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IndusBee 4.0 – Integrated Intelligent Sensory Systems for Advanced Bee Hive Instrumentation and Hive Keepers' Assistance Systems

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Abstract: The importance of insects, and honey bees in particular, for our ecosystem is undisputed. Currently, environmental problems from pesticides to parasites endanger the well-being or even the existence of honey bee colonies and insects in general. This imposes an increasing load on skills and activities of hive keepers. Sensors, instrumentation, and machine learning offer solutions on the one hand to effectively instrument bee hives and on the other hand to provide efficient assistance systems for hive keepers. By advanced hive instrumentation and intelligent evaluation of the acquired information hives can be monitored more easily and with less intrusion. Like in other industrial disciplines, e.g., Industry 4.0, operation can move from scheduled to event driven activity. The development in Micro-Electrical-Mechanical-Systems and Internet-of-Things field in general allows to achieve affordable integrated monitoring solutions. However, not in all tasks a dedicated instrumentation of each hive is required, and mobile assistance systems and devices to be employed in a single instance for the whole apiary will complement the instrumentation activity and the overall approach of our IndusBee 4.0 research project. Examples of this category are, e.g., honey quality assessment tool as an extension of established hygrometers or a system for improved automation of the tedious and time consuming screening for the varroa infestation of hives. This paper provides a review of activities in the field and presents the current status of contributions to both lines of research in our IndusBee 4.0 research project. With regard to hive instrumentation, in addition to standard temperature, moisture, and weight monitoring, an approach of acoustical in-hive monitoring with automated decision making and notification implemented in-hive in a SmartComb has been pursued. Further, integrated gas sensors are currently added to the SmartComb to explore the in-hive detection of infestation and illness, e.g., (American) foulbrood. Visual flight hole inspection is successively explored by a separate system in or at the hive. With regard to hive keepers' assistance systems, an approach automating the screening for the varroa infestation of hives was tackled first. Here, a cost-effective two step procedure, a first attention step for detecting candidate regions and a final classification step of these candidate regions, is applied. It is aspired to extend the approach to continuous in-hive varroa infestation monitoring. The integration of all information from hive instrumentation and assistance systems with data fusion and data analysis activities in apiary intelligence unit is aspired in the next step.

Keywords: Multi-modal bee health monitoring, Automated varroa screening, Machine vision, Machine learning, MEMS microphones, Industry 4.0, Apiary intelligence.

1. Introduction

The systemic relevance of insects, wild bees, and honey bees in particular, is a well-known fact and found its place in public awareness. Numerous threats from pesticides to parasites, *varroa destructor* in the case of honey bees, threaten these essential contributors to our ecosystem. One consequence is the need for manual pollination, as already exercised in Asia, or the intentions to automate the natural pollination service by bee-like drones. A most recent patent activity to be observed was by Walmart [24]. Activities like the 'More than Honey' documentary of M. Imhoof et al. or the book of Tautz [5] made the role and critical situation of bees and the implications for human life lucid to the public.

Due to these increasing challenges, hive keeping gets increasingly difficult and requires more and more skills and attention from the hive keepers. Traditionally, hive tending works on a scheduled and *post mortem* basis with numerous opening and inspection of the hives, which is invasive, disturbing for the bees and weakening their capabilities to resist the above named increasing challenges. The development in sensor & actuator integration technology, MEMS [7], in particular, Machine Learning, and general automation, e.g., Industry 4.0, which also makes bee drones like [24] possible, allows to introduce capable yet affordable hive instrumentation solutions to closely monitor and manage an increasing number of hives and conduct less invasive event-driven tending of bees with minimized openings at the right time. "Digital" bee keeping moves from scheduled and *post mortem* to predictive and event-driven operation, thus reducing effort, cost, and risk. Major bee research institutions, e.g., in Germany Hohenheim, Veitshöcheim, etc. [28-30] have dealt with related issues and goals employing in numerous cases rather costly and lab-size equipment. The ongoing vivid advance in sensor, actuator, electronics, and RF integration technology [7] provides an unprecedented leverage for well performing, yet cheap and disappearing application systems that seem to make Berkeley's Smart-Dust vision getting reality. Relevant examples are IR cameras, which become now available both miniaturized and at dramatically reduced cost, e.g., as an extension to Apple I-Phone or the FLIR Lepton One [7]. MEMS microphones are another perfect example of this development [7]. The surging development of Technical Cognition Systems, comprised of integrated sensors, electronics, RF, energy harvesting, and Machine Learning/AI, offers a leverage and an answer for many issues met in bee keeping. Two major lines of activities can be observed, i.e., *Bee Hive Monitoring* by sensors, embedded systems and custom software, and *Hive Keeper Assistance Systems* by discrete appliances for a group of hives in an apiary. Examples of this line of activity are, e.g., honey quality assessment tool as an extension of established hygrometers or a system for improved automation of the tedious and time consuming screening for the varroa infestation level of hives. One emerging approach for semi-automated varroa screening [25] will be discussed in this paper.

First, we will focus on the *Bee Hive Monitoring* with special attention to both affordable and disappearing instrumentation. As in all technical disciplines, the potential market size will determine the feasible technology for the application domain. For instance in [14] bee keeping statistics for the EU are provided, naming 14 million hives in the EU. As professional hive keepers typically have about 100 to 500 hives, price sensitive yet suitable and reliable solutions are required. Market size and cost limitation clearly advocate the use of off-the-shelf components, following up technology driving application fields, e.g., automotive, communications (smart phones), and automation/ Industry 4.0.

Numerous activities can be found in the last ten to fifteen years of teams of hive keepers and engineers, complementing the activities of major bee research institutes by practical instrumentation work in the field, e.g., [4]. This vivid spin-off and maker scene mostly focused on hive weighing by scales, temperature and moisture measurement, as well as weather station, tilt, and GPS sensing, employing affordable platforms, like Arduino or Raspberry Pi, in particular the Zero, along with affordable sensors, e.g., load cells for scale assembly for hive weight, e.g., [1,3, 8-13, 15], or feeder level monitoring. With regard to commercialization numerous bee patents have been filed, e.g., [17-21]. Actuation driven ideas are added here, e.g., for sustaining small colonies or thermal varroa treatment by suitable heaters and application procedures [20, 21].

More recently, acoustical [2, 17, 19] and visual inspection of hives, e.g., for activity/flight hole monitoring [11, 12], are beginning to be added to the instrumentation palette and the resulting data is going to be processed by appropriate methods from machine vision and machine learning [22, 23]. However, in these still few and quire recent approaches, predominantly large scale and rather costly microphone devices are used and camera systems still find restrictions in use to the limited computational power of the affordable computing platforms.

Inspired by intelligent condition monitoring (ICM) and Self-X capabilities added to automation and production systems in IIoT or Industry 4.0 field, the IndusBee 4.0 research activity has been started at ISE [32] both with *Bee Hive Monitoring* and *Hive Keeper Assistance Systems* in mind. The goal is to achieve miniaturized or integrated, affordable yet reliable sensor systems adapted to the task of bee hive monitoring and hand-held devices for apiary use and process their overall data by proven to advanced machine learning methods. In the Sections 2-4 of this paper, the initial version and application of a hive integrated acoustical monitoring system with MEMS microphones and accompanying sensors for temperature, moisture, and weight monitoring will be presented.

Due to the threat of the honey bee by the *varroa destructor* parasite, hives need regular screenings or varroa counting to estimate the degree infestation by the mite and initiate appropriate treatment procedures according to the screening outcome. Though the majority of hive keepers still relies on chemical treatment, e.g. formic acid application, numerous alternatives, e.g., acoustical treatment [54, 55] by ultrasound emissions, physical treatment by a laser based on visual analysis of bees at the flight hole [53], also found in salmon farming [52], thermal treatment [21], and, last not least, numerous activities on treatment free beekeeping, e.g., in [56-59], that in the light of expected resistance of mites to chemical treatment, rely on Darwinism in breeding robust bee populations.

Even in this latter case knowledge on infestation level of a colony would still be welcome, only the taken action would be different from conventional beekeeping.

A common form of the screening process involves the visual analysis of the hive debris and to detect and count the number of mites on a slider unit, as illustrated in Fig. 1 and estimate the might infestation level by heuristic calculation from the obtained count. This task also predominantly is delivered by manual work of the hive keepers several times in the year for every hive, which adds to the anyway increasing workload due to rising issues from pesticides to parasites and illnesses. The support or even automation of this tedious procedure seems to be natural and is regarded here as an instance of discrete assistance systems development for hive keepers [45], applicable to all hives of an apiary. There is an interesting relation to the general field of insect counting, where screening procedures, and related capture or tracking methods on insects [44], are used in various forms, e.g., to reckon insect populations and give timely information for pest population surges. Predominant manual evaluation is quite tedious, time consuming, and often contradicts the need for a swift response, e.g., the just in time deployment of a chemical agent in proportion to pest occurrence.

Insect counting can base on visual count, sweep nets application or various forms of traps, e.g., pheromones, light, sticky layer, liquids, or bait deployment [35, 40, 44]. Numerous of these procedures are destructive in the sense, that counted insects are killed.

In the case of bee keeping, varroa screening or counting can also base on such a destructive approach, also denoted as *flotation method*, where an amount or sample of bees is extracted from the hive, effectively drowned and the varroa releasing from their bodies is counted. There is a non-destructive version of the flotation method that covers the extracted bees with powder sugar, which also makes the varroa drop from the bees for counting without losing and just irritating the bees).

In general insect counting, further, collateral damage occurs, i.e., in pest control counting applications, also harmless and useful insects are trapped and killed, which is both bad under environmental considerations as well as making the manual or automated recognition and evaluation procedures more hard. Naturally, the field of machine vision and machine intelligence offer a plethora of similar problems to insect counting and also numerous proven methods immediately or after modification applicable for automated screening solution [33, 34, 36-39, 41, 43].

Fig. 1. Hive with debris on sliders for varroa screening.

In numerous activities, that can already deal with amazing number of different species and sizes of insects, e.g., [37], assumptions on background and density and spacing of insects to count are made [37, 41]. Often, real data confronts with strongly varying density of insects, i.e., closely packed or even stapled on top of each other, which gives rise to hard occlusion problems. Further, natural variations in phenotypes, e.g., size and patterning, changes in appearance from alive to pass away and decaying entity, orientation as well as dissected limbs etc. make automated recognition not too easy task.

With regard to potentially adding varroa screening to hive monitoring, automation of the tedious debris analysis based visual screening or counting procedure, inspired by related work in the fields of automated industrial quality control and Industry 4.0, a machine vision and learning approach is pursued in the IndusBee 4.0 research activity, which has been scarcely visited so far [50]. However, other most interesting complementing and/or alternative approaches for the same task can be found, e.g., based on visual flight hole monitoring, e.g., [53], acoustical analyses [63], similar to the activity presented in Sections 2 to 4 of this paper, or gas sensing, e.g., [51].

The overall goal of this line of activity is to achieve a simple, as possible affordable yet reliable hive keepers' assistance system from standard components for varroa screening in bee hives under cost constraints with a sufficient screening coverage for event-driven, right, and effective, treatment decisions and also for improving the house keeping by archiving the images of hive debris together with the evaluation or counting results and providing them for higher level data analysis, also fusing with other sensory information from hive instrumentation, to an Apiary AI [45].

In Section 7-9 of this paper, the first step and results of the emerging hive keepers' assistance system for automated vision-based varroa screening will be presented. Besides technical improvement, the long term objective is the achieving and adding of hive-integrated continuously running multi-sensor varroa infestation level estimation to advanced hive instrumentation. In current work, both vision-based, acoustical [63], as well as VOC integrated gas sensor-based approaches for varroa infestation level estimation and other illness detection, similar to the remarkable recent approach in [51], which is based on discrete hive-external set-up, are under investigation.

2. SmartComb for In-Hive Monitoring

For the continued and unobtrusive measurements in a bee colony, a system based on the Raspberry Pi Zero W (OS Jessie), as in numerous other approaches, e.g., [62], has been set-up in the particular shape of an instrumented honey comb, denoted as SmartComb. The basic version incorporates two temperature and moisture sensors (DHT22/11) at top and bottom to provide readings at different hive locations. Further it includes HX711 board for hive scale reading. The key feature for this paper is the included I2S MEMS SPH0645LM4H microphone, chosen for low-cost reasons. Additionally, prototypes of high performance Infineon MEMS microphones have been made available for this work, but PDM interface requires additional electronics effort and cost, so that cheap I2S MEMS have been used in first place. Fig. 2 shows the partially assembled SmartComb prototype.

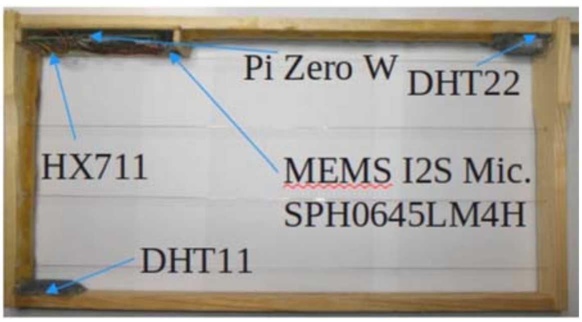

Fig. 2. SmartComb (Zander scale) prototype with acoustical, weight, temperature and moisture sensing.

After completion, the depicted measurement system was inserted in the colony center of one super and was supplied either from accu or, temporarily, from wired 5 V supply, which limits wiring to just two wire cable from measurement unit to hive exterior. As it is well known, that bee and their by products provide a harsh environment, special care on protective packaging of sensors, cables, and embedded system have been expended, e.g., by wrapping sensors in special mesh (s. Fig. 2).

The mechanical structure of numerous MEMS sensors can be open to dirt, e.g., wax, propolis, or other hive debris. The MEMS microphone has been mounted in a way avoiding any direct path for contaminating particles, while still being sensitive to in hive sounds, and hopefully, also to vibrations on the comb it is integrated in. The SmartComb of Fig. 2 provides a hive *fingerprint* of two separately located temperature and moisture reading, hive weight reading, and acoustic monitoring data. Additionally, it can be of interest to have separate weight data for each super, e.g., the honey storage super, which in late summer is predominantly used for hosting the feeder module. So, also feeder module weight, proportional to filling level, can be acquired and employed for *event-driven* refilling. Fig. 3 shows a first prototype of a hive integrated scale for the honey storage/feeder module.

Fig. 3. Separate local scale prototype for honey storage super and feeder module weight monitoring.

The whole setup materials cost of a SmartComb is less than $ 30 for 'lot size' one, excluding the scale(s) setup. The following experiments have been done with such a SmartComb prototype. Adding gas sensors or cameras will of course increase possibilities and the cost.

3. Acoustical Hive State Monitoring

The acoustical monitoring of the hive state can follow the same way and principles as in predictive maintenance and Industry 4.0 based on vibration and sound monitoring, e.g., for wear-out detection and failure time prediction, e.g., [2, 6].

Interesting states of the bee hive are enumerated in the following, possibly not exhaustive, list:

1. Ok/Calm or Normal State;
2. Agitated/Disturbed;
3. Knocking/Pecking at hive;
4. Scratching at hive;
5. Swarm mood;
6. Missing Queen;
7. Looting ….

The colony states 1-6 are mentioned also in [2, 22, 23, 63, 64] and much more relevant information, e.g., a reckoning on varroa infestation level, can potentially be taken from bee generated sounds [17, 19, 63]. Of course, dead silence in case of a perished colony hast to be taken care of in evaluation, too.

From the point of acoustical signal processing and machine learning, two general ways can be pursued after obtaining the raw data from the microphone(s) [6]. On the one hand, the classical approach based on *a priori* knowledge of domain-specific discriminant and invariant features followed by systematic dimension-ality reduction and classifier choice and training. This approach is both transparent and amenable to analysis and understanding (*white box*) and will work from small to large amount of labeled data at moderate computational cost. On the other hand, there is the currently very popular field of deep-learning neural networks, that are renowned for learning from scratch and to perform better than classical approaches, yet are not easily amenable to analysis (black *box*), need rich amount of labeled data, and potentially have significant computational requirements in use [6, 22, 23]. It seems worth mentioning, that there is a possible hybrid design approach pursued by ISE that merges the classical knowledge-based approach with learning or fine-tuning of system levels to rapidly achieve a transparent and well performing solution of moderate complexity [25, 26].

Thus, for the processing of the underlying sounds for reasons of transparency and hardware limitations, the classical approach was chosen with first-cut design parameters of, e.g., ROI (700 ms), 16k samples/s, and feature extraction (MFCC from python_speech_features), optional dimensionality reduction, and classification (kNN from python sklearn with k=3) . The number of classes was selected to four with 1-4 of the previous list of possibly hive states.

The SmartComb prototype was equipped with a foundation for comb completion by bees and inserted into a bee colony, freshly established in spring 2019 (s. Fig. 4).

In addition to the possible discernment of various interesting hive states, as enumerated in the previous list, for reasons of data storage and complexity management, a hierarchical approach seems to be favorable and was pursued in the work here. It relates to a common issue known well from, e.g., Industrial Quality Control and Intelligent-Condition-Monitoring (ICM) etc.: It is fairly easy to describe the 'Good' or 'Ok' state and lots of examples are commonly available, but it is extremely hard to *a priori* know all possible deviations from 'Ok' and acquisition of sufficient examples might be hard or even infeasible. This also relates to processing and storage requirements in data acquisition both system design as well as later on-line classification and advocates the use of one-class-classification (OCC) or anomaly or novelty detection in a hierarchical approach. These techniques are widely in use now from network intrusion problems to Industry 4.0 related ICM. The idea will be picked up in the following experimental section along with standard multi-class approach.

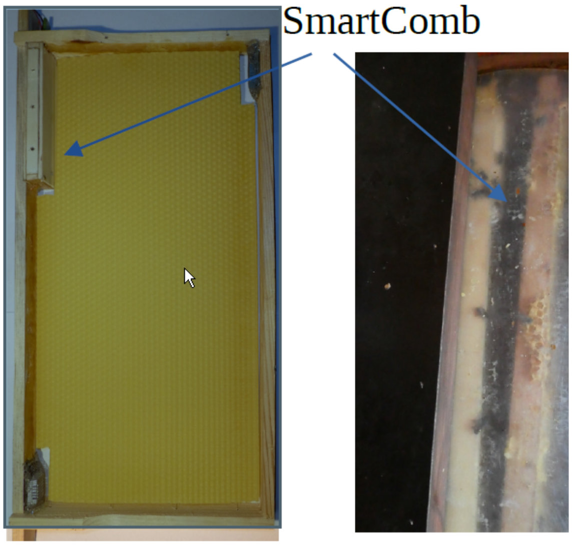

Fig. 4. SmartComb prepared for bee honey comb finishing (left) and inserted in a freshly established colony (right).

4. In-Hive Instrumentation Experiments and Results

The SmartComb of Fig. 4 was inserted in a living bee population and the hive was stimulated to provoke data of classes 1-4 given in the enumeration of Section 3 while continuously recording with the in-hive MEMS microphone. The obtained recordings were manually windowed, extracted, and labeled according to the meaning of the enclosed acoustical data in each window. Fig. 5 shows a feature space plot based on Sammon's dimensionality reducing mapping of the 13-dimensional MFCC data for the four classes with 25, 20 18, and 14 samples for class 1 to 4, respectively, obtained after data preparation and labeling process.

Dimensionality reduction, e.g., by automated feature selection has been investigated by standard Sequential-Backward-Selection (SBS) with the qsi separability measure [27], but in this particular case, the potential gain for the selected best features *2, 4, 5, 9, and 10* was negligible, so the 13-dimensional data set was used in the following multi-class classification. Training the chosen kNN-classifier with all data and a k=3 setting returned a resubstitution result of ~97 % ('OK' always 100 %) Following, a hold-out approach was employed where, the data was split up in 53 (15, 15, 12, 11) train and 28 (10, 5, 7, 6) test patterns, where 4 patterns of class 4 were present both in training and testing. Resubstitution gave ~98 % and generalization ~92.86 %.

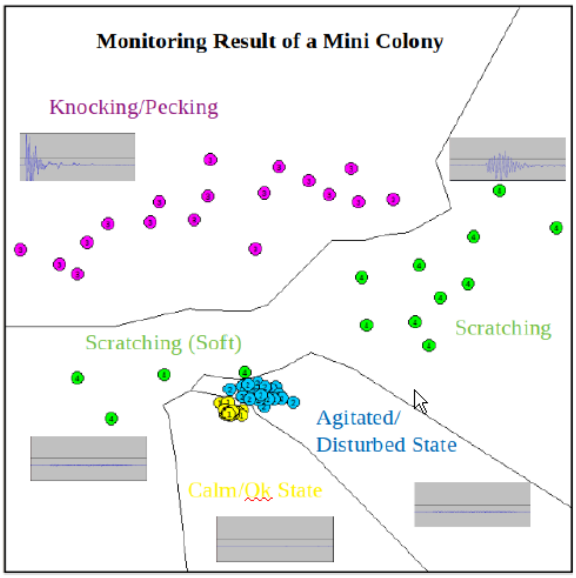

Fig. 5. MFCC **f**eature space plot for MEMS microphone based acoustical hive monitoring data.

For a sound statistical analysis the acquired and labeled data is still very small, but already shows the aptness of the chosen low-cost MEMS microphone, electronics, and assembly in the introduced SmartComb. In a following live test, the trained classifier was activated in the hive and the bee colony in the hive was monitored in response to status and external stimulation/excitation. The data and the classifier decisions were concurrently recorded and evaluated in the following. Fig. 6 shows an excerpt of the 475 conducted live classifications.

Fig. 6. Live classifications along with acoustical data recorded by MEMS microphone on SmartComb.

The chosen simple approach already worked well in the live test with repeated hive stimulations. Class 1 for 'Ok' state was always correctly discerned from all other sounds, but occasional confusion between class 2 and 4 could be observed, which was to be expected from the lower left of the feature space given in Fig. 5. The common fingerprint of the hive monitoring could now be extended by hive activity state classification as indicated in Fig. 7 for a subset of activated sensors.

The data in Fig. 7 naturally can be graphically displayed and tools and services, e.g., *Thingspeak* [31], are available and frequently employed.

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Tue Jul 16 12:56:22 2019 0.0Deg 28.0Deg 0.0% 61.0% -1.0g 0.0g [1]
Tue Jul 16 12:56:23 2019 0.0Deg 28.0Deg 0.0% 61.0% -1.0g 0.0g [1]
Tue Jul 16 12:56:25 2019 0.0Deg 28.0Deg 0.0% 61.0% -1.0g 0.0g [2]
Tue Jul 16 12:56:32 2019 0.0Deg 27.0Deg 0.0% 59.0% -1.0g 0.0g [2]
Tue Jul 16 12:56:33 2019 0.0Deg 27.0Deg 0.0% 59.0% -1.0g 0.0g [1]
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Fig. 7. Fingerprint of hive monitoring by SmartComb (First temperature/moisture sensor and global and local scales not in use here) complemented by live acoustical activity state classification**.**

Sustained departure from the 'Ok' state can be employed to send alerts to the hive keeper and, thus, initiate *event-driven maintenance*. Further, the current 'watch-dog' classifier can also be employed to limit the potentially massive amount of recording data [22] and the following post processing effort for training and classifier refinement, by only recording raw data of not 'Ok' state readings. Fig. 8 tries to elucidate the idea using the data with modified labeling, assuming all not 'Ok' data as being novel or abnormal without trying to distinguish the cause or related class on that level. That corresponds in ICM to perceiving a deviation from the desired state of operation without bothering with the detailed classification of the type of emerging problem yet. This basically allows the training of such a simple 'watch-dog' or OCC classifier just by the presentation of 'Ok' patterns, where a rich amount of examples is commonly available. This can be achieved by various methods and implementations, e.g., by a kNN classifier with a radius limitation, which is also available in the sklearn package.

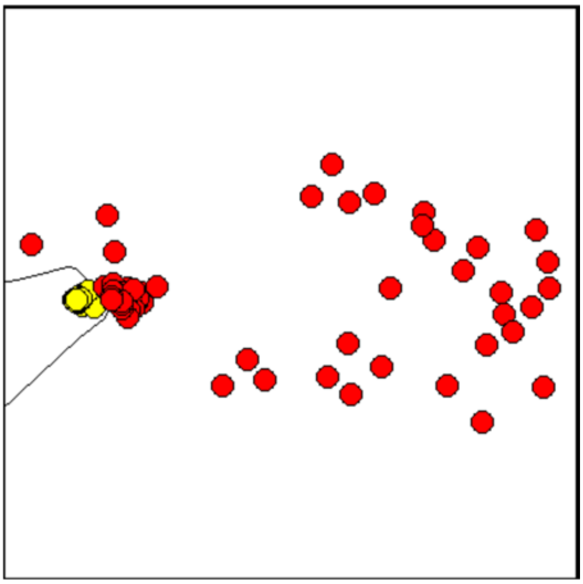

Fig. 8. Feature space plot similar to Fig. 5 with just 'Ok' class on a background of not 'Ok' or abnormal readings.

The radius limitation in kNN classification can be set manually as in rejection threshold definition or automatically computed from the available OCC training data. New sensory readings exceeding the set similarity threshold will be rejected, i.e., interpreted as novel or abnormal. This approach can also be used to selectively increase the training sample database, by recording only patterns judged as deviating from normal and interactively label that reduced set by human expert.

After this bifurcation, abnormal data might be subject to more detailed determination based on potentially scarce not ‘OK’ examples and a multi-class approach.

Fig. 9. SmartComb temporarily extracted from hive after several months of insertion in the bee colony.

The value of the regarded approach with integrated and low-cost devices also depends on long term stability. The deployed SmartComb has been in use in the hive for several month by now and has been completed by the bees even as part of the brood nest (s. Fig. 9). The microphone is still working fine, but the classification accuracy for new live tests is degrading. Fig. 10 shows the growing colony, which changes the acoustical properties of the hive and even in actually calm state it is generating a stronger signal, which leads to occasional confusion with the agitated/disturbed state of the previous colony size. Further considerations on microphone(s) placement, external sounds, colony size and evolution etc. have to be included in the design activities for a long term stable and invariant hive state determination. Microphones of neighboring hives could be exploited to reduce the influence of externals sounds. Further, the issue of exporting a developed hive state classifying system solution from one hive to one or several other hives has to be regarded similar to the issues and approach in [26].

5. Flight Hole Monitoring

Another source of valuable information on hive condition and health state can be gained by monitoring the activity at the hive’s flight hole, as depicted in Fig. 11 (left). The activities in this direction rank among the oldest applying electronic measurement equipment, e.g., photo detectors and electronics, to honey bee hive monitoring back to 1960ties [66].

Fig. 10. SmartComb in the bee hive with growing colony.

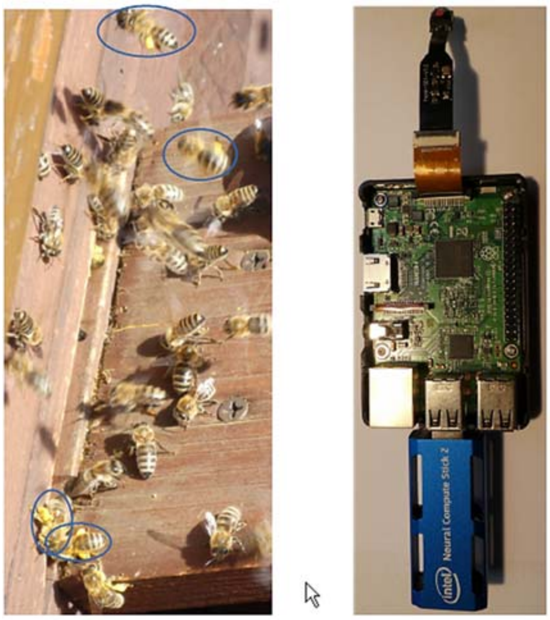

Fig. 11 Idea of embedded flight hole monitoring with Intel NCS-2 stick as one potential accelerator (Mock-up).

In [66] a bidirectional channel, based on infrared emitter and two detector has been conceived and applied with 32 such channels in parallel to count coming and going bees. This device was denoted as BeeSCAN counter and served to monitor bee activity. It should be mentioned here, that hive weight measured by integrated scales provides a correlating information to the balance of in and out going bees.

A different sensing approach was pursued in [61], where a similar flight hole discretization by tube-like channels equipped with capacitive sensing was introduced for the same purpose. Both approaches seem to be limited to the counting of the bees and obtrusively discretize the flight hole. Further, it must be assured by channel size that drones and queens can also pass without issues.

Thus, and with the objective to obtain more information, several approaches set out to use camera systems of various complexity to unobtrusively count, but also track bees, and analyze their behavior, e.g., [10, 12, 13, 53, 60, 62, 65, 67]. More information could be gained by detecting the payload of the bees, e.g., the amount of pollen entering the hive, and potential extrapolation on breeding activity, as suggested in Fig. 11 (left). Other goals are also related to pest control and infestation level estimation by observing and counting abnormal bee behavior, deformed wings or other abnormalities, and, in particular, the identification and counting of varroa mites entering the hive clinging to bees [53]. The approach of [53] combines the approach with laser-based varroa annihilation. In [67] depth perception is added, e.g., by stereo cameras or time-of-flight sensors. In any case, the three-dimensional nature of the problem, i.e., bees coming in and entering also bottom-up and varroa mites clinging on top, bottom, and sides of the bees, will make an exact counting a challenging task, and the number of overall varroa infestation on the hive leaving bees in ratio to those present in the brood will vary strongly with the hive life cycle over the year.

Nevertheless, the number of bees going out, the daily losses, and the information of pollen intake will, together with weight information from the scale(s), give valuable information on the bee hive health condition. Further, a continuous observation could also identify the hive entering efforts of other parasites and threats from wax moths, e.g., galleria mellonella, to wasps, and the bees reaction to these as further indicators of hive fitness.

All visual flight hole monitoring activities are challenging due to large amount of data from the vision sensors, significant invariance issues, and high complexity of identification and tracking task. It might be asking too much from platforms like Raspberry Pi, but adding an efficient accelerator is one alternative to moving to more bulky and expensive computing platforms. In Fig. 11 (right), one possible option is outlined, employing an Intel Neural-Compute-Stick (NCS-2) as a recognition accelerator. This part of the IndusBee 4.0 is still in a very early phase, but the realization of an integrated low-power and low-cost vision unit for hive-integration as an additional source of information for hive health state will be pursued.

6. Emerging Integrated Gas Sensor Extension of SmartComb

Complementing the standard sensory modalities employed for bee hive monitoring, the in-hive air can be analyzed similar to numerous applications in gas sensing, e.g., for intelligent ventilation systems in cars, smoke and fire detectors, or air quality analysis. For this purpose numerous sensors have been developed, e.g., the palette of sensors from Figaro employed in [51]. However, there are more integrated sensors available, e.g., the air quality sensor for VOC's SGP30-2 2.5K from Sensirion [68] that has been selected for the first extension of the SmartComb in our work. The target is to assess in-hive air quality and evaluate, whether a correlation to infestation, e.g., by varroa, or illness, e.g., (American) foulbrood can be achieved. In [51] a remarkable approach with a discrete gas sensing appliance external to the bee hives has recently been presented.

The SGP30 is a multi-pixel gas sensor for indoor air quality applications, with I^2C interface and very small 2.45 × 2.45 × 0.9 mm 3 DFN package, matching well with the current SmartComb, and low-power consumption. This and related sensors from same and other manufacturers offer a very compact and robust in-hive realization. With the encouraging results of [51] in mind, this will intensively be pursued to have extended SmartComb prototypes ready for measurement in the coming bee season in 2020.

7. Visual Varroa Screening Procedure

The typical visual varroa screening process bases on the analysis of the hive debris collected on sliders as given in Fig. 12. They differ in time inserted in the hive and the amount of debris mixing with the mites to be detected. The increasing degree of debris and target varroa objects on the slider unit with insertion time leads to increasing occlusion problems up to literally burying the mites, so that attractive simple methods might fail and more computationally burdensome techniques or even sensory extensions, e.g., [43], registration techniques, e.g., fluorescence photography, and scene improvements have to be considered. As manual inspection also becomes harder, usually a time in hive of 2-3 days is recommended as feasible inspection practice, e.g., [48]. However, this will be hard to meet for the aspired continued automated screening procedure without introducing cleaning steps for the slider units.

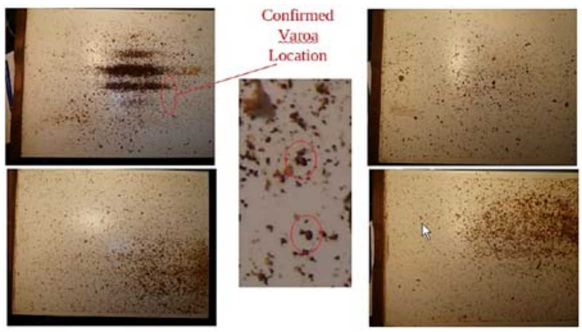

Fig. 12. Hive debris on sliders for varroa screening illustrating possible occlusion problems aggravating with insertion time.

A further significant challenge for an economic system version working with standard camera, e.g., available in contemporary mobile phones, is given by the fact, that the inspection area of the slider is very large compared to the size of a mite. In established manual analysis, hive keepers uses multi-scale analysis by a magnifying glass and hand-eye-coordination literally excavating mites from the debris in an iterative process. Additional complexity will be added for the ambitious goal to do this automated visual varroa detection and counting repeatedly in hive, as the constrained space will make invariant data registration very hard.

One existing varroa counting system could be found in the web [50] that seems to use a similar approach as the first stage in Section 8. According to some of the comments, the approach works well for rather clean sliders and degrades with increasing cloaking and occlusion. Updates seem not be available.

8. VarroaCounter Assistance System

Our current simple first-cut VarroaCounter system concept and implementation bases on standard blob analysis, e.g. [46], which has been employed in numerous machine vision application in the last decades, is illustrated in Fig. 13.

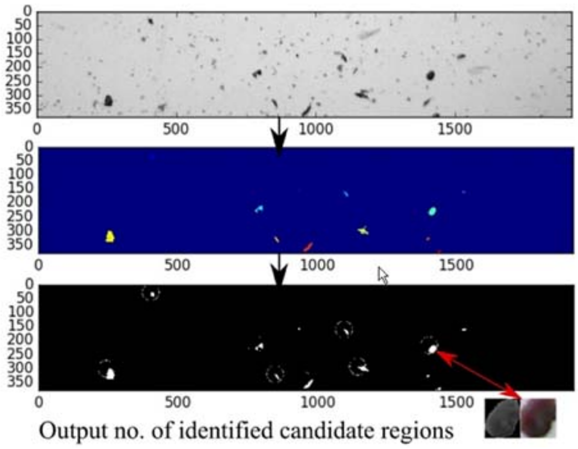

Fig. 13. Main steps of first VarroaCounter system for a subregion of a hive slider unit.

For the first approach, it is assumed for the sake of simplicity, that the slider image is grabbed by a basic commercial still image camera, e.g., the hive keeper’s mobile phone camera, under suitable normalization conditions. Perpendicular orientation, identical scale, focus settings, as well as uniform and constant scene illumination are prerequisites for robust recognition. As in related work [34, 37], the obtained color image (see Fig. 3 top) is processed by an segmentation step, identifying possible object, or varroa occurrences, using python and scikit [46] for our simple and computationally effective mite candidate detection algorithm. Instead of computing gray value image for the segmentation step from the color registration [34, 37], here, preliminary analysis showed the red channel itself to be best suited here for the varroa mite candidate segmentation. Under the assumption of the common white slider background and sufficient sparsity, a fixed thresholding with $15 < p_{ij} < 90$ was employed returning candidate regions. A simple morphological filtering step was applied to eliminate singular region detections and smooth remaining significant regions. Then established blob analysis [46] is run, which threads all found segmentation regions and returns a blob list and number of candidate regions for further assessment (see Fig. 13 center). Enthusiastically, the resulting number could already be interpreted as the aspired varroa counting result figure. But unfortunately, this will only be true under severe and somewhat unrealistic constraints, e.g., assuming in addition to sparsity, that no other objects, e.g., insects or insect parts would be present. Thus, in the second stage of the proposed VarroaCounter, the blob regions from the list will be subject to a confirming or rejecting classification by richer features, e.g., blob properties, pixel statistics etc., computed from the initial color image registration (see Fig. 13 bottom), potentially adding structural and/or textural information to the recognition process.

9. First VarroaCounter Experiments and Results

For the validation and improvement of the first-cut varroa counting assistance system, a collection of sliders have been accumulated from real apiary routine checks. Fig. 12 shows a few example pictures, taken by a simple still image camera. Various insertion times have led to violations of sparsity assumption and resulting occlusion problems (see Fig. 12, center). The slider samples are stored to be able to repeat recordings with different camera, scene, and illumination settings or for research application of available commercial hyper-spectral camera [49] similar to [43]. Both to check stage one of VarroaCounter and to obtain unique and ground truth data for the post classification step, shown in Fig. 14, a clean slider with only sparsely located 84 mites on it was prepared.

The stage one worked well for the easy example and returned both the correct number and list of locations of the 84 mites. For the first instance of the second, post-classification stage, a kNN classifier [47] is employed and trained with mite images given in Fig. 14 and additionally selected non-mite, background patterns. In the first place, histograms of blob regions where computed for post-classification. The corresponding, promising feature space for simple blob region histograms is shown in Fig. 15. Summarizing, the blob analysis, based on color thresholding, acceptably works with sliders sparsely populated by debris and mites.

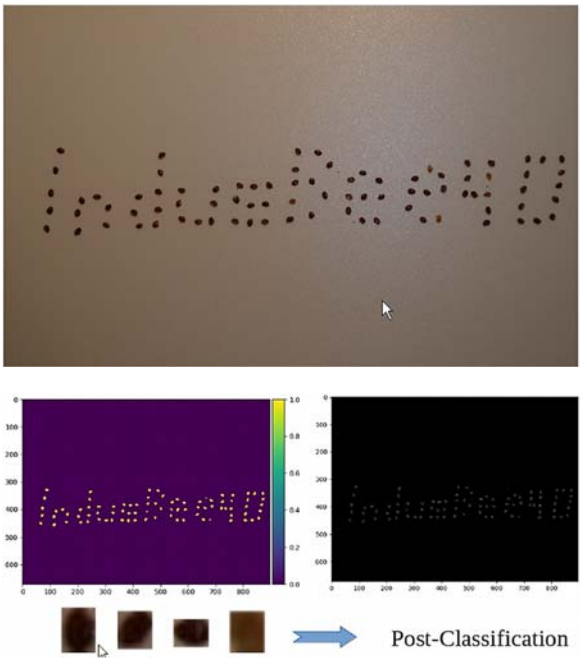

Fig. 14. Clean slider for stage one test and data acquisition for second stage classifier design

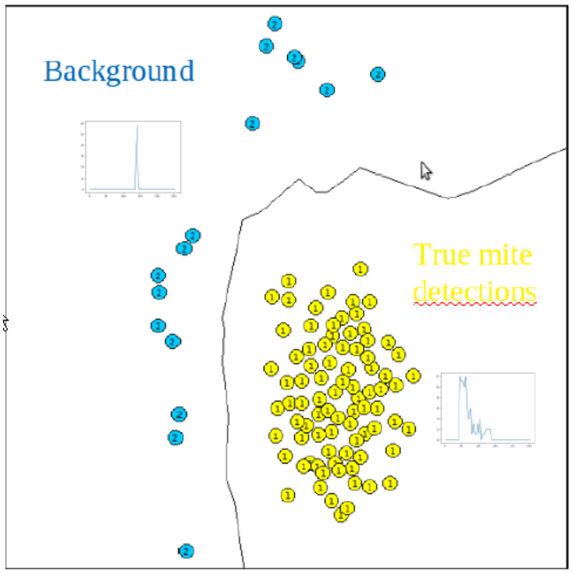

Fig. 15. Feature space of the post-classifier stage.

On densely packed sliders, too large blobs arise, which are harder to rule out and require more information. Structural and color textural features [42] will be regarded next in the work to increase the counting accuracy still with affordable standard equipment.

10. Conclusions

The essential role of insects in general, and wild bees and honey bees, in particular, has reached public awareness with increasing issues and problems, e.g., to assure pollination and related food production. An increasing number of threats from pesticides to parasites, e.g., the *varroa destructor* in the case of honey bees, threaten these essential contributors to our ecosystem and at the same time substantially increase the load on hive keepers to maintain and protect their bee colonies.

This situation triggered numerous activities on modifications and improvements of bee keeping. One goal of this paper was, to establish an, still evolving, survey of key activities. The main stream of engineering-based activities follow approaches in automation, including home automation, sensors, measurement, and instrumentation and set out to instrument bee hives and whole apiaries, in particular reading temperature, moisture, weight of hives as process parameters. More advanced approaches extend this to image and video analysis, e.g., for flight hole monitoring, acoustic monitoring, and in-hive air analysis by gas sensors for various purposes.

In this paper, these activities are picked up and transfer options of knowledge and methods from machine vision and learning, electronics system integration, automation, (I) IoT, ICM, and Industry 4.0 domains are exploited to provide advanced solutions, both for bee hive instrumentation and health monitoring as well as hive keeper's assistant systems on the apiary level. An effective, disappearing, and low-cost hive-integrated approach, benefiting from the ongoing advance in micro-/nano-technologies, for the field of bee hive monitoring and colony activity and state assessment was introduced and demonstrated. A simple and low-cost approach for improving automated varroa counting [25], pursued as a building blocks in IndusBee 4.0 [45], was presented as first step for bee hive keepers assistance. The suggested two-stage procedure demonstrated by a first prototype works well under some constraints.

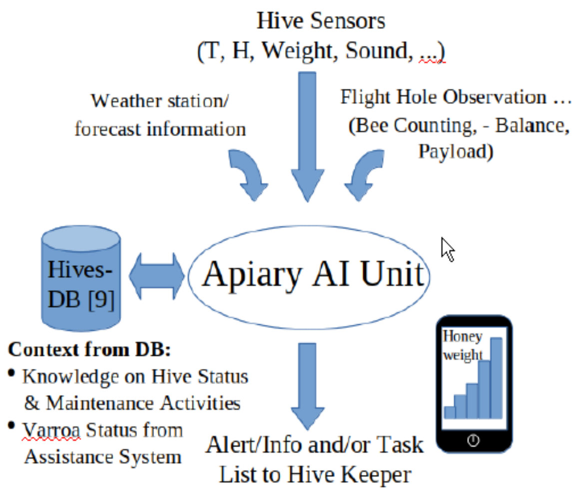

Fig. 16. Apiary AI proposed for aggregating and managing both hive monitoring and hive keeper assistance systems data of multi-colonies with sophisticated alerting, information, and scheduling for hive keepers.

In future work in our IndusBee 4.0 project [32, 25, 45] the following key issues will be pursued in the context of a hive-integrated, robust, and low-cost solution. The acoustic monitoring will be extended to a more comprehensive list of states, multi-microphone recording, advanced evaluation and adaptation strategies, and deployment to a larger number of colonies. In particular, the possibility of a correlation of bee sound information with varroa infestation level [63] will be investigated.

The SmartComb is with priority currently extended by advanced integrated gas sensors, e.g., also for potential varroa infestation level estimation and foulbrood or other illness detection [51].

The idea of visual external as well as hive-integrated continuous varroa infestation estimation will be advanced. For that aim, both presented stages have to see extension, e.g., by adding structural and color textural features [42] to overcome occlusion issues.

Visual flight hole activity monitoring will be pursued as outlined in Fig. 11., trying to collect more salient information on hive state and health condition, e.g., from pollen intake estimation or varroa infestation level estimation from varroa mites clinging to bees [53] etc. This last activity is probably the most complex one and needs further considerations for computational acceleration and appropriate choice of sensor, e.g., vision, depth, infrared, hyperspectral and related active illumination.

In particular, the creation of higher level intelligence unit, i.e., an Apiary AI as indicated in Fig. 16, that integrates data from all hives, external sources like weather stations and forecast information, and information from hive keepers' assistance systems, will be pursued. The context available on hive and apiary level will make more efficient data analysis and hive state determination possible. Sophisticated alerting, information, and scheduling for hive keepers can thus be achieved, potentially reducing both workload and disturbing of bees. For instance, varroa infestation level estimation could be consolidated by fusing information from various sources, e.g., visual (automated) counting, sound analysis, and hive-air analysis. Swarm prediction could be improved by fusing temperature development and sound analysis in hives etc.

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