A Low-Cost Process for Plant Motion Magnification for Smart Indoor Farming

Danilo Pena[a], Parinaz Dehaghani[b], Oussama Hadj Abdelkader[c], Hadjer Bouzebiba[d] and A. Pedro Aguiar[e]

Faculty of Engineering, University of Porto, 4200-465 Porto, Portugal

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Abstract: Smart indoor farming promises to improve the capacity to feed people in urban centers in future production. Non-invasive sensing and monitoring technologies play a crucial role in enabling such controlled environments. In this paper, we propose a new architecture to magnify subtle movements of plants in videos, highlighting non-perceptible motions that can be used for analyzing and obtaining characteristic traits of plants. We investigate the limitations of the technique with synthetic and real data and evaluate different plant samples. Experimental results present leaf movements from short videos that could not be noticed before the magnification.

1 INTRODUCTION

Vertical farming and modern greenhouses have worked to make their production more efficient, adaptable, and less harmful to the environment. They cultivate plants using optimized control and improved monitoring techniques, pursuing the ideal growth conditions to exploit the resources efficiently and increase production yield. The plant observations are fundamental to provide data for precise control and management systems for these environments. The RGB cameras are increasingly contributing to monitoring key metrics and traits in a non-invasive manner in this field. Plant movements are visible responses in the environment to optimize their survival, growth, and reproduction. Hence, they may reveal helpful information from the stimulus or genetic factors such as moving toward the light, growth in search of water and nutrients, or sensing changes in the environment (Bhatla and A. Lal, 2018). Although the plants can move their position and behavior by sensing external environment changes, these movements are often prolonged and seldom detectable (Bhatla and A. Lal, 2018; Rasti et al., 2021).

Studies have presented tools to assist plant growth, such as leaf area monitoring (Ngo et al., 2022), water and nutrient content estimation (Li et al., 2020), and health assessment (Chouhan et al., 2020). Moreover, efforts have been shown to facilitate plant evaluations over time using image processing techniques by ecologists, farmers, and researchers, such as leaf segmentation (Ghazal et al., 2020), texture and shape selection (Shah et al., 2017; Siricharoen et al., 2016), and leaf tracking (Gelard et al., 2018). However, these plant assessments and measurements are limited to their time evolution, which usually takes many days to present relevant changes in common species (Forterre et al., 2016; Skotheim and Mahadevan, 2005).

One way to evaluate the plant traits in a faster manner is by amplifying small changes in image acquisitions (Wu et al., 2012). Eulerian motion magnification is a method to amplify small motions in a set of frames and is helpful in various applications (Wadhwa et al., 2013), including but not limited to health care and monitoring, biology, structural analysis, and mechanical engineering. When amplified, the tiny motions may reveal information that seems invisible or imperceptible in normal videos, presenting meaningful temporal variations. This technique requires no special equipment, and it can be used by regular cameras at usual frame rates. The method was applied to tiny leaf color changes to detect the photosynthesis

[a] https://orcid.org/0000-0003-2767-5764
[b] https://orcid.org/0000-0002-9932-0690
[c] https://orcid.org/0000-0002-6722-4960
[d] https://orcid.org/0000-0002-5915-9441
[e] https://orcid.org/0000-0001-7105-0505

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process (Taj-Eddin et al., 2017), aiming to monitor plants.

Motivated by the above, we propose a robust motion amplification method to reveal leaf movements that are not perceptible by the naked eye. The video magnification approach assumes that the object of interest has small motions and background regions remain still (Le Ngo and Phan, 2020; Elgharib et al., 2015). Thus, video stabilization is a crucial step in this magnification process to reach accurate results. We apply video stabilization as a preprocess to remove the undesirable large handshake based on a robust feature trajectories algorithm (Ken-Yi Lee et al., 2009). Moreover, we utilize leaf extraction and mask to segment the region of interest (ROI) and apply magnification to only this region, achieving higher motion magnification quality. We added a plant segmentation algorithm (Riehle et al., 2020) to obtain an appropriate segmentation for our approach.

The system proposed by this paper can visualize, with a smartphone camera, without any additional instrument, the small leaf movements of the plant in a non-destructive manner. Such movements may be associated with the growth rate of the plant, helping researchers and farmers to investigate and design control systems based on faster metric acquisitions. We also explore the magnification bounds and robustness of our approach to provide a measurement tool for controlled plant environments, where the different aforementioned plant assessment systems can benefit from our method.

In summary, the main contributions of this paper include the proposed architecture system with special target to magnify small motions of plants using a low-cost setup, and its robustness and performance evaluation. We show that the proposed architecture attenuates considerable distortions related to the background noise or shaking artifacts, and increases the magnification quality when compared with a standard Eulerian phase-based technique (Wu et al., 2012). The dataset and its acquisition parameters are provided in a public repository (Pena et al., 2022).

The paper is organized as follows. In Section 2 the traditional phase-based motion magnification is discussed. Section 3 describes the proposed system and its architecture, presenting all steps to visualize the amplified plant motions. Experimental results are presented in Section 4, with bound evaluation, and comparisons between real and artificial plants. Finally, in Section 5, we present our final remarks.

2 EULERIAN PHASE-BASED METHOD

The Eulerian phase-based method (Wadhwa et al., 2013) is a technique to magnify the small changes in short videos. The algorithm amplifies the phase difference value computed between the current and first frames. Initially, the video is decomposed in spatial frequencies by a complex-valued steerable pyramid. This pyramid allows us to measure and modify local motions since its filters have an impulsive response with finite spatial support. Then, the local phase represented by the spatial scale and orientation of the steerable pyramid is isolated to a specific temporal frequency by using a temporal bandpass filter. The frame $I_\omega(x,t)$ of the complex steerable pyramid, filtered for frequency ω, has a local displacement $\delta(t)$ modeled as an intensity of complex sinusoid, given by

$$I_\omega(x,t) = A_\omega e^{j\omega(x+\delta(t))}. \tag{1}$$

The temporal filter removes the DC component and allows the amplification of the displacement $\delta(t)$ by a factor α for each sub-band, producing $\alpha\delta(t)$ pixels of shift. The sub-band, with the increase in phase is given by

$$\hat{I}_\omega(x,t) = A_\omega e^{j\omega(x+(1+\alpha)\delta(t))}. \tag{2}$$

3 PROPOSED METHOD

The proposed method aims to amplify plant movements in a shorter duration than many days of time-lapse acquisitions. We claim that in short video acquisition, we can highlight small plant movements for analysis. The architecture is separated into three steps, described in Figure 1, as: 1) The frames are stabilized using point feature matching. 2) We magnify the video motion using a modified phase-based Eulerian technique. 3) We use a mask based on the leaf segmentation technique, applying the magnification only to the ROI during the magnification.

3.1 Stabilization Process

The stabilization process is essential to avoid artifacts or amplification of the background shaking in the motion magnification stage. First, interest points are identified in the frame by corner detection using the features-from-accelerated-segment test (FAST) algorithm (Rosten and Drummond, 2006). Then, we estimate a transformation that corrects the distortion be-

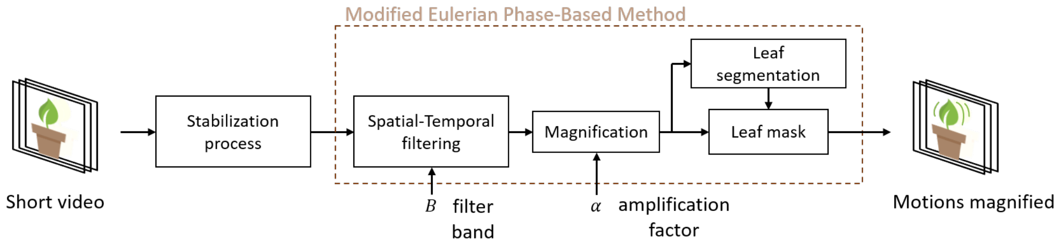

Figure 1: Overview of the proposed system.

tween the frames for these points. This affine transform provides the correspondence points of a frame in the next frame (Ken-Yi Lee et al., 2009). We compute the matching using the Hamming distance in a Fast Retina Keypoint (FREAK) descriptor centered around each point. Finally, we estimate the geometric transformation between two images using the M-estimator SAmple Consensus (MSAC) algorithm. The affine transform that produces the closest inliers between two sets of points is given by

$$T_t = \begin{bmatrix} s_t\cos(\theta_t) & -s_t\sin(\theta_t) & \Delta_{x,t} \\ s_t\sin(\theta_t) & s_t\cos(\theta_t) & \Delta_{x,t} \end{bmatrix}, \qquad (3)$$

where $\Delta_{x,t}$ represents translation motion, s_t scale factor, and θ_t indicates the rotation angle. Thus the cumulative transformation chain relative to the first frame is the product of all preceding inter-frame transforms. The compensated current frame $\hat{I}(t)$ is obtained by $\prod_{n=0}^{t-1} T_t$ containing the parameters of the affine transform of Equation 3.

3.2 Eulerian Phase-Based Motion Magnification

We use the Eulerian phase-based technique (Wadhwa et al., 2013) to magnify the small changes in the plant. Due to the high signal-to-noise ratio of pixel intensities reachable by controlled scenarios and the magnitude noise efficiency of the phase-based method (Wadhwa et al., 2013), we pay more attention to any undesirable motion that is not related to the ROI or even error in video stabilization that can cause large artifacts in the magnification. The current approaches fail to exclude irrelevant motions occurring at frequencies similar to the target motion frequency (Le Ngo and Phan, 2020). Thus, we model the magnified phase including motions from different sources, $\eta(t)$, related to shaking, distortions, and undesired movements by representing phase values in the frames that are not from the ROI motions, given by

$$I_\omega(x,t) = A_\omega e^{j\omega(x+(1+\alpha)(\delta(t)+\eta(t)))}. \qquad (4)$$

The distortion $\eta(t)$ is magnified with the target motion, producing the magnified image with $\alpha(\delta(t)+\eta(t))$ displacement. Hence, the stabilization process should ensure the removal of irrelevant motions from the frames as much as possible. In Section 4.3, we evaluate the influence of this noise background motion in the motion magnification of a synthetic video, simulating the translation motion not corrected by the stabilization process.

3.3 Plant Segmentation and Mask

The magnification is performed only in the ROI of the frame in order to obtain higher amplification factors and avoid artifacts in the video. We use a mask based on plant semantic segmentation (Riehle et al., 2020) to achieve the foreground segmentation from the frame. Such technique segments the ROI into two steps: pre-segmentation based on index, and segmentation using color space with a threshold. First, the method computes the excess green minus excess red index, an index-based segmentation method commonly used in plant applications based on the difference of another two indexes: the excess green index (ExG) and the excess red vegetative index (ExR). The ExG is calculated from an RGB frame by the following equation:

$$ExG = 2G - R - B, \qquad (5)$$

where R, G, and B are normalized RGB values. The ExR, an index that accentuates the redness of a frame, is computed by:

$$ExR = 1.4R - B. \qquad (6)$$

The combination of both indexes, ExG minus ExR, produces the ExGR, an approach developed to segment plants from background in images:

$$ExGR = ExG - ExR. \qquad (7)$$

The mentioned indexes are used as detectors with different thresholds to produce the mask. Additionally, one can obtain segmentation with different sensitivity and specificity by using two different color spaces (Riehle et al., 2020): HSV or CieLab. Depending on the dataset and the requirements, the combination of threshold and color space is chosen to reach the most representative frames. In our studies, we find the ExGR with a constant zero threshold and CieLab as most adequate for our acquisitions. However, for young leaves, we use only the ExGR index with a constant zero threshold, since they were not segmented in the HSV and CieLab color space histograms.

4 EXPERIMENTAL RESULTS

Indoor experiments were carried out using a regular camera of a smartphone connected to a ring light tripod, as presented in Figure 2. The ring light has 10 inches in diameter and provides a led power of 10 W with 6500 K of temperature. After acquisition and video processing using our proposed approach, we obtained a total of 20 short videos at 30 frames per second each, as described in Table 1, originally recorded at 12 seconds per frame, from 3 different plant samples: Peperomia, Fern, and artificial. The dataset and its acquisition parameters are provided in a public repository (Pena et al., 2022).

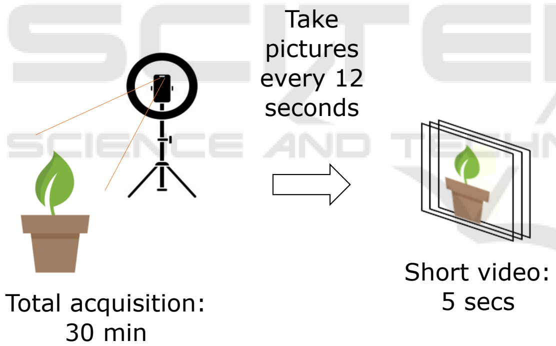

Figure 2: Acquisition setup.

The camera used was from a Samsung smartphone with 12 megapixels, 26 mm of focal length, 1.5 of aperture, and optical stabilization. The device recorded in flight mode while the software acquired pictures at a uniform and constant sampling frequency with an automatic and fixed focus on the object.

Unless mentioned otherwise, the evaluations were performed using videos that present plants with 30 min of recording. We computed the magnification using a difference of Butterworths filter with a quarter-octave bandwidth pyramid and eight orientations. The processing was performed in YIQ color space in the three channels independently, using 150 frames of 640x480. The frequency of the temporal bandpass filter was defined as the lowest component possible since we are interested in slow movements in the video.

Table 1: Parameters used in the acquisition and the magnification method.

Parameter	Values
Frame rate	30 frames per second
Time duration	30 min
Time-lapse	12 seconds per frame
Resolution	640 x 480
Magnification factor	100
Filter frequencies	0.01 - 0.2 Hz

4.1 Comparisons with Eulerian Method

The small motions from the plants in the frames often produce distortions in the traditional motion magnification method. Such slow motions occur at low-frequency components in time, where also occur motions related to the background noise or shaking artifacts. Therefore, we present a comparison between the Eulerian phase-based magnification and the proposed architecture with the difference between the first and last frames in the magnified video, illustrated in Figure 3.

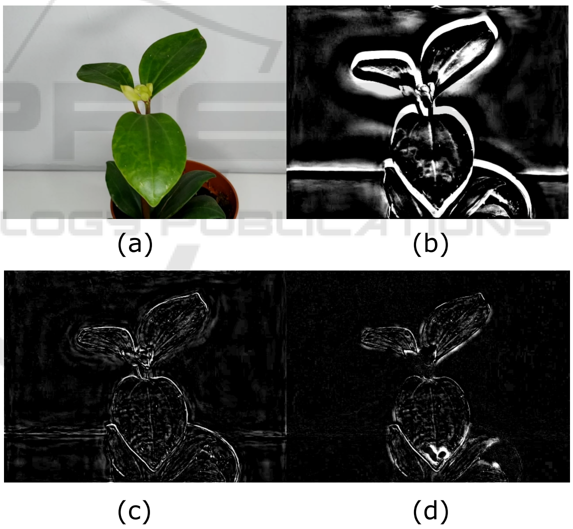

Figure 3: Comparisons between traditional magnification and the proposed method, where: a) it is the first frame of the original video; b) difference of frames for Eulerian phase-based magnification; c) difference of frames in the proposed method without masking; d) difference of frames in the proposed method with mask enabled.

Figure 3 presents the Eulerian technique magnifying motions that are not related to the plant. The shaking motion can be perceived in the horizontal line in the background, where even a rigid tripod could not ensure stability for the magnification. However, the proposed architecture attenuates such distortions due to the stabilization process. Moreover, the masking increases the magnification quality by enabling the system to magnify only the ROI.

4.2 Noise Evaluation

A simulated study of the effect of image noise was performed to assess the robustness of the proposed technique to different noise conditions, as presented in Figure 4. Since the magnification is phase-based, the noise is not magnified but phase-shifted instead. Unlike a linear magnification method, which amplifies the noise linearly, the proposed technique, based on the phase method, presents a low error increase, as expected (Wadhwa et al., 2013).

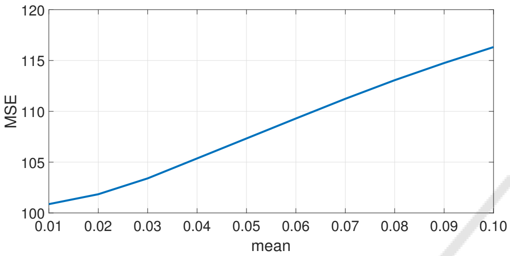

Figure 4: Error evaluation as a function of noise.

4.3 Stabilization Assessment

We evaluate the stabilization process and magnification of the proposed method using a synthetic video containing a green circle representing the ROI, and triangles representing the background. The ROI has its motion modeled by $\delta(t)+\eta(t)$ shift, where $\delta(t)$ is an oscillating motion, while the background has only translational $\eta(t)$ displacement, representing the distortion. The ROI and background share the same noise shift value integrated at time t. Figure 5 shows the ground truth, a shaking motion, and a stabilized version being magnified.

Figure 6 presents the mean square error (MSE) image over noise (σ) in $\eta(t)$. The evaluation shows that the stabilization produces lower MSE for high values of phase noise as expected.

4.4 Amplification Analysis

For non-distorted video, the quarter-octave bandwidth steerable pyramid provides approximately 4 periods of a sinusoid under the Gaussian envelope of the Garbor filter (Wadhwa et al., 2013). Using the Gaussian window, with width σ, to determine the bound, we obtain $4\sigma \approx \frac{4}{\omega_0}$ on the frequency ω_0, and the maximum displacement is given by

$$\alpha\delta(t) < \lambda, \tag{8}$$

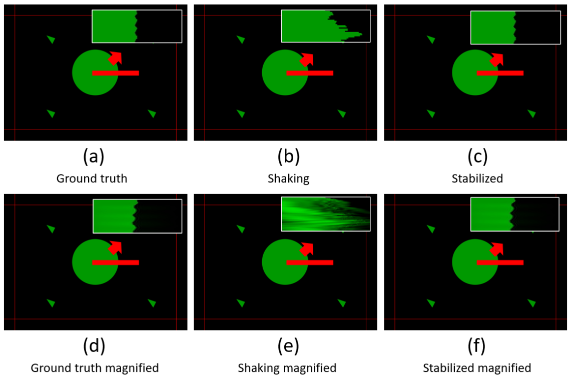

Figure 5: Synthetic frames: a) Ground truth; b) Shaking effect; c) Shaking motion after stabilization; d) Ground truth magnified; e) Shaking video magnified; f) Stabilized video magnified.

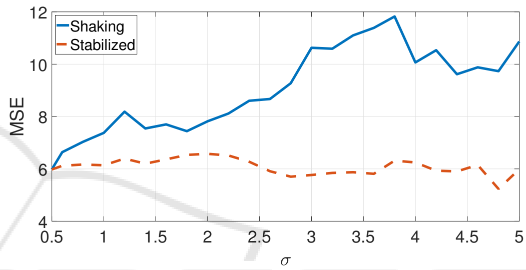

Figure 6: MSE between ground truth magnified as a reference, and noise and stabilized videos magnified.

where λ is the spatial wavelength. In an acquisition with the ROI at 20 cm of distance and a calibration factor of approximately 0.5 mm/pixel, we can determine the fastest plant movement at 10 seconds or slower for one pixel of displacement, based on the physical limitation of the plant speed (Forterre et al., 2016).

The results of our method indicate fast movements from young leaves after magnification that were not visible in original acquisitions. We use frames collected with a non-uniform background, facilitating for the stabilization process to track any translation in the frames. Figure 7 presents the movements from the growth process of the leaves by computing the difference between the first and last frames. The original video seems to be a static scene with no movements, as demonstrated in the supplementary material (Pena et al., 2022).

4.5 Comparisons with Artificial Plant

We tested the proposed system using videos containing simultaneously real and artificial plants. Figure 8 presents leaf growth motions from the Peperomia, while the artificial plant stays static. In the traditional Eulerian method, both plants present large

Figure 7: Motion highlighted in difference of frames.

motions magnified due to the shaking, while the proposed technique highlights the magnification on the young leaf.

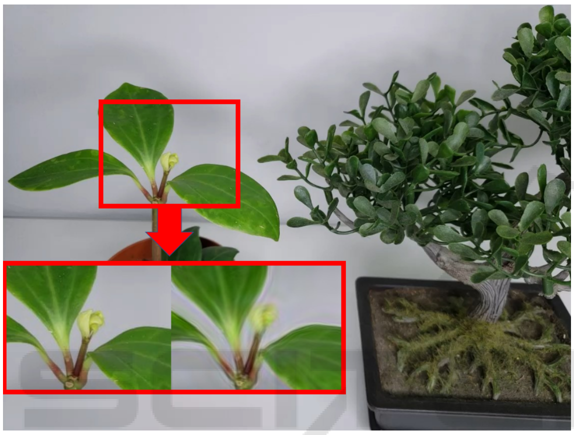

Figure 8: Young leaf growth magnified.

5 CONCLUSION

This paper proposes a non-destructive and low-cost technique to highlight the small movements of plants in short videos. The technique uses mainly the Eulerian magnification method to amplify phase differences with the stabilization process and automatic segmentation of the ROI. The method was tested in different samples and presented fast and magnified movements in short videos. The proposed method can be used for plant assessment systems in order to extract hidden metrics.

Future studies may investigate the performance of the technique over raw data, avoiding post-processing from the camera's Image Signal Processor (ISP). Moreover, the technique can be evaluated in growing and plant disease monitoring, obtaining in advance relevant features in such applications.

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