Quantification of leaf movement to study the circadian rhythm using the optical flow

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Abstract. Circadian rhythm is a biological rhythm in a plant that has a 24-hour period, which affects the plant activities such as metabolism processes, physiology processes, and plant behavior. Circadian rhythm represents the biological clock that entrained by the environmental condition affected by the earth rotation. As an alternative to monitoring the circadian rhythm in the plant was the use of leaf motion as a physical indicator. The objective of this study was to present the quantitation method for leaf movement to study the circadian rhythm using the optical flow method. The leaf movement was analyzed from the captured time-lapse imaging using an Infra-red camera to capture the day-night movement of the leaf of Chili (Capsicum annum L.) from top and side view projection. As a result, the quantification method could quantify the leaf motion of Chili for both top and side view projection with the higher movement observed at top view projection. The quantified motion could show the diurnal pattern of circadian rhythm clearly and will be used for further investigation related to plant behavior in response to environmental changes.

1. Introduction

Earth rotation caused light and temperature cycles to exist in the environment [1]. Every living thing relies on the circadian clock to anticipate environmental changes [2]. The circadian clock is endogenous timekeeping systems that allow plants to generate rhythms with periods approximate 24 hours known as circadian rhythms [2]. The circadian clock affects many biological processes and plant physiology such as photosynthesis, hormone secretion, and iron homeostasis [3]. Circadian rhythms can be used to study plant behavior both in constant and dynamic conditions. There are many methods to estimate the circadian rhythm, one of them is circadian rhythm can be measured based on prompt chlorophyll fluorescence [4].

Leaf motion is one of the physical indicators that has been used to investigate the existence of circadian rhythm based on De Mairan, 1729[5,6]. Estimation of leaf motion to produce a circadian rhythm consists of 3 stages: 1) taking and collecting images at a fixed interval continuously, 2) calculating the translation distance and the direction of the angle laterally from the collected image, 3) determining the period, phase, and amplitude of numerical data series [7]. In the previous study, several systems have been developed to estimate leaf motion [8]. In related research, the leaf...
movement analysis tool was developed, PALMA (Plant leaf movement analyzer) that works in the command line and combines image extraction with rhythm analysis using Fast Fourier transformation and non-linear least-squares fitting [8]. However, the system requires expensive hardware modules and commercial software.

One of the many methods that can be used to measure leaf motion is the optical flow method. Optical flow is an estimation method in a computer vision field that is concerned in estimating pixel-level motion from two consecutive images [10]. There are several variations of optical flow methods such as: 1) Knowledge-driven methods, 2) Data-driven methods, 3) Attention-based image analysis methods, and 4) Convolutional neural networks [9]. Knowledge-driven methods can display the relationship between the image and flow explicitly by modeling an energy function [10]. Data-driven methods can estimate weight from a large amount of data [9]. Attention-based image analysis has been widely used in many computer vision tasks, such as image classification, pose estimation, object detection, person re-identification, image super-resolution and semantic segmentation [10]. While, convolutional neural networks classically applied to classification, but recently allow for per-pixel predictions like semantic segmentation or depth estimation from single images [11].

In the previous study, the optical flow has been applied in several fields for example: for two-dimensional deformation measurement [12], virtual reality for animal navigation with a camera [13], to detect moving objects under moving camera [14], to estimate aerated spillway flows [15], etc. Several algorithms were developed to use optical flow for different or specific uses such as: Horn-Schunck algorithm, Newton-Krylov algorithm, Shi-Tomasi and Lucas Kanade algorithm which is used in this study [16, 17]. Shi-Tomasi parameter as a corner detector and Lucas Kanade algorithm which assumes that the neighboring pixels have the same motion [5, 6].

The objective of this study is to present the quantitation method for leaf motion to study the circadian rhythm using the optical flow method. The motion estimation method was based on optical flow, implementing the Lucas-Kanade technique and Shi-Tomasi corner detection to quantify the 2D lateral translation and direction angle of leaf motion. The system was applied to time-lapse images captured on Chili plant cultivation.

2. Materials and Method
This research was conducted at Smart Agriculture Research, Laboratory of Agricultural Energy and Machinery, Department of Agricultural and Biosystem Engineering, Faculty of Agricultural Technology, Universitas Gadjah Mada. The observed plants were Chili (Capsicum annum L.) carried out on August 30, 2017, until September 09, 2017.

2.1. Automatic Image Capturing System
The Chili plant is observed in a growth chamber, as shown in figure 1. The growth chamber dimension is (70 × 70 × 100) cm. The growth chamber equipped with an infrared camera and infrared LED as a night vision module. The IR camera is controlled by a Raspberry PI for the automatic and continuous image capturing based on time-lapse photography. The image capturing is done during night and day in every five minutes interval and the image captured is automatically uploaded into the Agrieye cloud system (www.agrieye.tp.ugm.ac.id). For irrigation purposes, the growth chamber also equipped with pipes to provide water irrigation from the outside without disturbing the capture image processes.
2.2. Motion Quantification

The plant motion is analyzed using an optical flow method with the Shi-Tomasi parameter as a corner detector and Lukas Kanade algorithm which assumes that the neighboring pixels have the same motion. The principle of optical flow is tracking a point from one image to another image between two consecutive images as displayed in Figure 2. The stem of leaf position at certain time $t$ notated as $S$ at $t$, and the present position at $S_{t+\delta t}$ when $\delta t$ is the different time or capturing interval.

Figure 1. Figure of (a) Growth chamber, (b) Top view camera, and (c) Raspberry Pi equipped with camera

Figure 2. Schematic of leaf motion quantification
Assumed the point to track is \( I(x, y, t) \) at time \( t \) has the same intensity at \( I(x + \delta x, y + \delta y, t + \delta t) \) and the equation can be expressed as

\[
I(x, y, t) = I(x + \delta x, y + \delta x, t + \delta t). \tag{2.1}
\]

Differentiating this constraint gives the optical flow equation \( \nabla I^T \mathbf{v} = -I \), where \( \mathbf{v} = [u, v] \) is the motion vector and \( \frac{\partial}{\partial t} \) the time derivative. For the individual points, this equation cannot be solved because it has two unknown values in \( \mathbf{v} \). The Lucas-Kanade method assuming that the neighboring pixels have the same motion \([18]\) and it is possible to obtain the motion vector \( \mathbf{v} \) by stacking many equations into one system equation as (2.2) for some neighborhood of \( n \) pixels.

\[
\begin{bmatrix}
\nabla I^T(x_1) & \nabla I^T(y_1) \\
\nabla I^T(x_2) & \nabla I^T(y_2) \\
\vdots & \vdots \\
\nabla I^T(x_n) & \nabla I^T(y_n)
\end{bmatrix}
\begin{bmatrix}
u \\
v
\end{bmatrix}
= -
\begin{bmatrix}
I(x_1) \\
I(x_2) \\
\vdots \\
I(x_n)
\end{bmatrix} \tag{2.2}
\]

The contribution of surrounding pixels is weighed by a Gaussian weighting and turn the matrix above into the structure tensor in equation (2.3) and we have the relation expressed as

\[
\begin{bmatrix}
\nabla I^T(x_1) & \nabla I^T(y_1) \\
\nabla I^T(x_2) & \nabla I^T(y_2) \\
\vdots & \vdots \\
\nabla I^T(x_n) & \nabla I^T(y_n)
\end{bmatrix}
\begin{bmatrix}
u \\
v
\end{bmatrix}
= \begin{bmatrix}
I(x_1) \\
I(x_2) \\
\vdots \\
I(x_n)
\end{bmatrix} \tag{2.3}
\]

where \( A \) is the matrix of \( M \) and \( b \) is \(-[I(x_1), I(x_2), \ldots, I(x_n)]\). This equation system can be solved in a least square method and the motion vector is given by

\[
\mathbf{v} = (A^T A)^{-1} A^T b \tag{2.4}
\]

when \( A^T A \) is invertible which obtained from the finding of Shi-Tomasi tracking corner. Accordingly, the position of It and It can be identified for further investigation. The distance between both points \( |V_i| \) then calculated using the Pythagoras theorem by input of \( \delta x = x_{t+dt} - x_t \), and \( \delta y = y_{t+dt} - y_t \) and the \( |V_j| \) can be calculated as (2.5) for individual translation distance of vector 1.

\[
|V_i| = \sqrt{\delta x^2 + \delta y^2} \tag{2.5}
\]

Accordingly, number of vectors in one-time estimation has detected from 1 to \( n \) as displayed in Figure 2, can be averaged the translation distance at estimated time \( t \) as (2.6):

\[
\bar{V}[t] = \frac{1}{n_{point}} \sum_{n=1}^{n_{point}} |V_n| \tag{2.6}
\]

where \( n \) is the number of vector points, and \( t \) is the discrete-time. Time series of translation distance can be visualized to represent the rhythm. OpenCV Library 3.4.5.20 running on Python 3.7 with PyCharm 2019.2 as Integrated Development Environment was used to perform the motion quantification.
3. Results and Discussion

Figure 3 shows the time-lapse image of the Chili (Capsicum annum L.) leaf captured from top and side view projection using the developed automatic image capturing system. The interval of capturing is 30 minutes and the saved images been analyzed using the quantification method for both projections. The consecutive image for top and side projection on day and night has clearly been seen by the utilization of infrared cameras for detailed movement in the dark and light cycle continuously.

Vector visualization of translation distance for both top and side projection is displayed in figure 4. The translation from the reference point of interest represented by the arrowed line where the length and direction of the arrow representing the orientation and distance of the movement. The rapid movement can be seen clearly for both top and side view projection. During one frame of observation,
the length of the vector line then is averaged to obtain the overall movement at one time. More detail investigation of the quantitative value will be explained in time series manner for each projection.

The time series of leaf motion from the translation distance that has been averaged are displayed in figure 5. The time series displaying raw data in gray dots for top projection and side projection. The raw data are then filtered with 30 minutes moving average and plotted in solid black line for both projections. According to the visualized time-series graph, it can be seen that the observed plant, Chili, having more active motion (higher translation distance) in the dark (or night) condition, while during the day the chili plants are more passive (lower translation distance). The motion of Chili plants observed from the Top and Side projections shows different behavior patterns as can be seen in time series behavior. Based on the top projection, the highest translation is obtained during the day while based on the side projection the highest translation is obtained at night.

According to the behavior of the movement, showing up and down translation distance, and its diurnal pattern could be used to resemble the circadian rhythm for further studies. The utilization of leaf movement as a biomarker without any additional marker, such as white ball or wire as a motion tracker, could simplify the motion quantification by the use of the Optical Flow method, adopting the Shi-Tomasi corner detector and Lucas-Kanade for the motion differentiation. Further consideration would be the estimation of period, amplitude, and frequency of the circadian rhythm oscillation to reveal the plant response to the environment.

![Circadian rhythm from top and side view projections](image)

**Figure 5.** Circadian rhythm from top and side view projections

### 4. Current Conclusion and Future Works

The quantification method for leaf movement to study the circadian rhythm based on computer vision implementing the Optical Flow method has been presented to estimate the plant circadian rhythm of Chili (*Capsicum annum* L.). The quantification method could quantify the leaf motion of Chili for both top and side view projection with the higher movement observed at top view projection. The
quantified motion could show the diurnal pattern of circadian rhythm clearly and will be used for further investigation related to plant behavior in response to environmental changes.

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