PLANT ELECTRICAL ACTIVITY ANALYSIS FOR OZONE POLLUTION CRITICAL LEVEL DETECTION

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ABSTRACT

The electrical activity signals in plants can provide useful information to monitor environmental conditions, such as atmospheric pollution. Nonetheless the study of the relationship between environmental stimuli and electrical responses of plants is still a critical step in developing technologies that use plants as organic sensing devices. In this paper an automatic method of analysis of plant electrical signals for ozone critical levels detection is proposed, based on the fundamentals of correlation theory. In order to classify the morphology characteristics of plant response to ozone exposure we used a segmentation of time series measurements of the electrical activity of plants before, during and after the stimulation. Then, we extracted the significant deviations from the baseline trend to detect and identify the response to a known stimulus, in terms of correlation coefficient. As a result, the proposed detection algorithm represents a novel monitoring method for detecting critical levels of ozone concentrations.

***Index Terms*—** Plant electrical signal, ozone pollution, spike detection, waveform correlation, data classification

1. INTRODUCTION

Atmospheric pollution has become one of the most serious environmental problems of the modern world. Its adverse effects are associated with the degradation of the quality of life, affecting the sustainability of urban ecosystems [1]. The problem of the poor air quality in highly anthropized environments exerts nowadays a high level of interest within the scientific community and public opinion because of the known strong relationship between exposure to many air pollutants and increased adverse effects on human health [2–4]. Among air pollutants, ozone is one of the most important greenhouse gas [5] with secondary origin, generated in the troposphere through a series of complex photochemical reactions involving solar radiation and ozone precursors, i.e. methane (CH_4), carbon monoxide (CO), volatile organic compounds (VOCs), and nitrogen oxides (NO_x), which are largely emitted from anthropogenic sources [6]. Background O_3 concentrations have risen from $\sim$10 ppb before the industrial revolution [7] to daytime summer concentrations exceeding 40 ppb in many parts of the Northern Hemisphere [8]. Due to its nature of reactive oxidant agent, ozone can generate several negative effects on human health including lung inflammation, reduced lung function, degenerative diseases, age related disorders and eventually cancer [9]. Ozone also acts as a corrosive agent for many materials, surface coatings and buildings [10]. Therefore, it is easy to understand the importance of a proper air quality management and the attention to new reliable approaches for ozone monitoring, such as the use of plants as biosensors. The most common air quality measurements exploit sensors based on the use of physicochemical properties in order to measure the concentrations of air pollutants. In comparison with the traditional monitoring systems, the use of biosensors has the advantage of showing the actual pollutants impact on living organisms, thus providing additional data to the electronic instruments. Moreover, this allows to take into account the concepts of bioavailability, dose and exposure, resulting in a more realistic approach to assess the pollutants impact on environment and human health [11]. An ideal monitoring system should be biologically-based and at the same time practical for wide use. Plants perfectly reflect this feature, being naturally widespread in our environment, easy and cheap to product and to maintain thanks to their self-sustainability. Moreover, plants are more sensitive than humans and animals in terms of physiological reaction to fluctuations of multiple parameters [12]. Because of their sessile nature, plants are indeed continuously exposed to a wide variety of environmental changes to which they are able to respond by adjusting their physiological characteristics to limit possible damages. These remarkable characteristics make plants suitable tools for environmental monitoring. On the other hand, the interpretation of the results could be made difficult by the influence of other environmental parameters and of the ecosystems heterogeneity, requiring the participation of specialists [11]. Moreover, this kind of analysis can give us just long-term exposure information. In the present study we propose a new approach to use plants as easy and dynamic bio-sensors able to provide real-time data on air quality changes, particularly referring to ozone concentration. Ozone effect on plants determines changes in growth

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and appearance of visible symptoms (e.g. chlorosis, necrosis) but this response is preceded by a series of biochemical events, the so-called "hidden injury" [13]. All these changes at physiological level are reflected in the generation of electrical signals. It is known from time that plants produce electrical signals when subjected to various environmental stimuli [14–17]. These electrical signals in essence represent changes in underlying physiological processes influenced by the external stimuli. Since plants react to environmental changes generating responses in the bioelectrical activity, this lead to the possibility to classify external stimuli from the typical electrical signal response [17]. The focus of our work was to find an association between ozone exposure and some typical features in the resulting plant electrical signal, in order to create a classification algorithm able to identify the stimulus. In order to obtain reliable results, automatic response detection and data classification for plant electrical signals are necessary to be developed. Many papers reported artifact detection methods for EEG and EKG analysis [18–20]. Various advanced methods have been applied to detect artifacts in EEG signals, such as independent component analysis (ICA) and support vector machine (SVM) [18], wavelet analysis [19] and autoregressive (AR) model [20]. These methods were appropriate for human biological signals and offline analysis. As for the analysis of plant bio-electrical signals related to environmental changes, the response detection algorithm needs to be simplified.

In this paper a correlation based data classification system for plant electrical signal analysis is proposed. A dataset of electrical signals was collected from ligustrum and buxus plants exposed to ozone in controlled conditions. These species have been selected for the study because of their widespread use in urban sites. To automatically segment the signals a derivative-based detection method was designed, similarly to those used in spike detection [21]. Finally, the detected signals were classified based on correlation waveform analysis of plant response to ozone air pollution. The proposed data classification method can be extended for various research purposes by defining weight coefficients and adjusting thresholds.

2. DATA ACQUISITION

The experiments were performed inside a closed growth chamber, the so-called iTreeBox, in order to control the ozone concentration and the other environmental parameters. A picture of the iTreeBox chamber is shown in Figure 1.

Inside the box plants were exposed to standard artificial light conditions by means of LED lights responding to the plants photosynthetic needs (PAR radiation). About 50 cm high plants of *Ligustrum texanum* and *Buxus macrophilla* were used for the experiments and each plant was placed in the chamber to be exposed to ozone stimuli in a controlled environment. Electrical signals were monitored by means of three

Fig. 1. The iTreeBox plant growth chamber

stainless steel needle electrodes, one placed at the base (reference for background noise subtraction), one in the middle and the other on top of the stem. After some preliminary test, the sampling frequency was set at 10 samples/s for all the recordings. All the experiments were carried out during the day time for about 8 hours and the ozone treatment always started at least one hour after the beginning of the electrical signal acquisition to allow the plant acclimating to the artificial light and the box conditions. Before exposing plants to the pollutant, several acquisitions in natural environment conditions (without ozone stimulus) were performed, in order to monitor the physiological electrical activity of each plant. The main ozone treatment consisted of 1 hour exposure to a constant concentration of 240 $\mu g/m^3$, that is the ozone alert threshold value, as set out in [22]. Moreover, further experiments consisted in exposing the plant to incremental ozone concentrations, in order to simulate more realistic environmental conditions, as in days of summer heat. The ozone was injected in the chamber with four increasing concentration values (60, 120, 180 and 240 $\mu g/m^3$) every 60 minutes, for a total exposure duration of four hours.

3. DATA ANALYSIS

The proposed detection algorithm of plant response to ozone is designed according to two approaches. The first one is based on a preliminary extraction of significant deviations from a certain baseline trend: in order to correctly identify the response in an automatic way, a derivative-based algorithm has been used. The second step is based on the classification of the ozone risk level by the method of correlation. In all applications we used the signals deriving from the experiments carried out in the iTreeBox chamber. The methods were developed under Matlab software. The detailed flow chart of the proposed system is shown in Figure 2.

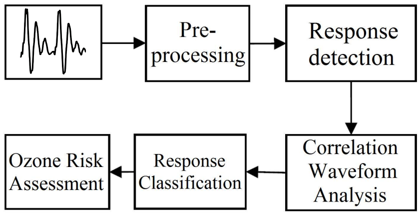

Fig. 2. Flow chart of the detection algorithm

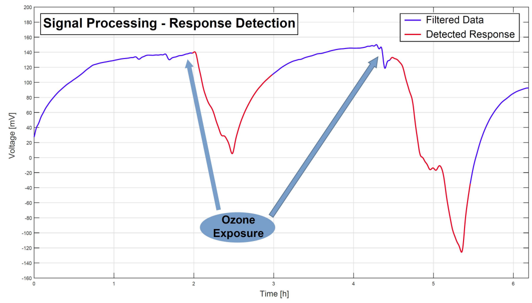

Fig. 3. Response detection of ligustrum plant signal after ozone exposure

3.1. Pre-processing of the plant electrical signal

The reference signals generated by a plant are generally contaminated by different sources of noise. Since most of the energy of such biological signals is concentrated at low frequencies, we applied a low-pass filter, followed in cascade by a moving average filter to further clean the signal. Given the fact that the responses to an ozone stimulus last approximately 60 minutes, the used low-pass filter has a cutoff frequency of 5 mHz.

3.2. Plant response detection

In general, in response to an environmental stimulus, the plant electrical activity appears irregular for a certain period of time. We use the different characteristics induced by ozone air pollution to detect the abnormal signal waveform. In order to automatically segment the data and correctly identify the response, we implemented a derivative-based algorithm. Given the voltage signal $V(t)$ and the following parameters vector:

$$P = (A_{dV}, \Delta t_d, S_V) \tag{1}$$

a response is defined to occur when the first derivative of the signal decreases below a negative threshold A_{dV}:

$$\frac{dV(t)}{dt} < A_{dV}. \tag{2}$$

In order not to associate very quick fluctuations to actual responses, we set another threshold, Δt_d, as a minimum time duration following the onset of the response. This condition enables the accurate detection of long-lasting effects on the plant electrical activity caused by ozone exposure. Based on the supplied data, it has been noticed that the central position of the response is related to the nearest local minimum of the plant voltage signal: if the response voltage initially decreases, after a certain time period it will start to increase in order to restore the pre-stimulation baseline trend. This property was used to estimate the minimum variation in the slopes of the ozone response and set an amplitude threshold, S_V, on the voltage signal. The ozone response is then detected and extracted whenever the difference between the central location of the response, V_c, and the basal voltage V_b, that is the value of the voltage signal preceding the onset of response, exceeds the threshold S_V:

$$|V_c - V_b| > S_V. \tag{3}$$

In our approach, the period taken for the plant to stabilize its potential after the stimulus has to be assigned to the same response. Since such a response model has a 60 minutes average duration, the value of V_c is calculated as the local minimum of the voltage signal, while V_b is estimated to be the voltage signal value for the preceding 30 minutes. An example of detected ozone response is depicted in Figure 3. A representative ozone response template, constructed by coherent averaging of the respective response segments of the recordings used for the training phase, was employed for subsequent comparison with all the responses detected by the proposed system. A window size of 60 minutes was used, in order to effectively include the long-lasting repolarization phase of the plant signal.

4. CORRELATION WAVEFORM ANALYSIS FOR OZONE RESPONSE CLASSIFICATION

Cross correlation is a statistical technique which can show whether and how strongly pairs of variables are related. It is an excellent tool to match images and signals with each other. It is robust to noise, and can be normalized for pattern matching. The correlation coefficient is a statistical measure of similarity of two waveforms; it produces a value, ρ, which falls within the range [-1,+1], where +1 indicates a perfect match between signal and template. Mathematically, the correlation coefficient is defined as follows:

$$\rho = \frac{\sum_{i=1}^{N}(t_i - \bar{t})(s_i - \bar{s})}{\sqrt{\sum_{i=1}^{N}(t_i - \bar{t})^2}\sqrt{\sum_{i=1}^{N}(s_i - \bar{s})^2}} \tag{4}$$

where t_i are the template points, s_i are the signal points under analysis, $\bar{t}$ is the average value of the template points, $\bar{s}$ is the average value of the signal points, N is the number of points in the template, and ρ is the performance measure. The correlation coefficient is independent of the relative amplitudes of two signals and independent of any baseline changes. Based on the supplied data, it was observed that the plant response to ozone stimulus is characterized by a specific waveform. The proposed detection system takes advantage of this property to classify the risk level of ozone air pollution by using the correlation coefficient. Several studies have offered guidelines for the interpretation of the size of a correlation. The interpretation of the correlation coefficient depends on the context and purposes. In our study an empirical approach was adopted, by giving numerous plant signals to the system in order to adjust and validate the threshold values of the proposed algorithm. The correlation-based classifier has been implemented to distinguish electrical responses to critical level of ozone exposure by identifying the detected responses with very strong correlation to the template. The corresponding decision rule has been chosen by setting a threshold value of 0.73 on ρ.

5. EXPERIMENTAL RESULTS

To examine the efficiency of the algorithms, a database of 84 day-long recordings of plant electrical activity was employed. The recordings were chosen to include a broad variety of waveform responses. The database was collected from both ligustrum and buxus plants, including experiments carried out with constant or incremental ozone concentrations exposure, mixed pollutants (ozone and sulphur dioxide), as well as with natural environment conditions. The complete recordings database is summed up in Figure 4. The correctness of a classification can be evaluated by computing the number of correctly recognized class examples (true positives, tp), the number of correctly recognized examples that do not belong to the class (true negatives, tn), and examples that either were incorrectly assigned to the class (false positives, fp) or that were not recognized as class examples (false negatives, fn). According to [23], the following performance measures for classification are considered:

$$Accuracy = \frac{tp + tn}{tp + fn + fp + tn} \tag{5}$$

$$Precision = \frac{tp}{tp + fp} \tag{6}$$

$$Sensitivity = \frac{tp}{tp + fn} \tag{7}$$

$$Specificity = \frac{tn}{fp + tn} \tag{8}$$

The detection results of the proposed algorithm are listed in Table 1. The classification system is shown to be capable of discriminating the response to critical levels of ozone air pollution from the depolarizations induced by effects of natural environmental conditions with 87% accuracy. However, individual thresholds were required for each plant species and were based on the initial training phase. The total performance is high since the achieved precision and specificity

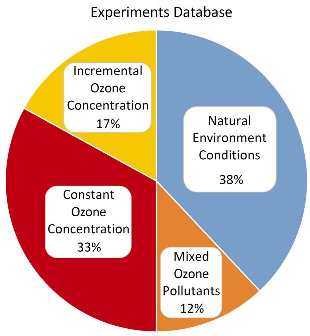

Fig. 4. Database summary for the 84 day-long test recordings

are high for the ligustrum plant dataset (96% and 95% respectively), compared to the results of the buxus plant dataset (89% precision and 77% sensitivity). The main advantage of the proposed system resides in the fact that the classification algorithm based on correlation coefficient, by recognizing the degree of similarity between plant electrical signal and template waveform provides a very efficient and innovative monitoring technology for detecting ground-level ozone pollution.

Table 1. Results from the classification algorithm

	ligustrum	buxus	Total Performance
Accuracy	92%	81%	87%
Precision	96%	89%	93%
Sensitivity	89%	77%	84%
Specificity	95%	85%	91%

6. CONCLUSIONS

In this paper has been presented an automatic method of analysis of plant electrical signal in order to detect critical level of ozone air pollution. The experimental data were coming from plants exposed to various ozone concentrations in a closed plant growth chamber, specifically designed to recreate typical environmental and daylighting conditions. The proposed classification algorithm is based on the correlation theory; it mainly recognizes the degree of similarity between a reference ozone response and the acquired plant electrical signal. Then the decision is made based on the correlation coefficient. The experimental results show that the proposed system achieves over all accuracy of 87%. Moreover the innovative approach to the problem of atmospheric pollution monitoring, based on plant electrical activity analysis, allows the classifier to be easily extended to other major air pollutant classes in future studies.

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