A Review on Plant Stress Detection and Analysis Through Electrophysiological Signals

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doi: https://doi.org/10.21467/proceedings.114.22

Abstract

The bioelectrical activity like ECG, EMG and EEG provides the health condition of heart, muscles, and brain in human beings. In plants, the sensible measurements of physical activity are in their infant phase. Substitution of technology used in biomedical field (human medicine) might consequently provide an understanding about electrophysiological signal activity in plants. These signals in plants when monitored show various dynamics in different stress conditions like osmotic, cold, low light, chemical, over watering etc. Several studies analysing and classifying features of ideal and stressed signal subtleties have shown promising results. In this paper we present a comprehensive review of research contributed to EPG signal analysis in different domains, applications of machine learning in plant stress detection and classification.

Keywords: Plant stress, Machine Learning, Stimuli, EPG (Electrophytography)

1 Introduction

The electrical signals in plants play most important role in many plant processes like photosynthesis, water intake, stress communication, respiration, learning and memorizing the eventual stimuli etc. Recording of various fundamental processes like photosynthesis, environmental stress variations, transpiration, water uptake and ion translocation in the form of a signal is labeled as plant electrophysiology or Electrophytography (EPG). The stress which is occurred by the nonliving things from surroundings and environment is termed as abiotic stress. The major examples of abiotic stress are high speed winds, extreme temperatures, drought, floods, over watering, over nutrients etc. This adversely affects the physiological condition of plant [1][2]. The stress which is occurred by the living organisms like bacteria, fungi, parasites, harmful insects, weed plants is termed as biotic stress. [3][4]. Electrophysiological signals of plants can be measured by two different techniques known as invasive and non-invasive methods. Invasive methods encompass a cut or split in the plant tissue for signal acquisition. Non-invasive methods require surface measurements by implanting thin metal electrodes slightly into plant tissue or just placing the sticking gel electrodes over the leaves of the plant [5]. The electrophysiological signals obtained from plants can be analyzed in different domains like time domain, frequency domain, time-frequency domain. Before starting the analysis, it is important to know the nature of the signal i.e. sample dimension (scalar, vector or matrix), dynamics related to sampling (stationary, cyclic, periodic or stochastic), time dependency (time variant or invariant), evenly or unevenly sampled and then we decide which type of signal features suits best to predict a model.

2 An Overview on Electrophytography

Electrocardiogram (ECG) and Electroencephalogram (EEG) are categorized as electrophysiological recordings of human beings. Similarly recording of various fundamental processes like photosynthesis, environmental stress variations, transpiration and ion translocation in the form of a signal is termed as plant electrophysiology or Electrophytography (EPG) [6]. Plants do not have any neural networks in their

Proceedings DOI: 10.21467/proceedings.114; Series: AIJR Proceedings; ISSN: 2582-3922; ISBN: 978-81-947843-8-8

physical structure but they are electrically impulsive and exhibit rapid electrical responses to respective excitations from the environment [7]. By accomplishing several experiments, it is biologically proven that plants respond to the unpredictable signals produced by other plants. Plants have their own immune strategies to fight with pests and this kind of perception of plant from environment id known as plant perception [8,9].

2.1 Types of potentials in plants

Action potential(AP), resting potental (RP) and variation potential (VP) are three different electrical potentials observed in plants. The electrical pulse propagating rapidly with a constant velocity by maintaining constant amplitude is known as AP [10,11].The AP propagates along the length of the cell membrane when phloem is stimulated. RP is the resting potential where charge inversion phenomena takes placealong the length of the cell membrane followed by every cycle of AP [12]. VP shows the variation in electrical pulse either to the short range or long range depending upon the intensity of the stimulus provided. So the study of plant electrophysiological signals provides best analysis of plants that are undergoing stress.

2.2 Types of plant stress

Plant stress is an unsympathetic effect on the physiology of the plant provoked upon a sudden change from normal environmental conditions. To design an experiment for measuring the plant physiology impact of stress on plant plays an important role. To evaluate the type of stress the plant is undergoing, measuring and anlysing electrophysiology of plants in both ideal and stress conditions is essential [13,14]. There are two major types of plant stress abiotic and biotic stress. The stress which is occurred by non living things from surroundings and environment is known as abiotic stress [15]. The stress which is occurred by living organisms like insects and parsites is termed as biotic stress [16]. Thus adverse effects on physiology of the plant shows the transitions in acquired signals, help to detect and classify different stress conditions during stages of occurrence or may be even in early stages of appearance of symptoms.

3 Review

The reviewed articles have adopted several methods for measuring the electrical potentials in plants. The selected articles and works presented are purely journal papers. The Table 1 shows comparison of different techniques used in signal acquisition by various authors, various methods of signal analysis, classification schemes opted and their respective best predicted accuracies. Several types of electrodes were used to conduct experiments for the study of electrophysiology of the plants. In the ascending decade the methods involved in signal acquisition have also experienced a drastic change. Nonlinear Hammerstein-Weiner (NLHW), Nonlinear Auto Regressive eXogeneous (NLARX) models were used to analyse signals acquired through invasive techniques of bay leaf, 2 cucumber plants, 17 zanzibar gem plants to incident light stimulus and where best prediction is obtained by NHLW models for the instants of turning on /off and peak intensity of light stimulus [17]. Signal pre-processing is more significant for any kind of signal analysis where plant signal acquisition also undergoes moving artifacts, powerline interference and various noise artifacts. Design of IIR filter to remove low frequency drift, WPT (Wavelet packet transform) for optimization of filter parameters according to the plant signals acquired is clearly explained in this article [18]. Machine-learning algorithms are obtained to study 11 statistical features of 11 tomato plants with different chemical stimuli, capturing both the stationary and non-stationary behavior of the signal. The classification has yielded a best average accuracy of **70%** and the best individual accuracy of 73.67% (Diagquadratic classifier) [19]. Evoked potentials of cucumber plants when undergone with electrical stimulation were processed through various machine learning models like BP-ANNs which gave an accuracy of 84.8%, SVM of accuracy 78.2%, and deep learning method 77.4% but where template matching algorithm has achieved a classification rate of 96.0% [20]. Signals acquired through invasive techniques from 11 tomato plants undergone with chemical stimulation are analyzed by extracting 15 features from windowed data and two multi-class classification schemes OVO (one vs one) and OVR (one vs rest) is performed, where Mahalanobis classifier produced the best accuracy **92%** in OVO strategy [21]. EPG signals acquired using Biopac MP36 by inserting subdermal electrodes into 15 days old soybean saplings. Low light, cold, osmotic stress are the three different stimuli provided. Spectral analysis by fast fourier transform, power-spectral density analysis is done on the signals so that the temporal dynamics have shown the complex non-linear behavior with the long-range persistence [22]. Machine learning algorithms (ANN, CNN, Optimum-Path Forest, k-NN and SVM) together Interval Arithmetic are implemented on the same data set obtained in [22]. 70% accuracy using skewness and variance as feature pairs, 73.67% accuracy using IQR and variance as feature pairs is the best achieved accuracy [23]. Four different curve fitting models – gaussian, polynomial, fourier, exponential are used to extract features from the raw electrical signal response to classify external stimuli thereby estimating the shape of the signal is dependent on stimuli applied. The coefficients of curve fitting models are used as the features and classification results using the 5th degree polynomial, Quadratic discriminant classifier (QDA) classifier have given the best accuracy of 98% [24]. 5 grafted tomato plants were undergone with drought stress and signal acquisition is done through invasive technique by inserting wire (silver coated copper wire of 0.5mm) into the petiole. Supervised machine learning algorithms were used to classify the stress. The training size used was 0.8. Gradient boosted tree (GBT) has given best accuracy of 98.5% and precision of 99.3% [25]. Signals are acquired from 12 tomato plants contaminated with spider mites. 34 features were extracted and GBT algorithm was chosen to build a classification model. The accuracies of GBT algorithm in day samples is 80% and in night samples is 65.8% , specificity in day samples is 81.1% and in night samples is 95.8% [26].At the moment all the approaches are not adequately connected for decision making that which approach is more suitable. The integration of automated data acquisition, signal analysis, machine learning implementation will provide the knowledge to best classify the stress in plants in early stages of symptom appearance which makes a drastic change in the agricultural sector.

Table 1 Comparison table

Author	Method of acquisition Type of species & stimuli	Approach of Signal analysis	Performance metrics
[17]	Invasive method by inserting EMG electrodes LABVIEW 2012 software Species: 1 bay leaf 2 cucumber plants 17 Zanzibar gem plants **Stimuli:** Light by LED	Nonlinear Hammerstein-Weiner (NLHW), Nonlinear Auto Regressive eXogeneous (NLARX) models	Best prediction is made by NLHW estimator over NLARX estimator
[18]	Invasive method by inserting EMG electrodes, in dark room inside faraday cage Sampling frequency – 10 samples/sec 11 Tomato plants **Stimuli**: H_2SO_4, Nacl, O_3	Design of IIR filter to remove low frequency drift, WPT (Wavelet packet transform) for optimization of filter parameters	Reported best methodology for signal pre-processing

[19]	Invasive method by inserting EMG electrodes, in dark room inside faraday cage Sampling frequency – 10 samples/sec 11 Tomato plants **Stimuli**: H_2SO_4, Nacl, O_3	Machine-learning with 11 statistical features, capturing both the stationary and non-stationary behavior of the signal.	Best average accuracy of **70%** and the best individual accuracy of **73.67%** (Diagquadratic classifier).
[20]	Evoked potentials obtained from cucumber plants **Stimuli:** Electrical stimulation	Machine learning algorithms	(BP-ANNs) **84.8%**, (SVM) **78.2%,** and deep learning method **77.4%. T**emplate matching algorithm has classification rate of **96.0%**
[21]	Invasive method by inserting 15mm EMG electrodes Sampling frequency – 10 samples/sec 11 Tomato plants **Stimuli**: H_2SO_4, Nacl, O_3	15 features were extracted from windowed data, two multi-class classification strategies OVO and OVR is performed	Mahalanobis classifier produced the best accuracy **92%** in OVO strategy
[22]	EPG signals acquired using Biopac MP36 by sub-dermal electrodes inserted . Sampling frequency – 125 Hz soy bean **Stimuli:** Cold stress, low light, osmotic stress	Spectral analysis by FFT, power-spectral density analysis and also respective histograms were plotted.	The temporal dynamics of the electrical signaling shows a complex non-linear behavior with long-range persistence.
[23]	EPG signals acquired using Biopac MP36 by sub-dermal electrodes inserted . Sampling frequency – 125 Hz soy bean **Stimuli:** Cold stress, low light, osmotic stress	Machine learning algorithms (A NN,CNN, Optimum-Path Forest, k-NN and SVM) together Interval Arithmetic.	70% accuracy using skewness and variance as feature pairs, 73.67% accuracy using IQR and variance as feature pairs
[24]	Invasive method by inserting 15mm EMG electrodes Sampling frequency – 10 samples/sec 11 Tomato plants **Stimuli**: H_2SO_4, Nacl, O_3	Classification using curve fitting models	Classification accuracy using curve fit coefficients is more better comparing with [21]
[25]	Invasive method of inserting wire (silver coated copper wire of 0.5mm) into the petiole 5 Tomato plants grafted were used **Stimuli:** drought stress	Supervised machine learning algorithms with training size 0.8	Gradient boosted tree (GBT) has given best accuracy of 98.5% and precision of 99.3%
[26]	12 Tomato plants contaminated with spider mites	34 features were extracted and GBT algorithm was chosen to build a classification model	It has been 80% for GBT

References

[1]. A. S, "Molecular Strategies for Development of Abiotic Stress Tolerance in Plants", *Cell & Cellular Life Sciences Journal*, vol. 2, no. 2, 2017.

[2] N. Tuteja, "Abscisic Acid and Abiotic Stress Signaling", *Plant Signaling & Behavior*, vol. 2, no. 3, pp. 135-138, 2007.

[3] F. P, "Biotic vs. Abiotic - Distinguishing Disease Problems from Environmental Stresses", 2003.

[4] N. Atkinson and P. Urwin, "The interaction of plant biotic and abiotic stresses: from genes to the field", *Journal of Experimental Botany*, vol. 63, no. 10, pp. 3523-3543, 2012.

[5] Kavya .S Y, Neetu.S, Indu.S, " A testimony of interplant communication through electrophysiological signal analysis", *Journal of communications in plant sciences*, vol.7, pp.34-43,2017.

[6] G. Souza, A. Ferreira, G. Saraiva and G. Toledo, "Plant "electrome" can be pushed toward a self-organized critical state by external cues: Evidences from a study with soybean seedlings subject to different environmental conditions", *Plant Signaling & Behavior*, vol. 12, no. 3, p. e1290040, 2017.

[7] U. Bhalla and Ravi Iyengar, "Emergent Properties of Networks of Biological Signaling Pathways", *Science*, vol. 283, no. 5400, pp. 381-387, 1999.

[8] K. Horowitz, D. Lewis and E. Gasteiger, "Plant "Primary Perception": Electrophysiological Unresponsiveness to Brine Shrimp Killing", *Science*, vol. 189, no. 4201, pp. 478-480, 1975.

[9] T. de, "Plants do not have a nervous system and certainly do not make conscious decisions about what to do next", *Evolutionary Ecology of Plant Reproductive Strategies*, 2005.

[10] S. Lautner, "Characteristics of Electrical Signals in Poplar and Responses in Photosynthesis", *Plant physiology*, vol. 138, no. 4, pp. 2200-2209, 2005.

[11] J. Fromm, "Long-distance electrical signaling and physiological functions in higher plants", *Plantelectrophysiology, theory and methods*, vol., 2006.

[12] L. Gurovich and P. Hermosilla, "Electric signalling in fruit trees in response to water applications and light–darkness conditions", *Journal of Plant Physiology*, vol. 166, no. 3, pp. 290-300, 2009.

[13] R. David and N. Anna, "Plant Stress Physiology", 2001.

[14] T. Sharkey, Erik T. Nilsen, David M. Orcutt", "The Physiology of Plants Under Stress: Abiotic Factors", *The Quarterly Review of Biology*, vol. 72, no. 4, pp. 476-477, 1997.

[15] A. S, "Molecular Strategies for Development of Abiotic Stress Tolerance in Plants", *Cell & Cellular Life Sciences Journal*, vol. 2, no. 2, 2017.

[16] N. Atkinson and P. Urwin, "The interaction of plant biotic and abiotic stresses: from genes to the field", *Journal of Experimental Botany*, vol. 63, no. 10, pp. 3523-3543, 2012. [17] S.K. Chatterjee, S. Ghosh, S. Das, V. Manzella, A. Vitaletti, E. Masi, L. Santopolo,S. Mancuso, K. Maharatna, 'Forward and inverse modelling approaches for prediction of light stimulus from electrophysiological response in plants', Measurement, vol 53, pp.101–116, 2014.

[18] Das, Saptarshi, et al. "Drift removal in plant electrical signals via IIR filtering using wavelet energy." *Computers and Electronics in Agriculture*, vol 118 pp.15-23,2015.

[19] S. Chatterjee et al., "Exploring strategies for classification of external stimuli using statistical features of the plant electrical response", *Journal of The Royal Society Interface*, vol. 12, no. 104, pp. 20141225-20141225, 2015.

[20] Chen, Yang, et al. "Plant electrical signal classification based on waveform similarity." *Algorithms*, vol 9.4 pp. 70, 2016.

[21] Chatterjee S.K, Das S,.Maharatna K, Masi, E, Santopolo L," A. Comparison of decision tree based classification strategies to detect external chemical stimuli from raw and filtered plant electrical response", Sens. Actuators B Chem, vol-249, pp.278–295,2017.

[22] G. Souza, A. Ferreira, G. Saraiva and G. Toledo, "Plant "electrome" can be pushed toward a self-organized critical state by external cues: Evidences from a study with soybean seedlings subject to different environmental conditions", *Plant Signaling & Behavior*, vol. 12, no. 3, p. e1290040, 2017.

[23] D. Pereira, J. Papa, G. Saraiva and G. Souza, "Automatic classification of plant electrophysiological responses to environmental stimuli using machine learning and interval arithmetic", *Computers and Electronics in Agriculture*, vol. 145, pp. 35-42, 2018.

[24] Chatterjee, Shre Kumar, Obaid Malik, and Siddharth Gupta. "Chemical sensing employing plant electrical signal response-classification of stimuli using curve fitting coefficients as features." *Biosensors, vol* 8.3, pp.83, 2018.

[25] Tran, Daniel, et al. "Electrophysiological assessment of plant status outside a Faraday cage using supervised machine learning." *Scientific reports, vol* 9.1, pp. 1-9, 2019.

[26] Najdenovska, Elena, et al. "Classification of plant electrophysiology signals for detection of spider mites infestation in tomatoes." *Applied Sciences, vol* 11.4, pp.1414,2021.

[27] K. Liakos, P. Busato, D. Moshou, S. Pearson and D. Bochtis, "Machine Learning in Agriculture: A Review", *Sensors*, vol. 18, no. 8, p. 2674, 2018.