An IoT solution for measuring bee pollination efficacy

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***Abstract*— In light of 'saving the bees', it becomes necessary to learn as much as possible about bees and other pollinating insects. Data about flying patterns of bees, intensity of bees, wingbeat frequency of bees and activity of bees are all factors that can contribute to optimizing pollination by insects. Somehow, the pollination process is often overlooked in new internet of things- (IoT-) developments for agriculture. Although individual bees can already be tracked, there has yet to be found a way to actually map bee activity on a field. In this paper, a system is presented that enables fruit growers to detect, quantify and optimize bee activity, based on sensor technology. The system can predict and map the behavior of pollinating flying insects in an affordable, robust and location-based manner. Firstly, the state of the art on bee mortality and on IoT in agriculture is briefly explored. Secondly, a literature study is performed on detectable bee characteristics and sound is described as a good way of affordable detection. Thereafter, specifications for a practical IoT solution are provided. Lastly, for one of the most critical aspects, a machine learning algorithm for sound based detection of pollinating insects, is constructed and tested.**

Keywords—Acoustic sensors, machine learning, pollination, flying insect detection, Internet of things

I. Introduction

The mortality of bees and other pollinators has become a real problem, especially in the last ten years [1], [2]. Bees, bumblebees, wild bees and all sorts of pollinator species are incredibly valuable to humankind. Research indicates a value of pollination between 153 and 167 billion dollars in the world, depending on the estimation method and valued parameters [3]. A vast amount of research has been conducted about why these pollinators are in distress: factors such as neonicotinoid pesticides [4] and varroa destructor [5] for honeybees and nosema bombi for bumblebees [6] come to mind. Some partial solutions, like educating beekeepers [7] are already implemented, but an absolute solution is yet to be unraveled. Artificial alternative solutions for pollination, like robotic bees, might not be viable or sub-optimal [8]. Evidently it becomes increasingly necessary to learn more about the behavior of our natural pollinators in order to anticipate and optimize the pollination process. The sparse pollinating insects that we have left, require maximal utilization. Data about flying patterns of bees, intensity of bee concentration and frequency of bee activities are all important factors and inputs in optimizing pollination by insects.

In other words, an affordable method for bee detection and identification could introduce us to new data on our pollinators and the pollination process. Some methods for analyzing the behavior of bees already exist, and will be discussed in the next chapter. After this, a new and improved IoT method will be presented.

IoT is expected to optimize food production by many means. Distributed, pervasive computing and precise monitoring of the facilities are expected to provide the optimal growing or living conditions for both vegetables and animals. However, before massively implementing smart sensor systems into agriculture, vital issues like security, anonymity and control over the access rights still need to be addressed [9]. According to P. Ray [10] smart products in agriculture need to be low cost, autonomous, energy efficient, interoperable, standardized, heterogeneous and robust. He indicates that features like artificial intelligence, machine learning and decision support systems are highly in demand in the agricultural industry. Gubbi et al [11] categorize the domain of 'smart agriculture' as a medium/large application, that will benefit from harvesting energy autonomously, from using Wi-Fi and satellite communication and from wireless sensor networks.

II. Flying insect detection and recognition

The most frequently used way of monitoring bees is looking at the beehive itself. A popular method is video monitoring the front of the beehive [12]. A. Tiwari, for example, did this recently for the prevention of colony collapse disorder, using neural networks and deep learning [13]. Beehive assessment is also often performed with acoustic sensors [14], [15]. Methods of beehive monitoring are already very established among beekeepers, for their usable and affordable nature. However, these methods don't provide a solution for mapping bee activity outside of the beehive.

A complementary way of monitoring bee activity is by sticking RFID tags onto bees or bumblebees [16], [17]. This method is very efficient for tracking a specific group of bees

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throughout their day, but if you want to track 'pollination data' in a certain field for example, you need location-based data of the whole population instead of insect based, reduced to a sample. The latter method is thus very limiting, because tagging all bees of one beehive costs a certain amount of money and effort.

A third method of monitoring flying insects is found in the way mosquitoes are detected. Mosquito detection has gained popularity due to the quest for malaria prevention. This has been done with laser sensors that progress wing-beat frequency [18] and with acoustic sensors [19]. The method for mosquito detection is rather interesting in comparison to the aforementioned insect detection methods, mainly because it is really initiated by the requirement for local detection instead of individual tracking. In other words, in detecting mosquitoes you don't need to know the location of one mosquito but you need to know if there are any mosquitoes in a certain area. This need for location-based detection is why acoustics are so interesting for the detection of mosquitoes [20]. On top of that, sensors based on acoustics require little energy, they are cheap, they are robust and their univariate signals are relatively easy to process with a machine learning algorithm.

For the past three years, researcher have started to get more and more interested in the possibility of acoustic detection of pollinators in the field [21]. Among some, there has even been discussion about using acoustics based (bumble)bee detection system for assisting scientists and farmers in rapidly detecting and responding to bee population declines [21], [22]. The fact that this method of localized acoustic sensor deployment is relatively cheap and robust, makes it really attractive for performing new research.

A few researchers have even developed their own approach on acoustically detection bees with or without machine learning algorithms ([23] respectively [21], [22]), but no research has been conducted about the practical boundaries for implementing such a system. In this paper, a new practical acoustic detection system is presented and tested. The advantages and disadvantages of this system are evaluated and discussed.

III. A PRACTICAL SOLUTION

A proposition for a product-service system that enables fruit growers to quantify, map and optimize their pollination was presented. This concept will be called 'Optibi' from here on. One might say that Optibi brings Internet of Things to agricultural fruit growing. It consists of a sensor, that captures the sound of insects and identifies them by means of a machine learning algorithm, a robust battery module, which provides the long-term autonomy of the sensor, and an app that makes the generated data interpretable for the fruit growers. The product is suitable for both tree cultivation and soil cultivation.

As seen in figure 1, the product consists of a bottom part and a top part. The bottom part, or the battery module consists of a huge battery, a solar panel, a retracting cable reel and a robust outer shell for outdoor use. This part is solely responsible for providing power to the top part, or the sensor module. The sensor module consists of a USB-microphone and a single board computer.

This design concept has been optimized completely for the needs of fruit growers. The battery alone is able to provide the sensor-module with power for about three weeks and is rechargeable by solar power as well as by mains current. Because of the retractable sensor module, the product can be used in tree cultivation as well as soil cultivation.

Fig. 1. Rendering of the product as a whole

When deployed, the sensor module will detect and record the sound fragments deemed 'interesting', by a small microprocessor that does the calculations in low-power mode. These fragments will then be sent to the cloud on a Long Term Evolution (LTE) mobile data network. This transfer happens in bursts to minimize battery drainage. On an external server, a machine learning algorithm identifies the flying insect through sound recordings (figure 2). The LTE wireless technology, as opposed to Wi-Fi, LoRa and other wireless technologies, was chosen because of its range, its local availability (in Belgium, where the research was conducted) and its ability to transfer sound data. However, an equivalent alternative can probably be found.

By spreading these sensors on a field and tracking the location of each sensor, it becomes possible to capture and map the insects on the whole field that can induce pollination. This information can then be used to the advantage of fruit growers [9], [10].

Optibi makes use of the fact that fruit growers are very independent people who know their field through and through. The app (figure 3) is designed to provide users with the right information and feedback to take well-founded measures and to optimize the pollination situation on their field. For this the growers get a mapped view of the pollination factors on their field, daily advice on the basis of their personal data profile and a representation of the raw data to interpret themselves.

The main advantage of this system, compared to the state-of-the-art, is the fact that it is able to record data in the field. Fruit growers do not care about bee or bumblebee activity at the hives, they want to know if they are actually pollinating their field and how well they are doing that. The system also facilitates expansion, and induces new research, in particular on the correlation between local bee activity and degree of pollination. In the very least it provides a helpful tool to efficiently build a database of in-flight insect sound, to use for optimizing new and already existing support vector machines (SVM's).

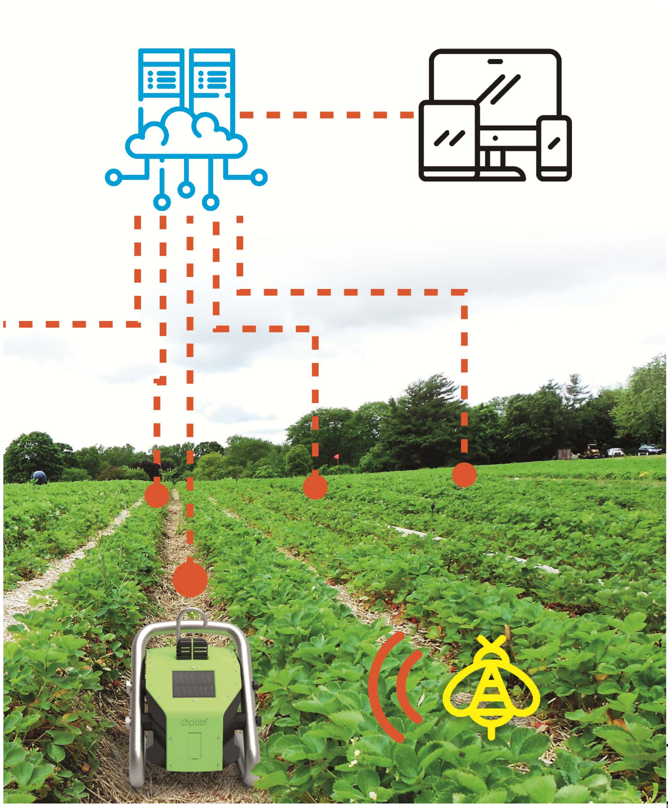

Fig. 2. The sensors are spreaded on a field. They will detect and record the sound fragments deemed 'interesting' by an analogue detection filter. These fragments will then be sent to the cloud, where the machine learning algorithm can process them. The results are displayed on an app.

IV. Insect-Species Algorithm

Very recently, acoustic and/or optical based classifiers have been developed[12], [21]–[23]. They were validated in training sets, not aiming for specific research applications. Here, the envisioned task was to detect bees and bumblebees. To that end, an algorithm with sound recordings as input was developed (Matlab, internally available) and validated.

As a first step in the species recognition algorithm we applied the goertzel algorithm [24] to extract the spectral content of the sounds generated by the fluttering wings of the insect. To classify these spectra, we used a multi-class ECOC model with SVM binary learners as building blocks. We used radial basis function SVMs with optimized kernel parameters, which were learned during the supervised training phase.

For testing the algorithm, a training database of bee sound, bumblebee sound and background noise was gathered by simply recording bees and bumblebees while in flight with a microphone. We did this by looking for highly populated areas for bees and bumblebees, excluding hives because they make other noise. We taped a small webcam for cross validation to a microphone and used OBS Studio's replay-function, which allowed us to quickly separate the sound fragments when we knew a bee has been recorded. Adding video made it easier to manually subtract all fragments wherein bees were audible and visible. The amount of different sound fragments for each of the classes are shown in table 1.

TABLE I. Sound Fragments Used in Testing

Sound	**The amount of different sound fragments for each class**	
	Quantity	***Total duration of all sound fragments together in seconds***
Wild bees	120	111s
Bombus Terrestris	116	231s
Background noise	24	1440s

Tbl. 1. Sound fragments used in testing

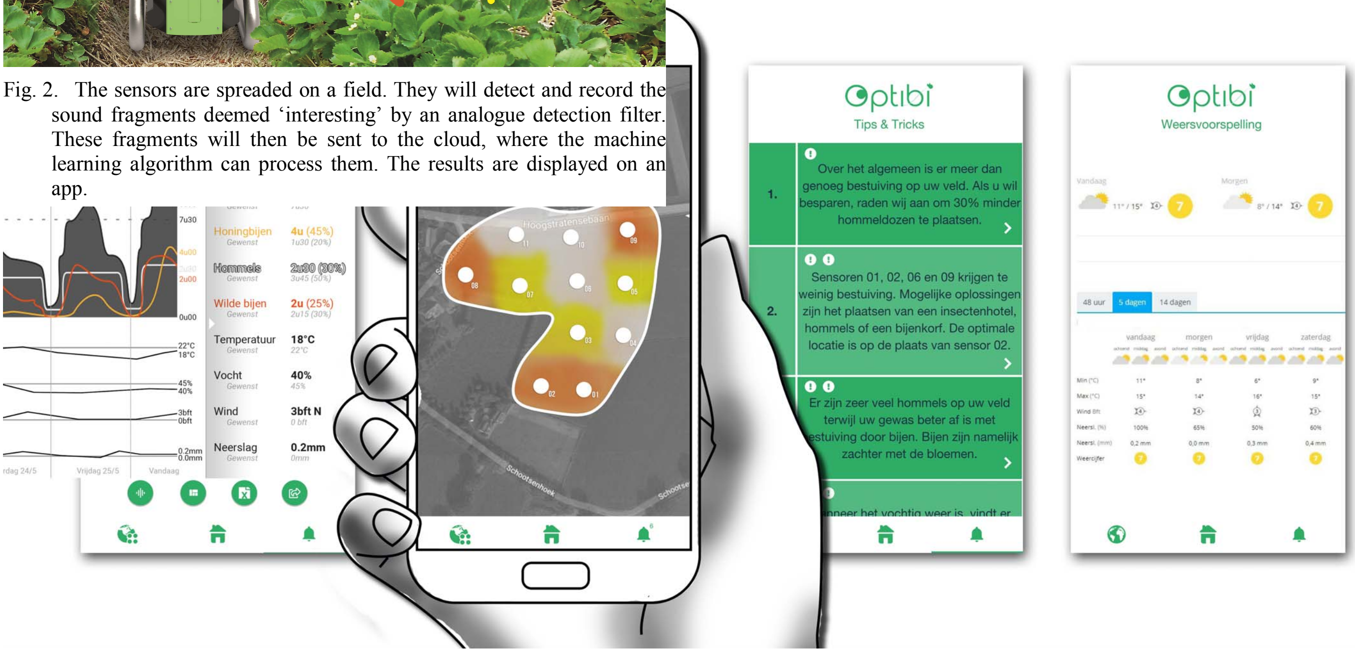

Fig. 3. The app is designed to provide users with the right information and feedback to take well-founded measures and to optimize the pollination situation on their field. For this the growers get a mapped view of the pollination on their field, daily advice on the basis of their personal data profile and a representation of the raw data to interpret themselves.

V. RESULTS

With these sound fragments, an SVM performance test was performed, using half of the fragments as training data for the SVM and the other half as a test group. These results indicated a success-rate of around 0.9.

TABLE II. CONFUSION MATRIX

Classes	Predicted classes		
	Bees	*Noise*	*Bumblebees*
Bees	**0.90**	0.02	0.08
Noise	0.12	**0.84**	0.04
Bumble bees	0.05	0.03	**0.92**

Tbl. 2. Succes rate percentages of classification

VI. CONCLUSION AND FUTURE WORK

The relevance of new IoT applications in the world of pollination and agriculture was supported by the state of the art on bee mortality, pollinator detection and agricultural IoT. Our own practical solution was explained and an algorithm on bee and bumblebee detection was built as a technological proof of concept. After testing it, we know this algorithm had a success-rate of around 0.9.

There are two unsolved issues with the system, but both of them can be resolved by creating the sensors and using them as a tool for research. Firstly, it is not sure from how far the sensor/microphone will be able to record the sound of a flying insect. This will probably depend on the kind of microphone that is used. Secondly, it is not sure how many sensors per square meter are needed to be able to compose a complete picture of the whole field. This will depend on the level of variation of data over distance, in geography known as kriging [25]. The problem is that the right tool to determine this two-dimensional pollination distribution does not exist yet. In fact, the Optibi system itself would be the best tool for this task.

What was proposed is basically a smart product-sensor-system that can detect and map any insect in flight inside a certain area based on their sound, provided the availability of a pre-recorded database of said sound. In other words, in this work only a pre-recorded database for bees and bumblebees was gathered, but our hypothesis is that this method can be used for detecting other insects as well. Aside from pollination in fruit field, the Optibi concept has a tremendous amount of potential for other applications comprising: detecting illnesses in wild bee colonies [26], detection of the invasive species like the Asian hornet [27], mosquito detection [20], the detection of fruit flies and other pests, the mapping of bee activity in urban areas, biological research, et cetera.

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