A low cost, high accuracy optical flow method for measuring 2D and 3D corn seedling growth: theory, experimental technique and validation

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1. Introduction

We propose the use of optical flow as a means of accurately measuring 2D and 3D growth of young corn seedlings. Our method is ultra-sensitive and operates in a non-intrusive, non-contact manner and can measure motions whose magnitude is as minuscule as 5 microns/second. Our 2D analysis, started in 1994 [3], uses a least squares integration method to locally integrate spatio-temporal image derivatives into an optical flow field [12]. Thus the work described here is an evaluation and verification of just one optical flow method for the use in (accurately) measuring young corn seedling growth. The 2D plant motion is displayed as a vector field of nearly uniform 2D velocities. A key assumption of the 2D growth analysis is that growth motion occurs locally in a 3D plane and its accuracy depends on this assumption being satisfied. We observed that the plant sways in 3D space as it grows, so this assumption does not hold over long time intervals. To capture this swaying over longer time intervals we extended our optical flow approach to 3D [4]. We use a single least squares calculation to integrate
all spatio-temporal image derivatives into a single 3D velocity. Each image in the sequence consists of two views of the same seedling: one view of the corn seedling is front-on while the second view is an orthogonal view (at
90 degrees) of the seedling made by projecting the plant’s orthogonal image onto a mirror oriented at 45° with respect to the camera. We compute
3D optical flow at the corn seedling’s tip by using a simple extension of the 2D motion constraint equation. Both the 2D and 3D methods assume orthographic projection, which holds locally in the image plane. This al-
lowed motions in pixels/frame to be directly scaled to meters/second. We con-
clude the paper by showing the accuracy of optical flow as a means of measuring 2D and 3D corn seedling growth.

2. Literature Survey
Measurement of minute increments in plant growth, using displacement transducers, has been used for a number of years [11, 13, 15]. Using trans-
ducers, resolution of measurement of growth can be as sensitive as 10⁻⁶
meters. However, the transducer technique for growth measurement re-
quires mechanical coupling of the transducer to the plant and the effect
of this mechanical engagement has not been documented. A non-contact optical technique of growth measurement had also been demonstrated using interferometry [9, 10]. However, this method of measuring plant growth requires an elaborate setup with mirrors, lasers and other instruments. The use of optical flow, as advocated here, avoids these problems and required a simple setup with just a black and white camera, a frame grabber, at most
one mirror (for 3D growth measurements) and a PC computer.

3. 2D Experimental Technique
We used an optical method we attribute to Lucas and Kanade [12, 1] to
approximate the local 2D image motion in a sequence of image of a growing corn seedling. Our choice of Lucas and Kanade’s method was motivated by its ease of implementation, computational speed and good accuracy [1]. As such, the work described here is a very careful experimental study of one optical flow method, rather than a comparative evaluation of many optical flow methods for our growth measurement task; see [1] for a comparative
analysis of 9 optical flow methods.

The local motion measured via an optical flow computation corresponds
directly with the 2D plant growth in the image. The instrumentation neces-
sary for this technique is comprised of a black and white camera, frame
grabber and computer with appropriate software. In our particular setup,
a colour camera (a Sony 3 CCD camera, model DXC-327 with a zoom lens,
model VCL-712BX, having a focal length range of 7.5-90 mm) was used
and the $480 \times 512$ pixel colour images were converted to $150 \times 150$ gray-value images by using a YIQ colour to grayvalue transformation and by partitioning out the same subareas of each of the images that contained the corn seedling before optical flow analysis. The Sony camera used in our experimentation has non-square pixels with a height of $9.8 \times 10^{-6}$ meters and a width of $8.4 \times 10^{-6}$ meters. To take this into account we scaled all the computed horizontal components of full velocity by $\frac{34}{25}$. This scaling has only a minor effect on the final computed full velocities as most unscaled full velocities were almost vertical. Corn seeds were sown singly in modified peat moss growing medium in black polyethylene tubes 10 cm long and of 1 cm inner diameter. A tube with a corn seedling at the primary leaf stage was inserted into a glass bottle containing water and coils from water baths set at various temperatures. In a first 2D experiment [3], the seedling shoot was exposed to the ambient room air temperature of $24^\circ C$ while the roots in the tube were exposed to the water bath temperature. The seedlings were grown initially at a temperature of $24^\circ C$ for about 1 hour. Following this period the water temperature was reduced to $12^\circ C$, held at that temperature for a period and then raised back to room temperature. In a second 2D experiment [7], we use constant root temperature and measured corn seedling growth in long image sequence (over 3 days), where the motion of a leaf emerging from the coleoptile at the end of the second day was measured separately. Constant scene illumination was maintained during both growth sequences. The windows in the experimental room were also blocked so that the room was devoid of natural light. This setup results in the scene being illuminated by ambient light, thus ensuring constant spatiotemporal illumination for all visible parts of the scene. Surface reflectivity was minimized by using a deep nap black rayon velvet cloth behind the seedling as the image background and placing the camera with a macro lens in close proximity to the front of the seedling. An image was acquired every 2 minutes during this activity. This sampling rate was determined from trial and error.

3.1. 2D OPTICAL FLOW

We computed optical flow from spatiotemporal derivatives of filtered versions of the images in a sequence taken of a growing seedling. Such differential techniques are based on the motion constraint equation:

$$\nabla I(x, t) \cdot v + I_t(x, t) = 0,$$

(1)

where $I_t(x, t)$ denotes the partial time derivative of $I(x, t)$, $\nabla I(x, t) = (I_x(x, t), I_y(x, t))^T$ is the spatial intensity gradient and $\nabla I \cdot v$ denotes the usual dot product. From this equation, we can see that constant scene
Figure 1. (a) The aperture problem: only the component of velocity normal to the line's orientation, $v_n$, can be recovered, the tangential component of velocity, $v_t$, cannot be recovered. (b) The Motion Constraint Equation (1) yields a line in $v = (u, v)$ space, the velocity with the smallest magnitude on that line is $v_n$. Another velocity on the line is the correct full velocity $v$.

Illumination is necessary, otherwise non-zero intensity derivatives due to illumination changes may lead to the detection of "false" image motion where none exists. Equation (1) yields the normal component of image velocity relative to spatial contours of constant intensity. There are two unknown components of full velocity $v$ in (1), constrained by only one linear equation. This is a consequence of the aperture problem (see Figure 1). The equation describes a line in velocity space. Any velocity on this line satisfies (1). The velocity on the line with the smallest magnitude is the normal velocity, which can be written as $v_n = \frac{-\nabla I(x, t)}{\|
abla I(x, t)\|}$. Another velocity on the line (at unknown location) is the correct full velocity $v$. Hence, further constraints in addition to (1) are necessary to solve for both components of $v$. One way to compute $v$ is to use a local constant velocity model (all velocities in a local neighbourhood are the same) in a framework suggested by Lucas and Kanade [12]. We use their method with thresholding modifications proposed by [17]. A study of various performance issues of this and other techniques is presented in [1] and those results led us to believe that optical flow would be suitable for measuring plant growth. We implemented a weighted least-squares fit of local first-order constraints.
(1) to a constant model for \( \mathbf{v} \) in each small spatial neighbourhood \( \Omega \) by minimizing

\[
\sum_{\mathbf{x} \in \Omega} W^2(\mathbf{x}) \left[ \nabla I(\mathbf{x}, t) \cdot \mathbf{v} + I_t(\mathbf{x}, t) \right]^2,
\]

where \( W(\mathbf{x}) \) denotes a window function that gives more influence to constraints at the centre of the neighbourhood than those at the periphery. Equation (2) can be minimized by solving

\[
\mathbf{v} = [A^T W^2 A]^{-1} A^T W^2 \mathbf{b}
\]

where, for \( n \) points \( \mathbf{x}_i \in \Omega \) at a single time \( t \),

\[
A = \begin{bmatrix} \nabla I(\mathbf{x}_1), \ldots, \nabla I(\mathbf{x}_n) \end{bmatrix}^T, \\
W = \text{diag} [W(\mathbf{x}_1), \ldots, W(\mathbf{x}_n)], \\
\mathbf{b} = -(I_t(\mathbf{x}_1), \ldots, I_t(\mathbf{x}_n))^T.
\]

Spatial neighbourhoods \( \Omega \) are 5 x 5 pixels, and the window function \( W^2(\mathbf{x}) \) was separable and isotropic; its effective 1-d weights are \((0.0625, 0.25, 0.375, 0.25, 0.0625)\) as in [17]. The solution to this system of equations is a least squares fit of a single full velocity to a local 5 x 5 neighbourhood of normal velocity measurements.

3.2. IMAGE PREFILTERING AND DIFFERENTIATION

Our implementation first smoothed each image in the sequence. This filtering helped to attenuate temporal aliasing and quantization effects in the input. We used balanced smoothing which involves using a 3D separable Gaussian filter with a standard deviation (\( \sigma \)) of 1.5 pixels-frame. Good digital approximations to Gaussians can be found using \( n \) coefficients, where \( n \) is the smallest odd integer greater than or equal to \( 6\sigma + 1 \). For \( \sigma = 1.5 \), to produce one smoothed image at frame \( i \) we used images \( i - 5 \) to \( i + 5 \).

For balanced smoothed images, we computed \( I_x, I_y \) and \( I_t \) using 4-point central differences with mask coefficients of \( \frac{1}{12}(-1, 8, 0, -8, 1) \). Hence the temporal support for a single flow computation was 15 frames (we used 5 smoothed adjacent images for differentiation and 11 images to produce one smoothed image), i.e., we used frames \( i - 7 \) to \( i + 7 \) to compute the flow for frame \( i \).

3.3. FLOW THRESHOLDING

Following Simoncelli et al. [17], unreliable velocity estimates were identified using the eigenvalues of \( A^T W^2 A \), \( \lambda_1 \geq \lambda_2 \), which depended on the
range of magnitudes and orientations of spatial gradients in local image neighbourhoods. The greater the range of magnitudes and orientation the larger $\lambda_2$ is and the more confident we can be in the computed velocity. If $\lambda_2$ is zero the matrix is singular and no velocity can be recovered. In the instance where there is little variation in the local normal velocities, $\lambda_2$ will be quite small, meaning full velocity cannot be reliably recovered. We used the value of $\lambda_2$ to ascertain the reliability of computed full velocities. In our implementation, if $\lambda_2$ (and hence $\lambda_1$) was greater than a threshold $\tau$, then $v$ was computed from (3), otherwise no full velocity was recoverable at that location. We have found in previous work [1] that $\tau$ is a good threshold; large $\tau$ values produce accurate but sparse flow fields while small $\tau$ values produce inaccurate but dense flow fields. For the results in this paper we used $\tau = 1.0$. This number is based on empirical observations [1] made on a large number of synthetic and real image sequences, including the image data analyzed for this paper.

Further thresholding of the computed flows was necessary to remove surviving outliers. We first remove all velocities with a negative vertical component (there were only a few of these). Second, we impose a similar velocity constraint on the computed flow on the basis that all velocities computed should be the same if the plant is growing uniformly for some short time interval. We do this using a number of thresholds. Viewing a velocity $v = (u, v)^T$ as a 3 component vector, $v_3 = \frac{1}{\sqrt{u^2 + v^2 + 1}}(u, v, 1)^T$ we can measure the angle between any two velocities, $v_{31}$ and $v_{32}$, as

$$\psi = \arccos(v_{31} \cdot v_{32}). \tag{4}$$

This metric was used as an error measure in [1]. For the 2D results in this paper, all velocities not within 3.5° of the average velocity in local $11 \times 11$ neighbourhoods (using (4) to measure the angles) were thresholded. Finally, we computed the average magnitude and angle plus standard deviations of the remaining velocities and removed all those velocities not within 1.0 standard deviation of these averages. The final result of all this thresholding was a flow field with nearly uniform velocities.

4. 2D Experimental Results

Our program computed the rate of growth in pixels per frame. We converted this to $10^{-1}$ meters per frame by imaging a metric ruler in the same 3D plane as the plant was in and computing the number of pixels per centimeter, we found that vertically 1 pixel corresponds to $7.853 \times 10^{-5}$ meters. Since the images were acquired at 2 minute intervals, 1 pixel/frame is $6.544 \times 10^{-7}$ meters per second. Figure 2a shows an image of the corn seedling, Figure 2b its normal flow field and Figure 2c the full flow field.
computed from the normal flow field after thresholding as described above. The average rate of growth for this image (the average full velocity magnitude) was $1.982 \times 10^{-7} \pm 8.393 \times 10^{-9}$ meters/second with a density of 93 velocities. Note that full velocities can only be computed where there is sufficient variation in the normal velocities (as indicated by the magnitude of $\lambda_2$), i.e., at the tip of the seedling in this case as shown in Figure 2b. Figure 3 shows the average magnitudes with standard deviation bars of the optical flow for each time (image) in the corn seedling sequence (as solid disks) and the seedling’s root temperature versus time (as open circles) for a sequence of 100 images. Note that the growth rate and the temperature were well correlated (Pearson’s product moment correlation coefficient, $r = 0.943$) as expected. These results show that optical flow is quite suitable under the circumstances described here for measuring corn seedling growth.

In further work [7], much longer image sequences (more than 2000 images) could be analyzed by optical flow and the growth not only of an original corn seedling but also (separately) that of leaves emerging from the coleoptile could be measured. The experimental setup and the optical method were the same as before.

One observation from these experiments is that a corn seedling only grew locally in a 3D plane (thus satisfying the assumptions made in using the motion constraint equation) but that over time the plant appeared to have significant 3D motion. This indicated the need to directly measure 3D growth.
5. 3D Experimental Technique

The experimental setup varies from the 2D growth study in one significant way: in order to obtain front and side views simultaneously we used a mirror situated about 10 centimeters from the plant and oriented at 45° to obtain a side view of the plant in the same image as the front view. The plant was about 15 centimeters from the camera. Figures 4a and 4d show two examples of such images. The corn seeds were sown in modified peat moss in black polyethylene tubes and exposed to a room temperature of about 20° celsius. The camera, plant/tube and mirror were contained in a wooden box, the inside of which was covered by a black velvet cloth to minimize illumination changes and specularities, to eliminate any room air currents and to keep the scene temperature constant (the box was illuminated internally by fiber optics).

6. 3D Optical Flow

In the computer vision literature the constant velocity model used in the 2D case to integrate normal velocities is known as an 0th order paramet-
ric model for image velocity [8]. Other parametric models assume a more complex local distribution of image velocities (i.e., non-zero velocity derivatives) and are not considered here as the local constant velocity assumption is satisfied for our data. Using higher order parametric models in the computation of 3D optical flow would also require us to solve the correspondence problem, that is to find the same image points in the two plant views corresponding to the same 3D point, a difficult problem.

We replaced/modified the 3 steps we used in the computation of 2D optical flow to increase computational efficiency and accuracy. We use the balanced/matched filters for prefiltering and differentiation proposed by Simoncelli [16]. A simple averaging filter $[\frac{1}{4}, \frac{1}{2}, \frac{1}{4}]$ was used to slightly blur the images before prefiltering/differentiation. The prefiltering kernel’s coefficients were $(0.0356976, 0.2488746, 0.4308557, 0.2488746$ and $0.0356976)$ while the differential kernel’s coefficients were $(-0.107663, -0.282671, 0.0, 0.282671$ and $0.107663)$. For example, to compute $I_t$, we first convolve the prefiltering kernel in the $t$ dimension, that convolve the prefiltering kernel on that result in the $y$ dimension and finally convolve the differentiation kernel in the $x$ dimension on that result.

It has been shown that derivative results (and hence, velocity calculations) obtained using his filters have about the same accuracy and are more dense but only use half as much image data as Gaussian smoothing and 4-point central differences [16, 2]. We performed the integration step in a single computation using all the normal velocities of the front and side views of the corn seedling to compute 3D velocity, $(u, w, v)$, rather than computing $(u, v)$ and $(v, w)$ separately from local $5 \times 5$ neighbourhoods in the front and side images because, based on 2D results, neighbourhooding
velocities are nearly always identical. This yields both computational efficiency and increased accuracy (as more data is being used). For normal velocities from the front view we used the given motion constraint equation for \((u, v)\) in equation (1) while we use a slightly different form of equation (1) for the side image, \(-I_y w + I_x v = -I_t\), to compute \((v, w)\). Note that the minus sign in front of \(I_x\) is necessary as a negative \(x\) velocity in the front image is a positive \(z\) velocity in the side image. These two equations yield 2 equations in 3 unknowns \((u, v, w)\). We measure \(I_x, I_y\) and \(I_t\) for the two views and use one of two forms of equation (1) to set up a linear system of equations which we can solve for in the least squares sense (we must have at least one derivative set from each of the views or a \((u, v, w)\) calculation is not possible). Note here that because we are using a constant velocity model (all normal velocities emulate from the same 3D velocity) no correspondence between left and side views is needed; if the image of some 3D plant point contributes an equation for the front view it does not have to contribute an equation for the side view as well and vice versa. Also note that because the front and side views of the corn seedling are made under perspective projection, they have slightly different sizes because their effective distances from the camera are 15cm and 25cm respectively (in image 400 [Figure 4d] the front (left) view is about 4 pixels higher than the side (right) view, while in image 10 [Figure 4a] their heights are roughly the same). Taking the perspective difference into account by scaling has only very minimal actual effect on the computed velocities.

We perform the 3D computation using those image points in the front or side images where \(\min(I_x, I_y) \geq \tau\) to obtain the front or side equations. We used \(\tau = 2.0\) for the results reported here and Figures 4b and 4d shows those points in the front and side images that are used in the 3D velocity calculation for 2 images (note that they are all at the tip of the plant). Our scheme requires the solution of a \(n \times 3\) system of equations

\[
N_{n\times 3}(u, v, w)^T = B_{n\times 1},
\]

where the row entries of \(N\) and \(B\) are determined using one of the two forms of equation (1). We use a weighted least squares calculation by computing a diagonal matrix \(W_{ij} = \min(I_{xij}, I_{yij})\) and solving for \((u, v, w)\) as

\[
(u, v, w)^T = \left( N_{3\times n}^T W_{n\times n}^2 N_{n\times 3} \right)^{-1} N_{3\times n}^T W_{n\times n} B_{n\times 1}.
\]

Solving this system of equation simply involves inverting a \(3 \times 3\) matrix. We also solved systems of equations [the two forms of (1)] separately to obtain \((u, v)\) for the front views of the corn seedling and \((v, w)\) for the side views of the corn seedling in the images by solving simple \(m_l \times 2\) and \(m_r \times 2\) least squares systems of equations \((m_l + m_r = n)\). In this case, the 2D \(u\) and \(w\)
values were almost identical to those in the 3D case while 3D \(v\) values are roughly the weighted average of the 2D \(v\) values (which are usually very close to start with).

7. 3D Experimental Results

We collected 506 images of a front/side view of a growing corn seedling (see Figure 4 and used them to obtain 500 3D growth vectors \((u, v, w)\). Our program computes growth in pixels per frame, we converted this to meters per second by imaging a metric ruler in the same 3D plane as the plant is in and measuring the number of pixels per centimeter. We found that 1 pixel corresponded to \(3.745 \times 10^{-4}\) meters. Since images were acquired at 2 minute intervals, 1 pixel/frame motion corresponds to a speed of \(3.112 \times 10^{-6}\) meters/second.

We display the data as 2D plots of magnitude \(\| (u, v, w) \|_2\) and two angles \(\theta\) and \(\phi\) describing 3D direction against time (image number). Since \(\vec{v}_{3D} = (u, v, w)\) is a 3D vector only two angles are needed to describe its orientation. We define \(\theta\) as the angle from \(0^\circ\) to \(360^\circ\) counterclockwise about the line-of-axis \((0, 0, 1)\) as

\[
\theta = \arccos(\hat{v}_p \cdot (0, 0, 1)),
\]

where \(\hat{v}_p = (u, 0, 0)\) is \(\vec{v}_{3D}\) projected onto the \(x - z\) plane and normalized to 1. Thus \(\theta\) is the amount of rotation of \(\vec{v}_{3D}\) about the \((0, 1, 0)\) axis. \(\phi\) is the angle of \(\vec{v}_{3D}\) with respect to \((0, 1, 0)\) vertical axis, that is,

\[
\phi = \arccos(\vec{v}_{3D} \cdot (0, 1, 0)).
\]

\(\theta\) and \(\phi\) are converted from radians to degrees by multiplying by \(180.0/\pi\).

The results showed that the growth on corn seedlings is not uniform but grows in fast and slow spurts as the plant tip rotates and sways in 3D space. To subjectively verify the correctness of our results we also made a movie of the plant growth with the growth measurements superimposed on the images and when visually viewed the computed growth measurements agree with the actual plant growth. Note that currently, we have no way of independently verifying the growth measurements by other means. However, we observe that the sum of the \(v\) values for the front and side view 2D velocity computations is 132.17 and 128.54 pixels respectively for the 500 images while the difference in the front and side tip positions (computed as the center of masses of all points contributing normal velocity data to the 3D calculation) between the first and last images is 133.59 and 129.25 pixels respectively, relative differences of 1.06\% and 0.96\% between the tip positions and the velocity sums over the entire image sequence. We believe this is an indication of the accuracy we are obtaining.
We have imposed the \((u, v)\) and \((v, w)\) vectors on images 10 and 400 of the sequence (see Figures 4c and 4f). These show the growth is taking place in roughly the same direction as the corn seedling tip is pointing in Figure 4c but in a different direction in 4f (although, in general, we note that tip direction and 3D velocity direction can be quite different). Lastly, we point again out one important advantage of our technique: that the apparatus for the optical flow method is rather inexpensive as one only needs a black and white camera, a frame grabber, a mirror and a PC computer.

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Figure 6. Plots of the 3D angles $\theta$ and $\phi$ against time (image number) for 500 3D velocity calculations.

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