Features	Minimum	Maximum	Mean	Median	Standard deviation
Major axis length	61	101	82	82	11
Minor axis length	16	24	20	21	2
Barley seeds, second type, Figure 1 (bottom right)					
Features	Minimum	Maximum	Mean	Median	Standard deviation
Major axis length	39	115	56	54	10
Minor axis length	16	57	25	24	6

**Fig. 3.** Influence of ρ on the mean (left) and the median (right) of the absolute value of the angle errors.

Figures 4, 5, 6 and 7. The best parameter is the one which provide the lowest mean or median of the absolute value of the angle error. The curves in Figure 3 illustrate the influence of ρ on the mean (left) and the median (right) of the absolute value of the angle errors. The rice, wheat, first type and second type of barley results are represented in respectively red star, green plus, blue circle, and black cross. In each case, the best postsMOOTHING parameter ρ is around one-fourth of the mean pixel length of the minor axis.

4 Comparisons with ground truth orientation

Figures 4, 5, 6 and 7 present a visual comparison between the ground truth orientations (left and plotted in red) and estimated orientations (right and plotted in green) for respectively the rice, wheat and the two barley grain kernels. Each

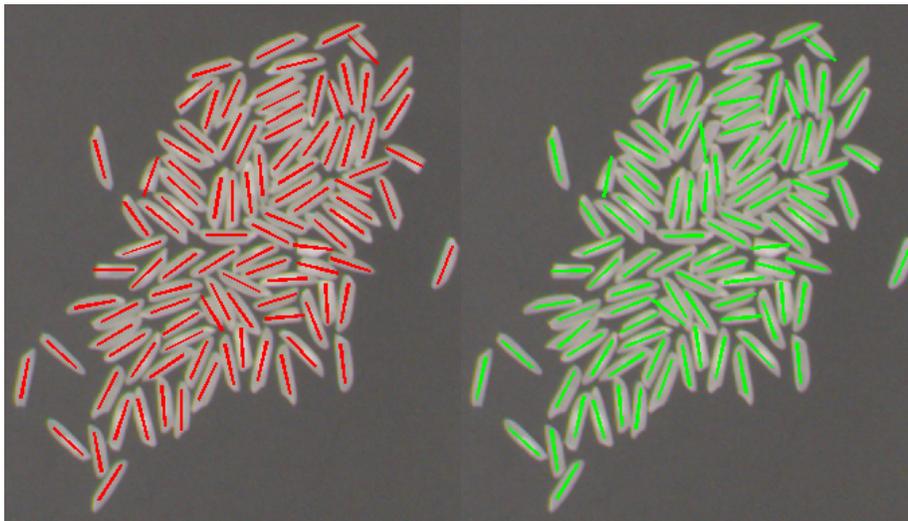


Fig. 4. Comparison of ground truth orientations (left) and estimated orientations (right) for the rice grain kernels.

sample contains one hundred grain kernels. Table 2 presents the statistics on the absolute value of the angle error for these hundred grain kernels. For all the four studied grain kernels, on average the error is of 2 to 3 degrees, same for the standard deviation. The median is around 2 degrees. There are very few bad orientation estimations, two of them are presented in Figure 8. One can note that the main estimation errors are due to overlapping or broken grain kernels.

Table 2. Statistics on the absolute value of the angle error.

Seeds	ρ	Minimum	Maximum	Mean	Median	Standard deviation
Rice	3	0.150	14.833	2.806	2.266	2.629
Wheat	5	0.023	15.025	2.628	1.798	2.494
Barley 1	5	0.043	24.473	2.266	1.572	2.722
Barley 2	6	0.006	9.274	2.464	1.825	2.202

5 Conclusion

The present work justifies the interest of structure tensors to evaluate orientations of grain kernels in images. Comparison with ground truth results proves that even if no arrangement is provided by the user, the grain kernel orientation can be retrieved in the samples. The tests of the present study explain how to find the best parameters for the structure tensor. The amount of postsMOOTHING

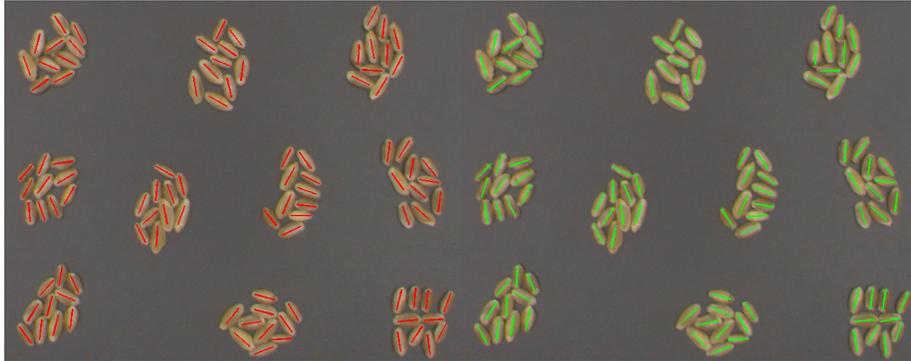


Fig. 5. Comparison of ground truth orientations (left) and estimated orientations (right) for the wheat grain kernels.

is linked to the minor axis of the ellipse which best approximate the grain kernels. The accuracy of the orientation estimation demonstrates the efficiency of the structure tensor as a preprocessing tool for segmentation methods. Implementation on industrial segmentation algorithms is done in [16].

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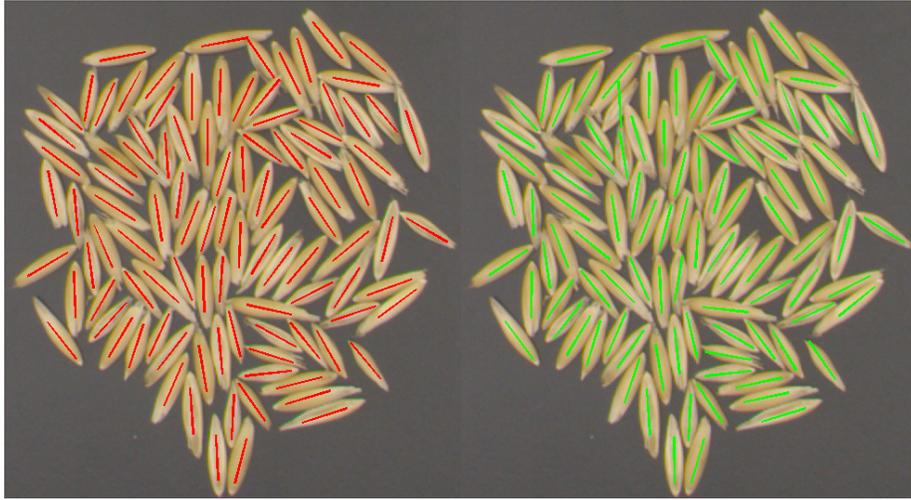


Fig. 6. Comparison of ground truth orientations (left) and estimated orientations (right) for the barley grain kernels, first type.

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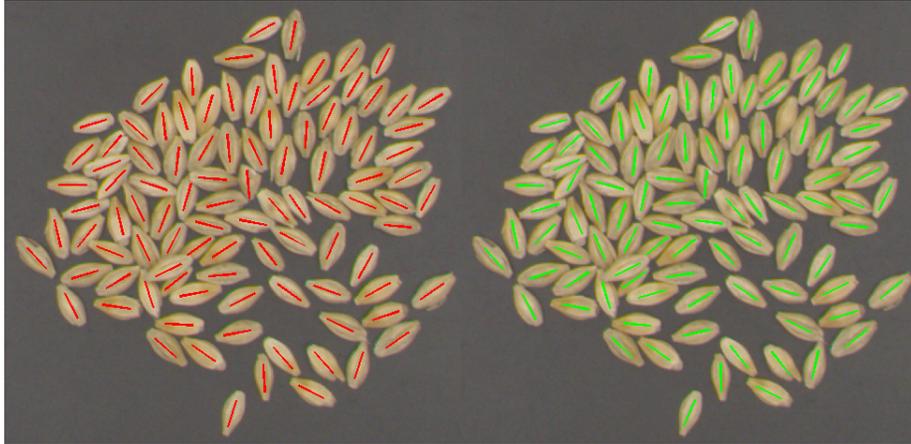


Fig. 7. Comparison of ground truth orientations (left) and estimated orientations (right) for the barley grain kernels, second type.

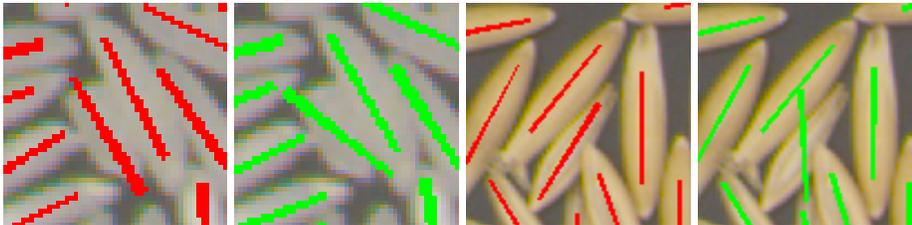


Fig. 8. Zooms on two bad orientation estimations. The two images of rice grain kernels at left are extracted from Figure 4. The two images of barley grain kernels at right are extracted from Figure 6. In the rice case, the bad orientation is due to a broken kernel. In the barley case, the bad orientation is due to an overlapping.