

PLANT ELECTRICAL ACTIVITY ANALYSIS FOR OZONE POLLUTION CRITICAL LEVEL DETECTION

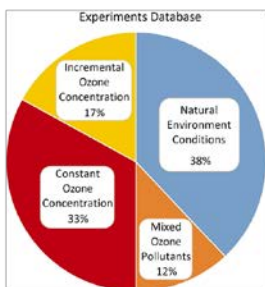
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Experimental Results

To examine the efficiency of the algorithms, a database of 84 day-long recordings of plant electrical activity was employed. The testing 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 various levels of exposure to ozone air pollution and in natural conditions.

The classification system has been evaluated by computing the number of correctly recognized class examples (true positives, t_p), the number of correctly recognized examples that do not belong to the class (true negatives, t_n), and examples that either were incorrectly assigned to the class (false positives, f_p) or that were not recognized as class examples (false negatives, f_n).



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

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

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

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

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%

Conclusions

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 good accuracy (87%).

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.

References

[1] Air quality in Europe - 2014 report, EEA – European Environment Agency, 2014.

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LA NOTTE DEI RICERCATORI

venerdì 25 settembre 2015

Alberi come Rivelatori dell'Inquinamento Ambientale

Progetto A.R.I.A.

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Progetto A.R.I.A.

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Abstract

The electrical activity signals in plants can provide useful information to monitor environmental conditions, such as atmospheric pollution.

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.

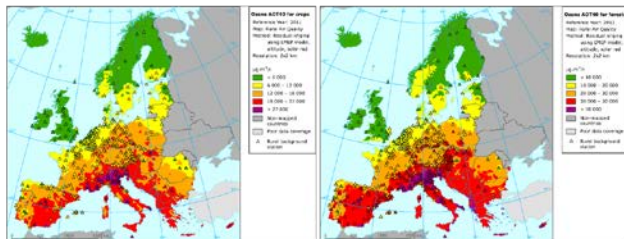
Ozone Pollution and Human Health

Among air pollutants, ozone (O_3) is one of the most important greenhouse gas with secondary origin.

Unlike primary air pollutants, ground-level (tropospheric) O_3 is not directly emitted into the atmosphere.

Instead, it is formed from complex chemical reactions following emissions of precursor gases such as nitrogen oxides (NO_x) and non-methane volatile organic compounds (NMVOC) of both natural (biogenic) and anthropogenic origin.

Since the formation of O_3 requires sunlight, O_3 concentrations show a clear increase moving from the northern parts to the southern parts of the continent, with the highest concentrations in Mediterranean countries [1].



Accumulated ozone exposure values, over a threshold of 40 parts per billion, for crops (AOT40c) increase from Northern Europe towards the South Mediterranean countries.

The gradient of the accumulated ozone exposure values over a threshold of 40 parts per billion for forests (AOT40f) is similar to that of the AOT40c (crops). AOT40f increases from northern Europe to reach the highest values in the countries around the Mediterranean.

Plants as BioSensors

The electrical activity signals in plants can provide useful information to monitor environmental conditions, such as atmospheric pollution.

The most common air quality measurements exploit sensors based on the use of physicochemical properties in order to measure the concentrations of air pollutants.

The use of biosensors has the advantage of showing the actual pollutants impact on living organisms, thus providing additional data to the electronic instruments.

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.



Data Acquisition and Analysis

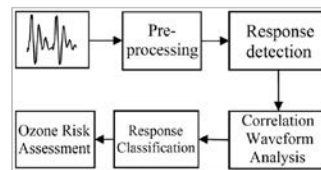
The experiments were performed inside a closed growth chamber, the *iTreeBox*, in order to control the ozone concentration and other environmental parameters.

About 50 cm high plants of *Ligustrum texanum* and *Buxus macrophylla* were used for the experiments and each plant was placed in the chamber to be exposed to ozone stimuli in a controlled environment.

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 *iTreeBox* plant growth chamber

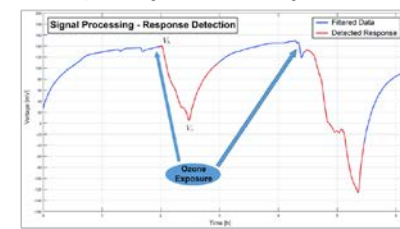


Flow chart of the detection algorithm

Ozone Critical Level Detection

The detection algorithm of plant response to ozone 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, similarly to those used in spike detection.



Response detection of ligustrum plant signal after ozone exposure

Given the voltage signal $V(t)$ and the following parameters vector:

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

$$\frac{dV(t)}{dt} < A_{dV} \quad |V_c - V_b| > S_V$$

Δt_d : minimum time duration following the onset of the response

V_c : nearest local minimum of the plant voltage signal

V_b : basal voltage preceding the onset of response

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

The proposed detection system is able to assess the risk level of ozone air pollution by using the correlation coefficient.

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.

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

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.