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WatchPlant: Networked Bio-hybrid Systems for Pollution Monitoring of Urban Areas

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Abstract

Growing cities are a world-wide phenomenon and simultaneously awareness about potential dangers due to air pollution, heat, and pathogens is increasing. Integrated and permanent monitoring of environmental features in cities can help to establish an early warning system and to provide data for policy makers. In our new project 'WatchPlant,' we propose a green approach for urban monitoring by a network of sensors tightly coupled with natural plants. We want to develop a sustainable, energy-efficient bio-hybrid system that harvests energy from living plants and utilizes methods of phytosensing, that is, using natural plants as sensors. We present our concept, here with focus on Alife-related methods operating on the gathered plant data and the bio-hybrid network. With a self-organizing network of sensors, that are alive, we hope to contribute to our future of livable green cities.

Introduction

According to estimates of the UN,[1] 68 percent of the world's population will live in cities by 2050. Although living at high densities can have advantages in logistics and stimulate cultural life, there are well-known disadvantages including dangers to health of city dwellers, which may even be intensified by climate change (Dye, 2008; Harlan and Ruddell, 2011; West et al., 2016). In the new EU-funded project 'WatchPlant' (2021-2024), we want to address challenges connected to pollution, mainly air pollution in cities. While the ultimate goal should be to avoid any pollution, we need to master monitoring environmental features in urban areas. Only complete and up-to-date (ideally real-time) data can allow for evidence-based policies and timely interventions to protect the health of citizens. State-of-the-art city air pollution methods, however, are resource consuming (energy, space, etc.) and hazardous themselves (e.g., poisonous materials), expensive, and cannot easily be scaled up to create a dense mesh of measurement stations (Snyder et al., 2013). In WatchPlant, we address these major challenges with novel concepts focused on energy-efficiency and phytosensing (Mazarei et al., 2008; Chattoraj et al., 2001), which is measuring environmental features via living natural plants (see Fig. 1 for a schematic overview). We want to miniaturize measurement stations, make them energy efficient, apply energy harvesting, and form networks of phytosensors. A challenge of deploying dense sensor networks for air quality monitoring is cost efficiency that we address by designing and developing miniaturized stations based on low-cost sensors. The idea is to use low-cost sensors for phytosensing to replace high-cost standard sensors. In addition to measuring plant parameters, we also need to measure other relevant features based on physico-chemical variables, such as temperature, humidity, a number of relevant gases (e.g., NO_2, O_3, SO_2), and particulates (e.g., PM2.5, black carbon, ultra-fine particles). This hardware approach is paralleled by software-focused efforts. We want to apply methods of machine learning and Alife to filter, model, compress, and predict the measured plant signals and to make the system adaptive, robust, and scalable. The end product will be a self-organizing adaptive network of living sensors, basically a large-scale bio-hybrid system. These technical efforts are complemented with a multi-scale modeling of plant physiology, environmental features as time-space-distributed natural phenomenon, and novel methods of environmental modeling to correlate large-scale, real-time plant data with environmental features. While the major ambition of our project is focused on a novel approach for in-situ sap (fluid transported in natural plants in xylem cells or phloem sieve tubes) sampling for energy harvesting and sensing of key biomarkers, we want to focus in this paper on the networked living sensors supported by machine learning and Alife methods. We want to make use of high-end and low-cost off-the-shelf sensors with phytosensing as the core of the project to use living plants as sensors.

In 'urban ecology,' the human life counts as artificial: "Human beings–and especially their cities, seemingly so 'artificial'–fail to fit neatly into ecological theory" (Collins et al., 2000). However, in WatchPlant we plan to introduce more technology to the city to reconnect natural and artificial life. Living organisms inhabiting cities, such as natural plants and human beings, are both subject to (air) pollution

[1] https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html

and suffer equally. In combination with our sensor network, they form a mixed society (Halloy et al., 2007; Hamann et al., 2015) or bio-hybrid system (Wahby et al., 2018; Mariano et al., 2017). Key idea of our project is that measuring different features in plants (i.e., phytosensing) will allow to estimate and predict otherwise difficult to measure and difficult to model environmental features. Thus, besides typical sensors applied on plants (e.g., photosynthesis activity, sap flow) we also plan to use electrophysiology (Volkov, 2012; de Toledo et al., 2019; Oyarce and Gurovich, 2010) and novel chemical sensors for sap. This way, plants do not only serve as alive sensors but also as integrators of past environmental features and highly sensitive early-warning systems for pollution. We network them, gather data over space and time, and we use methods of self-organizing sensor networks, machine learning, and evolutionary computation to interpret (Pereira et al., 2018) and maximize an energy-efficient exploitation of the available data as described in the following sections. As the project is still young, we only present our main concepts for the next years here.

Measuring pollution and impact on human health in urban areas

Environmental monitoring in urban areas represents an important task for understanding socio-ecological interactions, consequences of climate change, impact of pollution on human health, and environmental sustainability. Specifically, different environmental factors, such as nitrogen dioxide (NO_2) and particulate matter (PM), have an impact on human health causing heart diseases and strokes, lung cancer, chronic lung diseases, and respiratory infections.[2] Hence, it is of highest importance to determine a co-dependency between pollutants and their common influence on living organisms. Environmental epidemiology is used to determine how environmental exposures impact human health using predictive models. A relationship between specific environmental features and human health can be established. However, environmental pollutants influence not only human's health, but all living organism of the environment (Paoletti et al., 2010; Seyyednejad et al., 2011). So continuous monitoring of plant's health can constitute a new a kind of "well-being sensor," which could be representative of how pollutants affect the different biological organisms in the environment. Currently, there are well established methods to measure air status in air quality measurement stations and obtain data to apply in epidemiological models, that is, predictive models to understand the effect of environmental features (e.g., air quality) with human health. Here in WatchPlant, we aim to use these modeling approaches to predict environmental status of cities by the use of plants (i.e., specifically by the interpretation of physiological parameters, such as transpiration, sap flow, sap biomarkers, and photosynthesis between other). In this sense, one of the challenges in WatchPlant is to address the biochemical signaling of the plant trough phloem sap sensing. Phloem sap consists mostly of sugar and flows through the plant from sugar sources to sugar sinks. Phloem sap contains all the molecules produced by photosynthesis including key ions and molecules, such as carbohydrates, amino acids, and phytohormones, that can be used for monitoring the plant. Thus, by the specific and selective sensing of these molecules, it could be possible to understand the biochemical status of the plant at real-time. This can provide information of the plant's response even before effects can be seen in the organism. In addition, they can help to understand the correlation between different plant parameters and their influence in the plant response. Specifically, WatchPlant addresses the analysis of new under-sampled parameters in phloem sap where a wide amount of compounds for long-distance signaling are produced by the plant in response to environmental stresses, including air pollution, which can provide high-quality information unavailable today and hardly explored yet. Hence, AI and specifically Alife methods can help in providing new perspectives to understand the correlation between these new under-sampled parameters in the phloem sap, physical parameters, such as transpiration, and their dynamics in the physiological response of plants in a multi-variable context. However, accessing specifically phloem sap constitutes a major challenge because it is mandatory to avoid the reaction of the plant to invasive measurement and also because a long-term sap extraction is necessary. To achieve the challenge of obtaining sap, we plan to use micro-technologies to create a sap-device for the efficient extraction of this biological fluid. This strategy has already been used for medical applications in interstitial fluid extraction or drug delivery (Takeuchi et al., 2019). However, WatchPlant will address, for the first time in natural plants, the use of this technology to obtain a continuous access to sap combining micro-technologies with fluid modeling to optimize the plant-device interaction and maximize the sap volume obtained. In addition, WatchPlant aims to obtain information about the internal state of plants by using a decentralized approach of self-powered sensors, using clean energy sources, such as solar cells and even the extracted sap as radically new energy source. Thus, taking the advantage of continuous access to phloem sap, this fluid will be used not only for sensing but for energy harvesting, using sap as a radically new energy source which will constitute another breakthrough in this project. According to the use of living plants for energy generation, different approaches have been carried out using fruits taking the advantage of the high carbohydrate content of juice (MacVittie et al., 2015) or using microbial biofuel cells placed at the roots (Cabezas et al., 2015). Unfortunately, these approaches struggle to succeed in most applications due to dif-

[2] https://www.stateofglobalair.org/sites/default/files/soga-2018-report.pdf

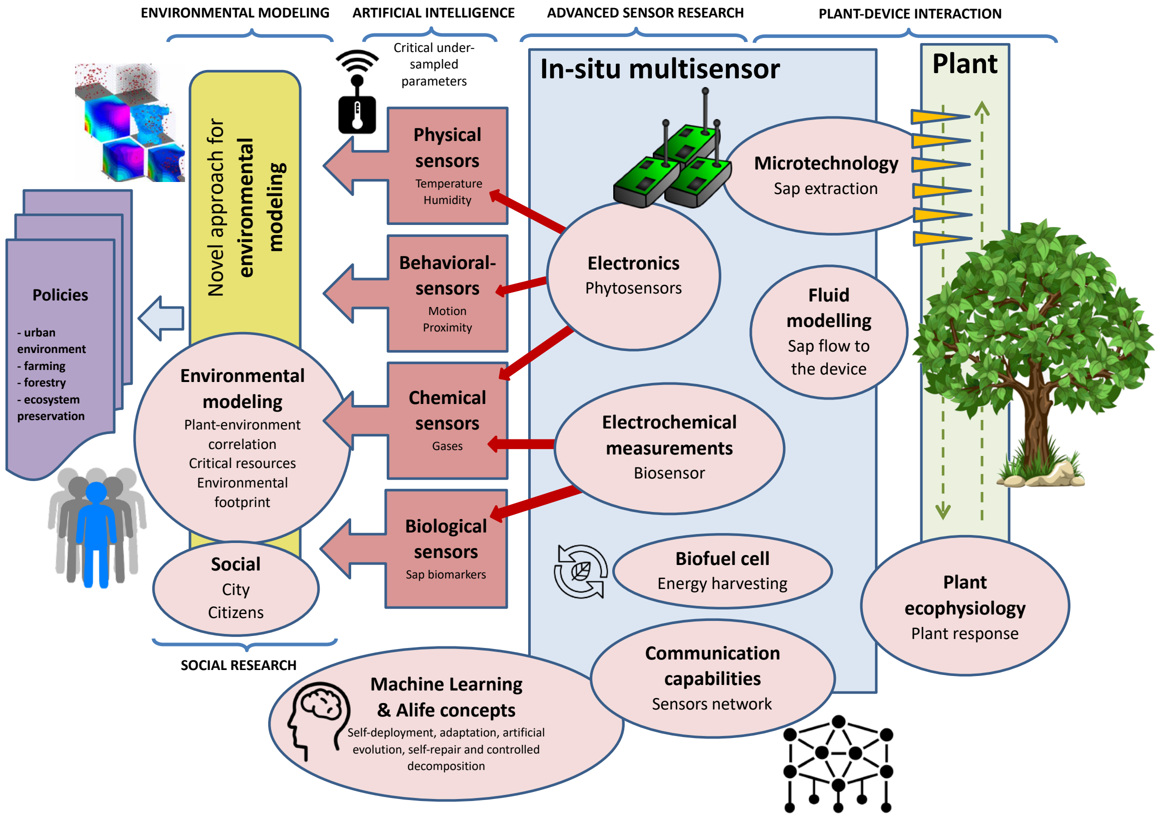


Figure 1: Schematic overview of project WatchPlant indicating the four major aspects: plant-device interaction (bio-hybrid interaction), advanced sensor research, AI methods, and environmental modeling (including impact on policies).

ficulties to create long-lasting interactions between device and host, the seasonal availability of fruit, or the size of the plant (easily replanted) in the case of of microbial BFCs. For these reasons, WatchPlant constitutes a promising alternative for energy harvesting from any kind of vegetal organism to develop self-powered sensors, including those for sap analysis and phytosensing. Combined with a complex sensor network, we develop a “smart bio-hybrid organism” with AI-components, capable of decision-making and self-adaption for sensing, communication, and energy management. Our final objective is to use plants as living sensors to measure pollution and its impact on human health in urban areas.

Alive sensors: Natural plants as phytosensors

Using a plant as a sensor instead of the standard approach of using technological sensors, can add value in monitoring the environment (Zinnert, 2012). A plant is exposed to and influenced by many different environmental factors and has a physiological response (Gresshoff, 1993). A specific combination of pollutants, pathogens, and other parameters might have significantly stronger impact on the plant than each of them in isolation. Therefore, the plant detects a superposition of several environmental pollutants, such as NO_2, O_3, PM, as well as nutrients from soil and water, heat, and light stresses, among others. Within the project we also want to study the impact of electromagnetic fields from GSM (4G/5G) and WiFi on plants, although electromagnetic waves do not necessarily need to count as pollution (harmful effects on humans are questionable or disputed). To some extent, a plant evaluates by its physiology whether and how much this combination of influences is endangering itself or possibly other living organisms. The standard approach of using several different technological sensors does not have the intrinsic knowledge of the plant’s physiology to determine the impact of mixed pollutants on living organisms. Hence, it is important to monitor not only biological responses but also changes of main environmental parameters for a more specific detection of pollutants.

The reactions of plants to environmental stresses can be detected on physiological, biochemical, and molecular levels. For instance, reaction to O_3 includes changes of physiological parameters, such as stomatal conductance, plant biomass, photosynthesis and transpiration rate; biochemical responses change production of reactive oxygen species and nitric oxide that can perturb the redox homeostasis via changes in ascorbate and glutathione, and in turn can significantly impact on the proteome (Iyer et al., 2013). Electrophysiological reactions to stress are reflected on the bioelectrical signaling level that plays central roles in cell-to-cell and long-distance communication. It includes changes in the action potential, variation potential, and system potential, which motivated the concept of "plant electrome" (Pereira et al., 2018). These responses are species-specific, however, they can be generalized for groups of species on different levels of detail; from more general physiological levels up to more specific biochemical and molecular levels. Monitoring of (electro-)physiological changes is technologically less demanding than a biochemical analysis, especially in real-time, although it is also rather specific. For instance, discriminating between stresses due to O_3, NaCl, and H_2SO_4 is currently only possible based on an analysis of the biopotential dynamics (Chatterjee et al., 2015).

For experimental validation of this approach, a phytosensing system is developed further (an innovation previously developed within EU-funded projects *flora robotica* (Hamann et al., 2015) and *Biohybrids*). For an example experiment setup, see Fig. 2. The system is designed for real-time monitoring of (electro-)physiological parameters of plants, air, soil, and water quality, as well as main environmental parameters. The general concept consists of providing flexibility for connecting different sensors to embedded devices while outsourcing complex computation to a connected mini-PC. Thus, the device supports multiple analog and digital input signals and buses. Current experiments and tests are performed to study the bio-signaling system, transpiration, and sap-flow mechanisms. Electrochemical tissue impedance spectroscopy is primarily used as ionic interface to biological fluids (in addition to sensors based on functionalized surfaces). Environmental parameters are represented by air quality (e.g., CO_2, NO_2, O_3, SO_2, PM), soil (moisture/temperature, ph/chemical sensing is also possible), different EM fields (e.g., RF emission, magnetic fields), and other elements (e.g., light, mechanical influences or supply voltage). The phytosensing system supports multiple actuation mechanisms (e.g., RGB LEDs, text-to-speech engine, power relays, robot actuators) for creating bio-hybrid feedback loops. This system is commercially available in different variants and thus makes bio-hybrid experiments accessible to a large community with minimal entry threshold. In WatchPlant we aim to implement this technology with new features regarding sensing and energy harvesting to create an intelligent bio-hybrid system for air quality monitoring.

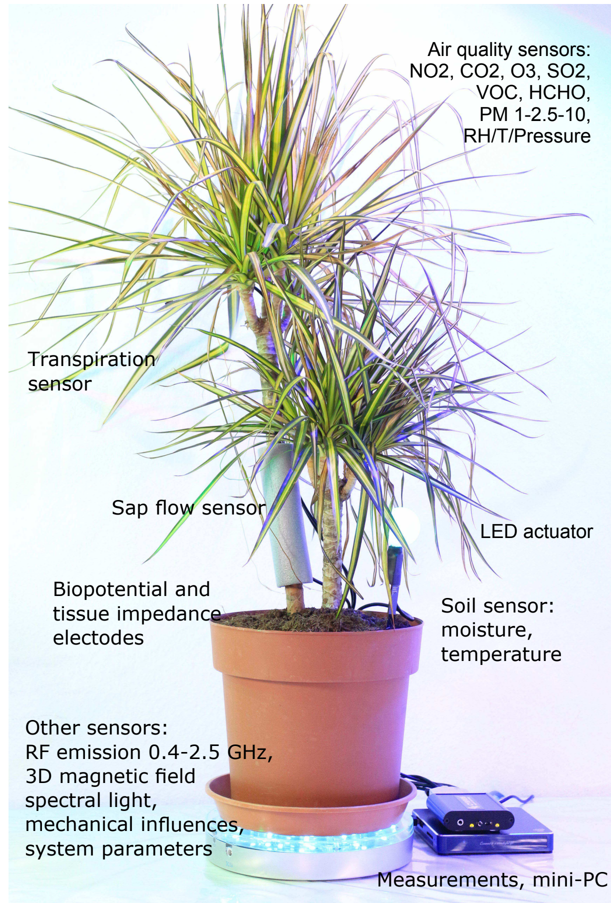


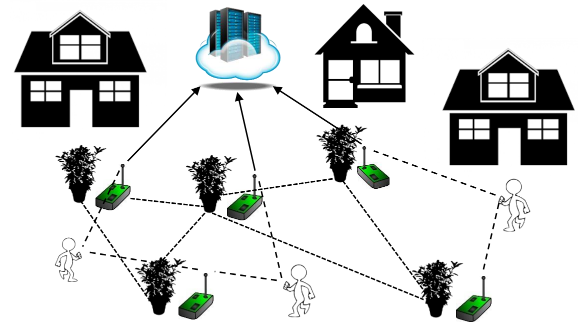
Figure 2: Example of different electrophysiological, physiological and environmental sensors, available in the phytosensing system, totally about 80 physical and synthetic sensor-data channels sampled every second; manufacturer – CYBRES GmbH.

Developing and leveraging a distributed bio-hybrid sensor network

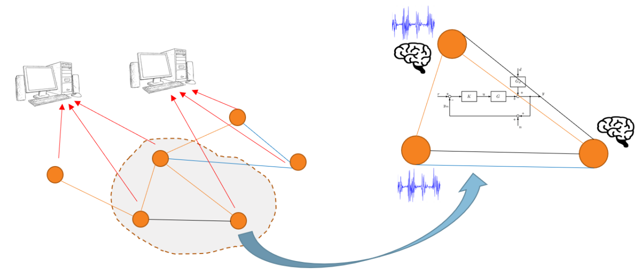
The sensor network perspective on WatchPlant is primarily focused on two aspects: resilience and coverage. Our vision is to deploy a long-term highly reliable and adaptive living sensor network that can efficiently and effectively monitor environmental features and interact with close-by pedestrians as shown in Fig. 3(a). The network will be heterogeneous with sensor nodes that are capable of exchanging information using various communication technologies (WLAN, 5G, also 4G, 3G, and Bluetooth). The network will be able to exploit the existing city infrastructure and utilize its sensory information, as well as information obtained from other existing services, such as weather forecast. Pedestrians can connect to the network using their handheld devices and learn about the current environmental conditions (e.g., air quality, temperature, etc.) or be warned in the case of disasters. The decentralized sensor network will be supported by micro-models at the level of local groups and on each node to model local phenomena and try to predict the measured signals, as shown in Fig. 3(b).

The living sensor network should reliably monitor the environment in a self-organized manner for a long period of time. However, the network is subject to a high degree of uncertainty; some sensors might be relocated, get damaged, or simply fail at harvesting enough energy for some time. Considering these uncertainties and the mobility of human users, the network requires a sustained ability to adapt to agent and link failures, caused by intrinsic sources (e.g., malfunction) or outside sources (e.g., damage). We require a high degree of resilience that we want to implement by using ad-hoc routing protocols that allow messages to be forwarded through multiple nodes without relying on a fixed topology. We ensure network connectivity by implementing techniques applicable in real-time and in a decentralized/distributed approach. However, we need to consider the cost of maintaining connectivity. In the case of wireless networks, the cost is paid as energy for radio communication and as energy and computation time required to execute algorithms. Hence, we face a tradeoff between energy efficiency and network connectivity control. In order to increase the network's resilience (decreasing the time required to return to the connectivity level prior to the disruption), the number of links should be increased. However, an increased number of links generally increases costs. Hence, the topology design, conciliating the algebraic connectivity maximization, and network cost minimization, represent a convex optimization problem that we identify as network challenge in the project. For example, one way to optimize for energy efficiency, is to reduce the sampling frequency of measuring and to exploit the provided micro-models to perform (spatial/temporal) inter- and extrapolation. Also, we can minimize the overhead of the applied routing protocol (Woo and Singh, 2001).

Considering the network coverage aspect of Watchplant, the self-organized living network needs to autonomously detect areas where the sensor nodes are sparse or broken and request the manual addition of extra sensors, the replacement of malfunctioning ones, or the repositioning of sensors. Sensors pre-process data and upload it to the cloud as input to macro-models that holistically model the whole city. Similarly as in the case of resilience, the coverage is an optimization problem that we want to solve in a decentralized approach. A down-link from the cloud to the sensors helps to improve the micro-models that, in turn, reveal areas inadequately covered by sensors. In addition, resolving the coverage optimization problem should include constraints related to limited energy resources of sensor nodes, as well as heterogeneity of used communication technologies and their particular communication ranges.



(a) realization of the living sensor network with a dynamic topology



(b) decentrilized ML-approach to model local phenomena

Figure 3: Concept of the bio-hybrid sensor network: sensors at plants for phytosensing, sensors have simple ML-based local models of plants and environment, sensor nodes connect to each other, to handheld devices, and to the cloud for more complex environmental modeling.

Alife approach for an energy-efficient bio-hybrid network

A key challenge in our project is to implement intelligent behaviors on the sensor nodes to make good decisions about when and what to communicate. Each communication consumes energy and our sensors are harvesting their energy themselves from their environment and the natural plant, which makes energy a scarce and fluctuating resource. As we need to use different communication technologies in WatchPlant, we have a heterogeneous sensor network. The networks will be hybrids of spatially and temporally decentralized topology (neighbor-to-neighbor) combined with centralized topology (cloud). Also, for measurements of electromagnetic background noise we can turn off all radio communication in the network temporarily. For short range data exchange, for example, of WatchPlant sensor nodes in close proximity, we plan to use Bluetooth components, while for mid-range communication we employ an IEEE 802.11 WLAN layer. For long-distance communication we use GSM-compatible devices. Since each of these has different energy requirements, the main issue with respect to data exchange (measurements and other informa-

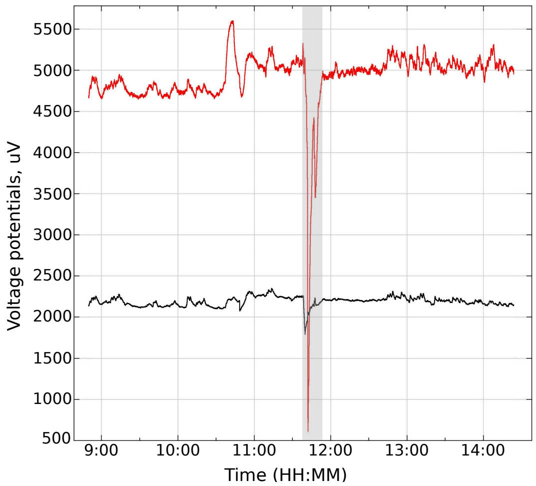


Figure 4: Example of an electrophysiological plant experiment; two-channel Bio-potential measurements (red indicates channel 1 and black indicates channel 2). Note the bio-potential response (highlighted in gray) to the touch event at 11:40.

tion) is when to select a particular technology because energy resources of nodes are dynamic and limited. Hence, a challenge for WatchPlant is the question of how to switch between provided communication technologies in order to minimize energy usage, while at the same time achieving required data exchange and accomplish a desired degree of coverage of an area (street, blocks, a whole city).

In the last decade, machine learning (ML) approaches (Bishop, 2006; LeCunn et al., 2015) have been extensively applied to a wide range of problems, such as classification, regression, and time-series forecasting in different application areas, such as recommender systems, computer vision, and self-driving cars. We plan to apply ML approaches to acquire knowledge from posterior measurements of natural plants. Our living sensor network monitors dynamic environments that change in multi-dimensional features on different timescales. A key application of ML in WatchPlant will be to analyze time-series of plants to correlate environmental features via phytosensing with public health. Two main tracks will be the classification of observed significant changes in the measured signal and the prediction of expected future plant signals. An example are the electrophysiological and sap measurements of plants that we will analyze in a model-free approach with ML (see Fig. 4 an example). We want to classify for specific immediate measurable events (change of light, concentrations of gases, etc.) and for long-term effects, for example, due to weeks of exposure to increased pollution. Data classification is a crucial problem in data mining. During the past decade, many classifying algorithms for time series data have been published: Bagnall et al. (2017) used the nearest neighbor (NN) classifier, a support vector machine (SVM) is used for classification and regression analysis (Cortes and Vapnik, 1995), and (Salamat and Tonello, 2019) presented the application of SVM in mission/path planning. The data classification can be assumed as a special case of nonlinear regression and function approximation. Therefore, nonlinear regression techniques, like artificial neural networks (ANN) can be applied to data classification and forecasting problems. The classification of external stimuli (NaCl, H_2SO_4, O_3) via the plant's electrical response has been reported, for example, by (Chatterjee et al., 2015) and (Pereira et al., 2018).

The two most interesting aspects of WatchPlant for Alife methods are the data-driven micro-models of interacting living plants and the online adaptation to ensure energy efficiency of the self-organized sensor network both powered by methods of evolutionary computation (EC). We can evolve artificial neural networks to develop predictive filters and models of plant signals to minimize communication between sensors and the cloud. The concept is that if the receiver node can predict the measurement in a certain percentage of cases, then no communication is necessary (assuming sender and receiver share instances of the same model). Similarly, we can apply EC to develop a highly specialized compression of plant signals using ANN to minimize the payload of messages when communication is necessary. These models could be adapted even online and shared among the nodes. In particular, we want to test and study online and offline evolution. For offline evolution we may start from a simple genetic algorithm but may also test state-of-the-art approaches, such as MAP-Elites (Mouret and Clune, 2015; Cully et al., 2015), especially when facing tradeoffs. In the case of optimizing communication efficiency, the tradeoff is between compression performance and information loss giving rise to a multi-objective optimization problem (Marcelloni and Vecchio, 2010). For online evolution we may use simple techniques, such as (1+1)-selection (Eiben and Smith, 2015). We can start from simple 'flat' ANN but may test also recursive ANN or LSTM networks (long short-term memory) and Transformers (Wolf et al., 2020) because we have time series as input.

Ultimately, we want to provide micro- and macro-models to the plant sensors that adapt online to the dynamic environment and collectively improve their performance tightly coupled with the observed behavior of natural plants. This way we will have a bio-hybrid system forming a complex system of interacting agents with half of them being alive (plants and humans) and half of them are constantly adapting artificial (intelligent) agents (sensor nodes). Our approach should in the long-term trigger research on ecologies of bio-hybrid systems as previously done, for example, by (Ch'ng, 2010) for vegetation modeling using Alife methods. Similar is also the concept of 'machine behavior' (Rahwan et al., 2019) proposing an ecosystem of AI agents. Only here we have a social–ecological system of human city dwellers and natural plants supported by a decentralized phytosensing system who share challenges of survival and well-being in exposition to air pollution.

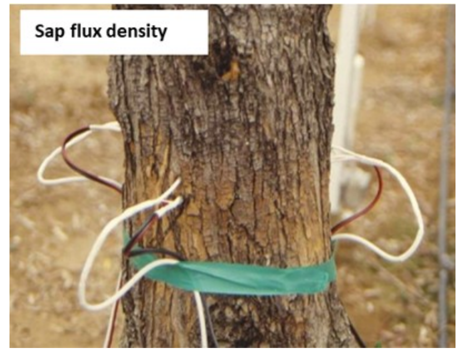
Opportunities of an Alife system with social impact and guidance for public policy

The WatchPlant bio-hybrid organism is envisioned to constitute a revolutionary tool to use plants themselves as "well-being sensors," repurposing plants as eco-integrated bio-robots to be used for sensing in cities. The otherwise unspecific plant response represents a kind of well-being sensor, which can be used to estimate pollution events in an early stage, even before the plant shows visible reactions. Provided with this information, human society can perform specific actions and efficiently apply resources and appropriate policies. The new bio-hybrid organism developed in WatchPlant will positively impact several of our key challenges, such as climate change, by early reaction, which can have a huge impact on both human health and the economy. As an example of the possible impact of this technology, WatchPlant will address its applicability to air quality monitoring as proof-of-concept of the new bio-hybrid system by evaluating risks of air pollution exposure for humans (trough the effect of these contaminants in plants). The obtained conclusions could be used to apply several policies and actions in many scenarios.

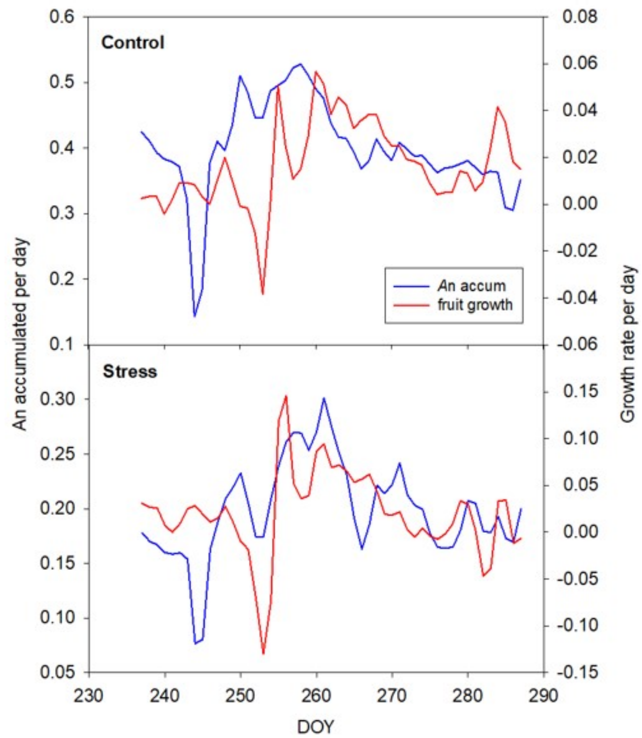
On the one hand, and specifically in the pandemic context of COVID-19 (Wu et al., 2020; Konstantinoudis et al., 2021), prevention of respiratory diseases caused by air pollution in cities is of highest importance. We need to avoid future social and economic crises that could confront healthcare institutions around the world again with overburdening clinical, economic, and operational challenges.

On the other hand, the WatchPlant device could be applied not only in shaping policies to improve human health, but also in actions to preserve ecosystems with policies for habitat and biodiversity preservation, and to mitigate nutrient and organic pollution from agriculture. We also envision a wide applicability of our novel technologies in food security, to produce safe and healthy food and to ensure fair agriculture. This technology can play a key role in rural growth through strengthening precision agriculture and forestry and shifting the focus from compliance to performance (e.g., nutrient or water management). The use of plant sensors in precision agriculture is not new and their use has always been justified as a means of integrating the plethora of abiotic and biotic signals and stresses that crops face during their development (Fernandez, 2014). We plan to combine the use of sensor outputs with physiological process-based models to extract the relevant information from them. As an example, we will use sap flow sensors to infer stomatal conductance (Hernandez-Santana et al., 2018), and hence photosynthesis rate, to put the state of the monitored plant into a physiological context (see Fig. 5 as an example).

Following this example, we plan to proceed similarly for other measured plant variables, with special attention paid



(a) sap flow sensors on the stem of an olive tree



(b) accumulated photosynthesis rate A_n and growth rate over days (day of year)

Figure 5: (a) Sap flow sensor to estimate xylem sap flux density in an olive tree under field conditions. From sap flux density it can be inferred the stomatal conductance and, by coupling a biochemical model of photosynthesis, the actual photosynthesis rate A_n; (b) Once the instantaneous An is determined, it can accumulate the amount of CO_2 absorbed during the day. The plot shows a good correlation found with the daily fruit growth measured with a mini-dendrometer.

to the novel monitoring of under-sampled compounds in the phloem sap. This will help us to develop robust algorithms in our bio-hybrid system to interpret the gathered data, and to relate and integrate it with knowledge about the physiological response of plants to pollutants or other stresses. The experience from the application of this approach in commercial fruit tree farms for precision agriculture will serve as a starting point for the implementation in urban environments to deal with air pollution. Thus, WatchPlant could lead to increased efficiency and competitiveness, social inclusion, new business models and opportunities, and renewal of governance models through improved participation of society. In summary, all these innovations combined with efficient energy use, provided by the clean self-powered capabilities of the developed bio-hybrid system, will enable WatchPlant to help solving the main goal of creating an integrated system to support citizens to face the challenges of our future cities.

Conclusion

With the concepts of our project WatchPlant, we try to develop a novel approach for (air) pollution monitoring in urban areas that is sustainable, scalable, and leverages our co-inhabitants, natural plants, using phytosensing. Additionally, we develop a novel and ambitious approach for energy harvesting using the plants' sap. The main focus in this paper is on technological aspects related to methods from the Alife community to realize bio-hybrid technology. We interpret cities as bio-hybrid systems of humans, plants, and an integration technology that monitors the well-being of plants to correlate the data with human health and air pollution. In model-free approaches we plan to apply methods from machine learning and evolutionary computation to develop predictive filtering and energy-efficient messaging in a network of bio-hybrid systems. Ultimately, we want to connect human and plant life in cities as a social–ecological system by a decentralized phytosensing system. WatchPlant will provide new tools to help decreasing pollution in the environment and to improve human health.

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