Locally Oriented Anisotropic Image Diffusion: Application to Phenotyping of Seedlings

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Abstract. A variant of the Perona-Malik anisotropic diffusion equation is introduced for the segmentation of multiple objects with crossings. The diffusion is automatically applied at the crossings locations along the main orientations of the objects. Application of this process is given for illustration on an original problem of plant imaging with the monitoring of the elongation of multiple crossing seedlings.

1 Introduction

Since its introduction some 3 decades ago by Perona and Malik [12] partial differential equations (PDE) as a mathematical framework for image processing have raised a considerable attention [14]. This interest is mathematically motivated by the possibility of a variational interpretation of the action of the PDE. Also, PDE inspired by physical modeling constitute a vast field of investigation to be considered for its own sake or for new approaches to various image processing applications (restoration, segmentation, in-painting, to name few areas where PDE have been competitively applied). In this report, we revisit the recently introduced oriented diffusion equation [5] where a diffusion process is applied to an input image with a selective function of the angle between the local gradient and a global orientation of reference. For gradient along the reference, there is no diffusion, while gradients perpendicular to the reference are associated to maximal diffusion. As such, the oriented diffusion equation of [5] is interesting when a single direction is taken as reference for the whole image. This is the case in the tagged grid MRI sequence considered for illustration in [5]. However, there are practical situations where a selective diffusion process would be useful if applied with a local orientation of reference. This is the case when the targeted information task is the individual restoration of multiple objects crossing with various angles. As an extension of [5] we therefore propose a locally oriented anisotropic diffusion process with a local orientation of reference at the scale of an imagette. We demonstrate the usefulness of this approach with an original bioimaging application. The report is organized as follows. We first describe the orientation diffusion equation of [5] and discuss

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the limitation of this approach in the case of our plant imaging application. We then introduce our new anisotropic diffusion equation and illustrate its performance on our application.

2 Locally Oriented Anisotropic Diffusion

Anisotropic diffusion applied in image processing has been introduced in [12]. It is a process inspired from the physics of temperature diffusion in which an input image ψ_0 is transformed in an output image ψ taken as the solution of the partial differential equation given by

$$\frac{\partial \psi}{\partial t} = \mathrm{div}(g(\|\nabla\psi\|)\nabla\psi), \qquad \psi(x, y, t = 0) = \psi_0 \ . \tag{1}$$

The anisotropy of this diffusion process is governed by $g(.)$ a nonlinear decreasing function of the norm of the gradient $\nabla\psi$. Function $g(.)$ is a nonlinear decreasing function like

$$g(u) = \exp\left(-\frac{u^2}{k^2}\right) , \tag{2}$$

in the original work of [12] where parameter k can be seen as a soft threshold controlling the decrease of $g(.)$ and the amplitude of the gradients to be preserved from the diffusion process. Many variants of the diffusion process of Eq. (1) have been proposed (see [14] for a review). The benefit of such diffusion processes lies in the ability to smooth data in a nonlinear way, while preserving important image features (contours, corners, ...). Recently an oriented variant of the anisotropic diffusion process of Eq. (1) has been proposed in [5] to control the diffusion process with the direction of the gradient instead of only the norm of the gradient. The partial differential equation of [5] reads

$$\frac{\partial \psi}{\partial t} = \mathrm{div}(g(A.\nabla\psi)\nabla\psi), \qquad \psi(x, y, t = 0) = \psi_0 \ , \tag{3}$$

where A is a vector field defining the particular direction to preserve from the diffusion process. In [5] application of Eq. (3) was given in a case where the vector field A was selecting a single direction in a whole single image. In certain situations the directions to be preserved can spatially change in the image. This is for instance the case with the separation of multiple crossing objects in image. Crossing objects appear in various fields of science like for instance vessel or muscle fibers crossing in biomedical imaging [4,8,2], crossings roads in remote sensing [9], or assemblies of crossing nano-objects with microscopes in physics [3]. The restoration of each object in such images of crossing objects is an important problem if one is interested in performing individual measurements on each object. In this work, we consider this crossing objects problem with the oriented anisotropic diffusion of Eq. (3). In [5] illustration is given with a unique direction in the vector field. To deal with multiple crossing objects, we have implemented a locally oriented anisotropic diffusion process that preserves a local orientation of reference at the scale of an imagette. To this purpose, we propose to perform a crossing detection before applying diffusion. We then apply the diffusion process of Eq. (3) locally only in the vicinity of the crossing objects. The crossing is characterized by two directions. The idea is to diffuse in one of these directions to restore and

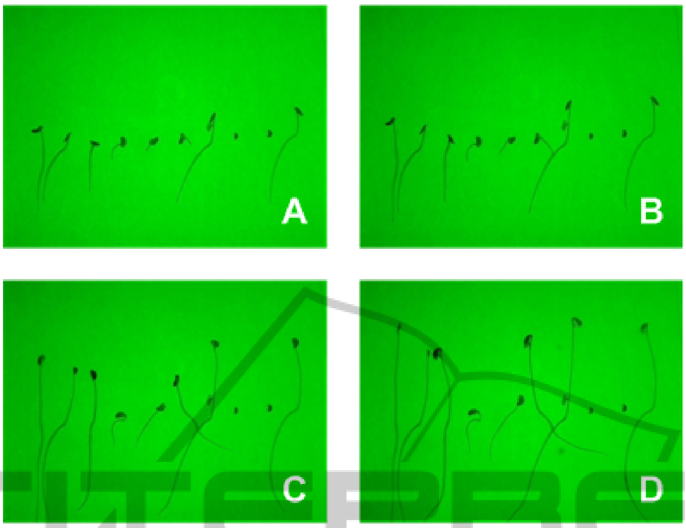

Fig. 1. Sequence of acquired images with green backlight during seedling elongation with a 2 hour time step between each snapshot A, B, C and D. The typical duration of the elongation process can be several days.

segment one object and then to repeat this process in the other direction to restore the other object. We apply this strategy to a real world problem from plant science in the next section. For illustration in this work we have taken as in [6] the nonlinear function $g(.)$ in Eq. (3) as a hard threshold

$$g(u) = \begin{cases} 0 & \text{for} \quad u \geq k \\ 1 & \text{for} \quad u \leq k \; . \end{cases} \tag{4}$$

With this choice the diffusion process simply corresponds to a threshold on the gradients oriented in the direction of the vector field A. Gradients oriented in the correct direction are preserved while other direction are erased. This is obtained in one iteration in the diffusion equation.

3 Application to Seedling Elongation

Seedling elongation is an early stage of the development of plants. During this stage, the seed is in the soil. Following a geotropism, the upper part of the seedling grows to reach the light and activates photosynthesis while the lower part of the seedling is going deeper to anchor in the soil and access to water and nutrients. In field conditions this seedling elongation is not accessible to plant analysts. However, non invasive monitoring of seedling growth is accessible in vitro with computer vision machines [11, 7, 13,15], French et al., 2011, [1]. A set of seedlings can for instance be positioned on an horizontal row in a gelose box. A backlight system associated with a camera then produces sequences of images like in Fig. 1. From such image sequences, the temporal evolution of the length of the radicle of the seedling is measurable with classical binary image skeletonisation [11, 7, 13,15], French et al., 2011, [1]. However, other traits like the respective size of the organs of the seedling are not accessible from the skeleton and require more elaborated image processing approaches. A difficulty visible in the images of Fig. 1 is that the radicle of the seedlings can cross. To overcome this difficulty we propose the following pipeline including the diffusion process of Eq. (3) implemented in the algorithm of Fig. 2. In the images of Fig. 1 the seedlings are well-contrasted from the background. The segmentation of the seedlings can thus be done after a simple thresholding. The resulting binary image is skeletonized. Crossings are detected in this skeleton around points of the skeleton having connectivity higher than two. Regions of interest including a single crossing are then defined. Such a region of interest serves as input to the algorithm detailed in Fig. 2.

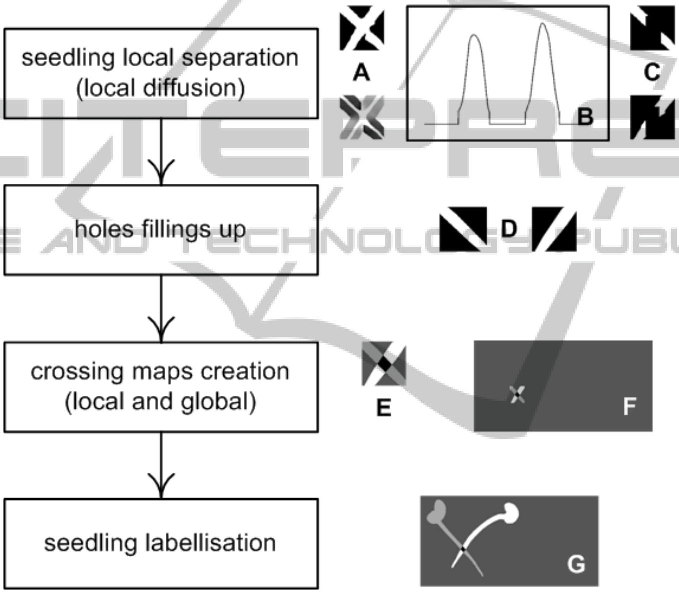

Fig. 2. Four steps seedling crossing segmentation algorithm. In a first step the algorithm load (A) an input binary image corresponding to a crossing in the input image. (B) Histograms of the orientation of the gradients are calculated. Two main directions of the crossing are present in this histogram. The diffusion equation of Eq. (3) is consecutively applied in each one of these two main directions to produce two images preserving the respective other direction (C). The threshold k in Eq. (4) is consecutively chosen equal to the main directions of each modes in the histogram in (B). In the second step, the holes in the binary images are filled (D). A seedling crossing map is created in (E-F) in a third step and the seedlings are labeled (G) in the fourth step.

As illustrated in Fig. 3, seedlings crossing in the sequence are correctly separated. We have tested successfully the algorithm of Fig. 2 on various species including species with several seminal roots like wheat. In these cases crossings are very common and separating the different roots is crucial. Finally, the good performance of our algorithm in this study is important for two reasons. First it enables to perform the elongation monitoring at more advanced stages of development. Second this enables to concentrate

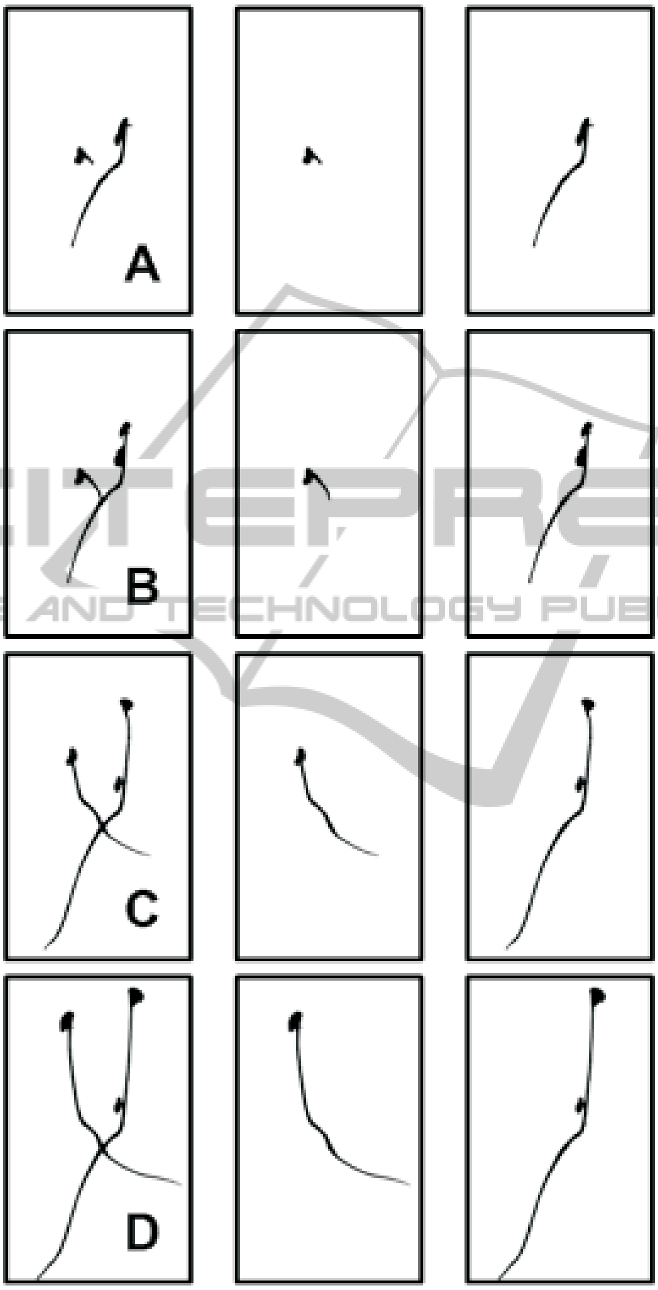

Fig. 3. Results of our crossing seedlings segmentation on two crossing seedlings of the image sequence of Fig. 1. In the left column a binarized version of a crop form Fig. 1 at instant A, B C and D. The two other columns represent the output of the algorithm of Fig. 2 with the two labeled seedlings.

higher number of seeds of different types of species in the field of view of the camera and therefore contributes to increase the throughput of the monitoring.

4 Conclusions

In this work we have presented an extension of the partial differential equation of [5]. In our case, a detection of the part which requires to be diffused is first performed and the partial differential equation is then applied locally only in these parts. This presents the interest to speed up the diffusion process by comparison to a global approach. This also avoids diffusion artefacts in areas where no diffusion was needed. Application of our PDE was given here for illustration in the domain of plant science with crossing seedlings during their elongation stage. In our case the segmentation of the crossing seedlings was obtainable from a simple threshold and the partial differential equation was only applied in the crossings area to separate the seedlings. However, for some species with very thin roots, the contrast between background and seedlings may not be so favorable and it could be interesting to apply the oriented anisotropic diffusion locally in the whole image to separate seedling around crossings and also to restore the edges along the curvated roots in non crossing areas. Plants are highly anisotropic structures organized along branching structures. Plants growth or plant pathogens spreading along these structures therefore constitute a natural field of applications for anisotropic diffusion with PDE to analyze or modelize these spatio-temporal phenomenon.

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