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Intelligent Autonomous Pollination for Future Farming - A Micro Air Vehicle Conceptual Framework With Artificial Intelligence and Human-in-the-Loop

YI CHEN, (Senior Member, IEEE), AND YUN LI, (Senior Member, IEEE)
Dongguan Industry 4.0 Artificial Intelligence Laboratory, Dongguan University of Technology, Dongguan 523808, China
School of Computer Science and Technology, Dongguan University of Technology, Dongguan 523808, China

Corresponding authors: Yi Chen (leo.chen@ieee.org) and Yun Li (yun.li@ieee.org)

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ABSTRACT Food security is one of the societal challenge topics. As one-third of all food consumed by humans relies on animal pollination currently, this research provides an emerging solution to food supply reduction caused by population shrinking of natural pollinators, so as to reduce its impact on ecological relationships, ecosystem conservation and stability, genetic variation in the crop plant community, floral diversity, specialisation and evolution. This paper develops a conceptual technical roadmap of autonomous pollination for future farming using robotic micro air vehicle pollinators (MPrs). The research provides new insights into autonomous design and manufacture and into possible ways to increase the production efficiency which shortens the time from lab to market. The autonomous MPrs are realized using artificial intelligence and human expertise in the loop for smart agricultural industry. Further, this work identifies scientific and technological advances that are expected to translate, within proposed regulatory frameworks, into the pervasive use of MPrs for agricultural applications and beyond.

INDEX TERMS Artificial intelligence, autonomous pollination, future farming, industry 4.0, micro air vehicle, pattern recognition.

I. INTRODUCTION

In the era of Industry 4.0 (i4), many industry sectors have experienced a shift in the way that businesses are conducted, brought about by the proliferating use of combining artificial intelligence (AI) with human intelligence (HI). Reflecting one of the most innovative activities, robotics and autonomous systems (RAS) are essential to the global economy, which has positive effects on society regarding efficiency is immeasurable and emerging into our daily lives. AI could add $232BN to UK's GDP by 2030 according to new research by PwC [1]. This makes AI the most significant commercial opportunity in today's fast-changing economy, in which, the RAS is to play an increasingly essential role in the world's industrial sections, including manufacturing, healthcare, and smart city. Although AI is still a few years away from servicing us in our daily life and work, AI has already been impacting on the world in a few subtle ways profoundly, such as a facial recognition payment solution, cyber-security, healthcare, and precision farming [2], [3].

In this research, autonomous pollination is one of the critical technologies for precision farming in the near future. According to the data from the world economic forum, the world's population is expected to increase significantly over the next few years, but the capacity for food production will struggle to keep pace. AI is driving efficiency in our current farming methods to increase production and reduce wastage without adversely affecting the environment. Systems such as John Deere's AutoTrac [4] enable considerable machines to plant crops in a far more uniform and accurate way and can reduce overlap in agricultural processes such as tilling, planting and fertilising, which in turn reduces the

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use of chemicals and increases productivity. Cainthus provides a machine vision approach [5], using deep learning, to create facial/pattern/objective recognition systems which are able to identify/classify individual cows/horse/sheep by their facial/body features in a few seconds, and enable considerable herds to be monitored with the minimal human involvement. Further, they are also able to detect and alert the lameness signs at an early stage in a cow according to the body shape cross-checked with other characteristics. Sensors installed on the farm facilities or mobile robots (such as drones and automatic guided vehicles) are utilised to collect field data (such as images/videos) under real-time conditions. Meanwhile, AI driven autonomous systems are able to assist farm workers to carry out crops-growing tasks, to predict the outputs of farming production over a few months in advance for the next a few actions planning, incorporated with digital agriculture technologies [6].

For future precision farming, pollination performs one of their principal activities and is responsible for 90% of the living things on our planet, which is a transfer of pollen from the anther (the flower's male organ) to the stigma (the female part of the flower). Some plants can pollinate themselves and this is called self-pollination, which includes two types: autogamy and geitonogamy; Other plants need pollen to be transferred between different flowers in the different individuals of the plant, and this is called cross-pollination. Some plants can be pollinated both ways by either wind or animals, but most plants are not capable of autonomous self-pollination.

Pollination strongly influences ecological relationships, ecosystem conservation and stability, genetic variation in the plant community, floral diversity, specialisation and evolution. As estimated, one-third of all food consumed by humans is the result of pollinators, which are the biotic agents that move the pollen, such as western honey bees, other bees, moths, butterflies, and birds.

Mainly, western honey bee are prolific pollinators due to co-evolution between them and the flowering plants from which they extract food. There are two main reasons causing the intensifying pollination shortage [7]: (1) In the USA, the pandemic colony collapse disorder (CCD) of the Western honey bee (Apis mellifera), which caused 37% bee species population shrinking without proven scientific cause, has thus stirred substantial concern for the general welfare of regional humanity. (2) Other regions in the world (in Africa and Europe), the Food and Agriculture Organization (FAO)'s [8] data reveals that the global population of managed honeybee hives has increased >45% during the last half century, however, FAQ's available data also reveal a much more rapid (>300%) increase in the agriculture fraction that depends on animal pollination during the last half century, which may be increasing demands for agricultural pollination services and stressing global pollination capacity.

When pollination is needed on a large scale in future sustainable farming, for example, field crops, orchards, or commercial seed production, new technologies must be explored to overcome this challenge of global future food security.

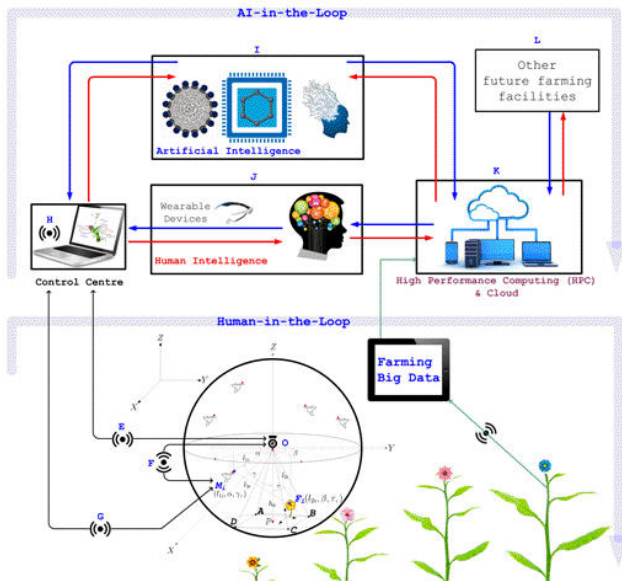

FIGURE 1. **The Conceptual Technical Roadmap for Autonomous Pollination using MAV with AI and Human-in-the-loop.**

A robotic micro air vehicle (MAV) pollinator (MPr) is one of emerging solutions to sustain worlds' food supply. This paper aims to provide a conceptual technical roadmap of autonomous pollination system (APS) for future farming using robotic MPr with flapping wings.

MAVs with flapping wings have been significantly developed during recent years, owing to their characteristics of small sizes, energy efficiency and agility. They offer a wide range of potential in the civilian and military applications. So far, there are some successful flapping wing MAVs, such as Nano Humming-bird [9] by Aerovironment Inc., DelFly [10] by TU Delft, Harvard Microrobotic Fly [11], Harvard RoboBees, Robot Dragonfly by TechJect, FESTO BionicOpter and Mosquito robot, etc. Most of the resesarch work has focused on robot structural design, circuits design or flight simulations, the fewer (FESTO) have addressed the 'intelligence' of the 'autonomous' robotic systems. To fill this gap, this paper proposes an autonomous robotic pollinator using computational intelligence approaches.

The contribution of this work can be outlined as a technical roadmap of autonomous pollination for future farming using a robotic MAV system with AI-in-the-loop (AIL) and Human-in-the-loop (HIL). As shown in Figure 1, each MAV_i of the robotic swarm are controlled by the central control system (CCS) via wireless signal connections. Real-time field data, such as crop and flowers, are captured by cameras and other sensors (e.g. thermal sensors) to the CCS. The intelligent CCS generates the control signals. The system is designed through computational intelligence (CI), which is a set of nature-inspired approaches offering a wealth of capability for complex problem-solving. Compared to the traditional optimisation methods, CI does not need to reformulate the problem to search a non-linear or non-differentiable space. In order to leverage the benefits of a diverse range of CI approaches, the computational intelligence integrated solver (CIS) has been utilised in this research [3], [12].

The remainder of the paper is organised as follow. Section II introduces the conceptual autonomous pollination with AIL and HIL, and describes the overall technical roadmap, including a few subsections with detailed key steps to implementation. SectionIII introduces the autonomous pollinating process using MAVs. Section IV summarises a few criteria that evaluate MPrs' performance and introduces the intelligent pollination management system. Section V discusses the potential ethical and regulatory issues. Section VI makes an initiative discussion on the social, economic and environmental impacts coming from the MPrs. Section VII concludes the paper and highlights future works.

II. AUTONOMOUS POLLINATION

Associated with AI and Human, the RAS revolutionises the world's economy and society over the next twenty years, whose key application areas include: manufacturing, healthcare, offshore energy, environmental monitoring, search and rescue, defence, and precision farming, which have been highlighted by the a few economic unions, such as: the UK Government in 2013 as one of the eight Great Technologies that underpin the UK's Industrial Strategy for jobs and growth; the Chinese government's 'Next Generation Artificial Intelligence Development Plan, which articulates an ambitious agenda for China to lead the world in AI. In this section, a conceptual autonomous pollination involving AIL and HIL is to be introduced, which shows an AI-centred and Human-centred RAS system in precision farming, with a wide range of applications, for example, space farming in future long-duration missions and colonies on the Moon or Mars.

A. AI-IN-THE-LOOP

AI has been widely applied to many academic and industrial problems. In fact, it could be labelled as a essentially approach to every problem in the era of industrial 4.0. AI is assisting human to make the decisions, and which can help to scale their existing experience and knowledge to address ever-expanding frontiers with uncertainties.

As shown in Figure 1, the conceptual loops of the *AI-in-the-loop* (AIL, loop 'H-I-K') and *Human-in-the-loop* (HIL, loop 'H-J-K') are presented, which will realise scientific advances of both AI and Human's expertise, respectively.

The loops of AIL and HIL can create a feedback system that let people correct robots' errors instantly with nothing more than their brains, or the way backwards,

in which, it provides the greater understanding of AI and bio-mimetic approaches to: (1) persistent autonomy, advanced empathetic multi-modal interaction between people and machines in autonomous operational activities for precision farming; (2) advanced robotics with micro-sensing and computing in farming embodiments; (3) adaptive compliant actuation at a multitude of scales; (4) form factors, semantic understanding of environments from noisy sensor data and beyond.

The two loops can present not only the advances, but also the research methods and practice to achieve them will be realised, e.g. hardware-in-the-loop architectures for re-usability and easy, low-cost experimentation.

B. HUMAN-IN-THE-LOOP

There are billions of neurons interconnected in the human brain. Human thoughts and their emotional states affect the interactions between these neurons. Every interaction between these neurons creates an electric discharge which cannot be measured using current technology. The interactions among those neurons can cause brain patterns/states with different amplitude and frequency changing, which can be employed for emotional states determination. Even one of the techniques of AI, deep learning, is taking this model and with higher computing performance provided by high-performance computing facilities, such as the high-performance computer (HPC) system.

Electroencephalography (EEG) is one of the widely used technologies to measure brain's voltage fluctuations of electric activities caused by the neurons' interactions, which are captured, measured by EEG sensors and displayed to screen. The data sets obtained from the EEG sensor can be utilised for the determination of control signals for robotics.

To involve Human's expertise, this RAS farming system includes a mind control system (HIL, loop 'H-J-K') for MAVs through a brain-computer-interface (BCI), consisting of a 32 channel EEG, a few MAV robots, and a CCD camera, etc. HIL enables people to correct robot mistakes using brain signals. Using data from an EEG monitor that records brain activity, the system can detect if a person notices an error as a robot performs an object-sorting task. The team's novel machine-learning algorithms enable the system to classify brain waves in the space of 10 to 30 milliseconds. This HIL-controlled robotics has associated by AIL to 'assess' in a prescribed way that computers can recognise.

For example, a human engineer is required to look at 1/4 computer screen with various data plots, each of which displays a type of task status with uncertainties for the robot to execute, which can be taken as the mutual training process (for both AI and Human) and the act of modulating one's thoughts can be taxing, particularly for people who supervise tasks in navigation or construction that require intense concentration via Virtual Reality (VR) or Augmented Reality (AR) technologies. The Mind Control MAV (via HIL loop 'H-J-K') records and processes brain electric activity. The motivation behind this research resides in creating low-cost products for future farming applications including real-time big data required for diagnosing farming status of pollination assessment.

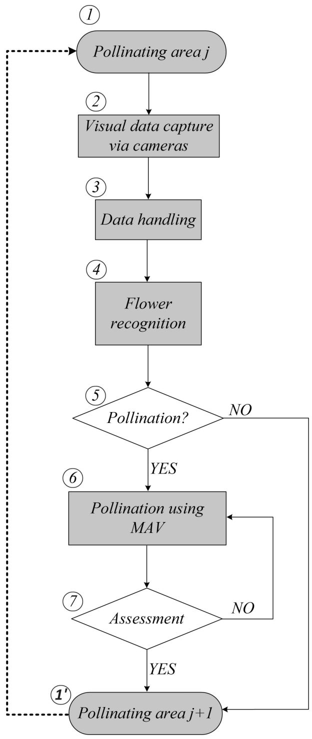

FIGURE 2. Conceptual Workflow of Autonomous Pollination.

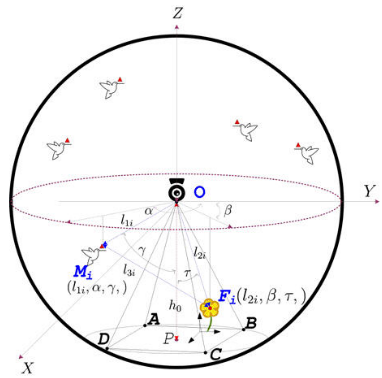

FIGURE 3. The Coordinate System of the MAVs and Flowers.

C. AUTONOMOUS POLLINATION TECHNICAL ROADMAP

Inspired by the biology of the natural pollinators (NPrs), this work is developing an autonomous artificial pollination solution, which is a hummingbird-like MAV robotic system that could perform an artificial pollinator role in agriculture, disaster relief and other multi-disciplinary applications.

As shown in Figure 2, the conceptual framework of autonomous pollination can be summarised in seven steps:

- Step ① is the step that the CCS assigns the MAV pollinators (MPrs) to the specific pollinating area j, that is, the MPrs are ready to perform the pollination of the specific type of crop flowers in this working area j.
- Step ② is to capture visual data, such as flower photos, or other types of data if necessary by cameras and other data acquisition systems, such as olfactory cues which might help to learn about the status of the flower, i.e., whether it releases pollen or whether the stigma is receptive.
- Step ③ is to handle the raw data collected from specific data sources, and then screen, filter and pre-process the source data.
- Step ④ is to perform actions of flower recognition using the data stream from previous steps, which identifies the specific flowers for pollination.
- Step ⑤ is to validate and assess the flower recognition data from the previous step, and then, a decision is made concerning whether the pollination process should continue (*YES*) or terminated and thus should proceed to Step ①′ (*NO*).
- Step ⑥ is to perform the autonomous pollination using MAV.
- Step ⑦ is to assess the effectiveness of pollination, and then to decide whether the pollination work is accepted by the CCS (*YES*) and move the MAV pollinators to the next step, or not (*NO*) good enough and the pollination need to be repeated.
- Step ①′ is to handle the pollinating data for the current working area j, analyse results, visualise the results data, send results to data storage (or data cloud) and move the MAV pollinators to the next working area $j+1$.

D. FROM THE MAV TO THE FLOWER

Environmental effects, such as solar radiation, air disturbance and electrodynamic influence, are all assumed to be negligible in the autonomous pollination modelling context. In addition to the assumptions made in deriving the equations of motion for all types of the MPrs modelling, the bearing connecting of the mechanical components is assumed to be perfect and to cause no significant frictional losses, that is, a friction-free environment. This assumption implies that the power supplies, control systems, and communication equipment, etc. are assumed to be fitted within the APS in a practical installation. Unless stated otherwise, all of the models are based on the conditions stated above.

As shown in Figure 3, an autonomous pollination system with MPrs has two generalised coordinate systems. The first is a fixed camera O centred Cartesian coordinate system - $\{X, Y, Z\}$, and the second is the Spherical coordinate system - $\{r, \theta, \psi\}$. The centre of the fixed camera is denoted by $O(x_0, y_0, z_0)$, which is defined as the origin of the $\{X, Y, Z\}$ system, where, (x_0, y_0, z_0) are set to $(0, 0, 0)$, that is, $O(0, 0, 0)$.

The computer vision associated sub-system with a high resolution camera locates at $O(0, 0, 0)$, which can provide the real-time coordinates l_{1i}(simplified as l_1), l_{2i}(simplified as l_2), α, β, γ and τ as the known parameters. Without loss of generality, a MPr locates at $M_i(x_1, y_1, z_1)$ (simplified as M) and its targeting flower locates at $F_i(x_2, y_2, z_2)$ in the Cartesian coordinates, which can be converted to their Spherical

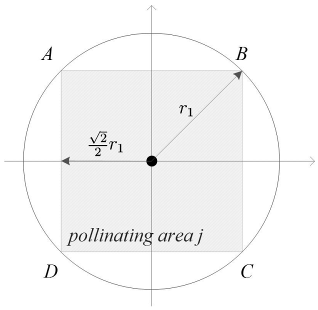

FIGURE 4. MAV Pollination Working Area and General Coordinate System.

coordinates, namely $M_i\ (l_{1i}, \alpha, \gamma,)$ and $F_i\ (l_{2i}, \beta, \tau,)$ (simplified as F), as given in Equations (1) and (2).

$$\begin{cases} x_1 = l_1 \sin\alpha \sin\gamma \\ y_1 = -l_1 \cos\alpha \sin\gamma \\ z_1 = l_1 \cos\gamma \end{cases} \tag{1}$$

$$\begin{cases} x_2 = l_2 \sin\beta \sin\tau \\ y_2 = l_2 \cos\beta \sin\tau \\ z_2 = l_2 \cos\tau \end{cases} \tag{2}$$

Then, the dynamic distance from a MPr M to a flower F can be expressed in Equation (3).

$$l_3 = \sqrt{2l_2 l_1 (\sin\gamma \sin\tau \cos(\alpha+\beta) - \cos\gamma \cos\tau) + l_1^2 + l_2^2} \tag{3}$$

E. TERRAIN MODELLING OF THE POLLINATION WORKING AREA

As shown in Figure 3, the camera is installed at location O, r_0 is camera's working distance, h_0 is the minimal distance from location O to working area j at P, $\overline{OP} = h_0$. Assuming that a working area is a plane (flat surface), Figure 4 defines the working area j, which is a unit area $ABCD$ that the MAV pollinators are assigned to carry out their pollination activities.

$\overline{PB} = r_1$ is the radius of the working circle $ABCD$, as shown in Figure 4, the areas of circle $ABCD$ and square $ABCD$ are given in Equations (4) and (5), which implies that the working areas depending on the camera's working distance r_0 and its locating distance h_0.

$$S_C = 2r_1^2 = 2\left(r_0^2 - h_0^2\right) \tag{4}$$

$$S_S = \pi r_1^2 = \pi\left(r_0^2 - h_0^2\right) \tag{5}$$

F. DATA CAPTURE AND DATA HANDLING

As shown in Figure 5, the field data (such as: image, video, 3D space data, audio, etc.,) can be captured by the camera and other types of sensors, for example, laser scanning device, sonar, digital camera, etc. Generally, there are two types of data: (1) Odometry Data for MAVs and (2) Surrounding Data for Flowers. All raw data from cameras or sensors need to go through the 'data handling' process, including data filtering, denoising, normalisation, etc., and then hand over to the next step: flower recognition.

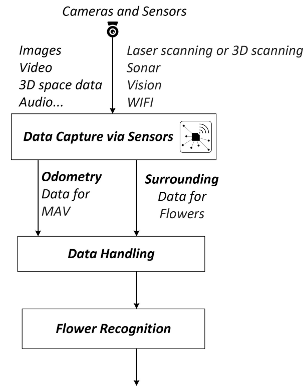

FIGURE 5. Framework of Data Capture and Data Handling.

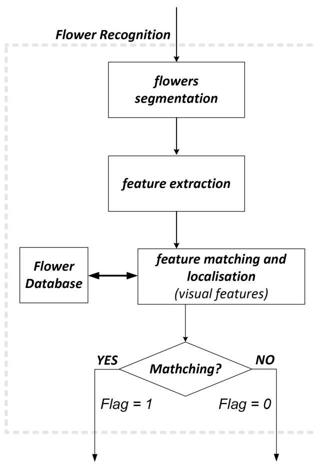

FIGURE 6. Framework of Flower Recognition.

G. FLOWER RECOGNITION

Flower recognition is one of the critical steps for artificial pollination. For example, the seedless watermelons that need pollen donors, because the pollen of seedless watermelon is sterile and can not produce fruits. Furthermore, with the addition of genetically modified organisms (GMOs) plants and wild plants that can be crossed with crop plants, the recognition of flowers will be also a fundamental step for the artificial pollinators.

By adopting computer vision data from previous steps, this step performs the recognition of flowers from photographs, which starts with the localisation of the flower in the image, followed by identifying and extracting the specific characteristics of this flower, and finally finding the best match against the 'flower database'. The specific research on plants, in which the fast segmentation algorithm(based on user's inputs) and the implementation of several visual features (suitable for flowers differentiation) may be required. As shown in Figure 6, the flower recognition can

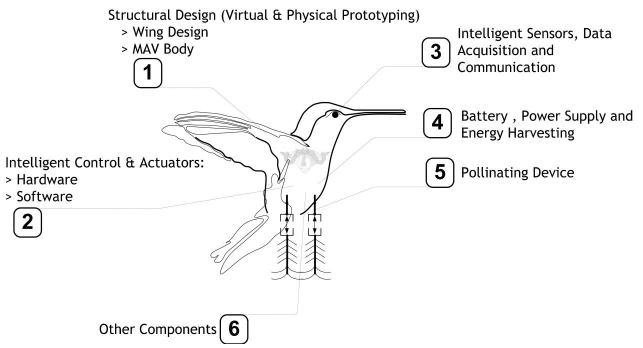

FIGURE 7. The Architecture of A MAV Pollinator.

be summarised as: flower segmentation, feature extraction, feature matching against flower database and localisation, and finally, a result will be concluded to decide whether the process goes to pollination or termination.

III. POLLINATION USING THE MAV

The MAV is a class of unmanned aerial vehicle (UAV) along with restricted size and remote or autonomous. In recent years, the flapping wing inspired MAVs, for example, the hummingbird-like and insect-like robot, have been one of the most rapidly developing UAVs by more and more researchers for their extraordinary ability to control the energy-efficient flight with small size.

As a short-term solution to the problems of CCD while the underlying causes are discovered and solved, in this paper, we seek to introduce a robotic hummingbird-like MAV solution for future farming, which is capable of autonomous pollination in a field of crops.

A. MAV POLLINATOR

A swarm of artificial MAV pollinators (MPrs) will consist of a large number, also named as μMAV in this research, probably hundreds to thousands of agile robotic MAVs, which are capable of servicing a previously-defined working area of crops. The working areas will be delimited by a few sparse border markers that serve to broadcast brief messages to the swarm, act as localisation beacons for the MPrs, and also may function as recharging stations. Once the MPrs are released from the working stations - the 'hives', they will disperse and move through the crops searching for flowering plants using computer visual cues. Optimal coverage will be controlled by CCS using optimal operational implementation autonomously. Pollination will occur as μMAV pollinator lingering on the specified flowers in current working area, then move onto the next working area.

As shown in figure 7, the architecture of a μMAV pollinator can be implemented as a pilot scheme, which can be categorised into 6 parts:

- part 1, structural design using virtual & physical prototyping), including: *MAV Body*, *Wing Design* and all the components for robotic structural framework.
- part 2, intelligent control & actuators, including: hardware and software.
- part 3, intelligent sensors, data acquisition and communication.
- part 4, battery, power supply and energy harvesting.
- part 5, pollinating device, which can be an active pollinating brush (p-brush). Similar to NPrs, MPrs' 'p-brush' should be highly effective at catching pollen with a branched structure on each p-brush hair.
- part 6, other accessory components, e.g. MPrs launcher.

B. INTELLIGENT PATH PLANNING

Intelligent path planning is one of the essential aspects of MPrs autonomy, and the autonomy level of the MPrs depends on the approaches to generating the optimal path planning and control the MAV. Usually, path planning is often seen as a global optimisation problem, in which the feasibility of the candidate paths subject to the mission, environment and MPrs' physical constraints.

Finding real-time trajectories helps MPrs to be moving in a dynamic environment and generating an optimal trajectory/path from the starting position to the target flower, while satisfying all constraints is a challenge in both theory and practice. At current stage, there is no solution that can solely be used to solve this challenge. In the last a few years, researchers have been working on path planning problems and several approaches have been proposed, which can be basically divided into two categories: (1) 'mathematical modelling' and (2) 'data-driven modelling'.

With the increasing data capacity supported by the next generation cyber-physical system for industry 4.0, including smart sensors, high-performance computing facilities and intelligent algorithms,etc., the 'data-driven modelling' approaches or hybrid approaches have become more and more popular.

In this research, as shown in Figure 8, there are 7 organised modules for the intelligent path planning scenario, which include:

- *module 1:* Landmark extraction. The initial odometry data are taken as the inputs for the 'landmark extraction' module;
- *module 2:* Data association. It is to match observed landmarks from different odometry data (e.g. laser scans) with each other, which is also called the re-observing landmarks;
- *module 3:* Data update and optimal path generation.
- *module 4:* Control design for MPrs pollinating.
- *module 5:* MPrs dynamical modelling of pollinating.
- *module 6:* Pollination management.
- *module 7:* Computational Intelligence Assisted Design (CIAD) [3] as the intelligent optimiser.

C. POLLINATING PROCESS

Before pollination, the initial field data of the pollinating area A_i have been collected by the sensors, such as: the quality, quantity, types and locations of the crop flowers by sensors

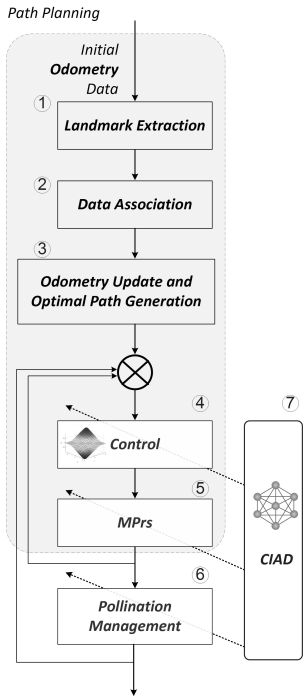

FIGURE 8. Data-flow of Intelligent Path Planning, Control and Pollination Management.

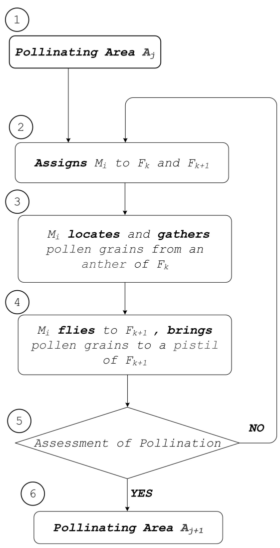

FIGURE 9. The Pollinating Process by MPrs.

(including: cameras), and transferred to the CCS system for pollinating mission preparation and pre-launch operations. Figure 9 shows the major 6 steps for the autonomous artificial pollinating process by the MPrs assigned to the pollinating job for the working area A_i.

- *step 1:* The specific MPr swarm arrives at pollinating area A_j with the job assigned by the by CCS system;
- *step 2:* Using previously collected field data and its analysed results by CCS system, after the MPrs' arriving, each of the individual MPr M_i $(i = 1, 2, \ldots, M)$ has been assigned to its workload, including crop flowers F_N waiting for pollination, where N is the crop flower number for each M_i;
- *step 3:* MPr M_i locates and gathers pollen grains from an anther of flower F_k $(k = 1, 2, \ldots, N)$;
- *step 4:* Without loss of generality, let's start under the most straight-forward situation, when a MPr M_i flies to flower F_{k+1}, it brings pollen grains to a pistil of flower F_{k+1}, then M_i moves to its next target flowers F_{k+2} and F_{k+3}. The pollinating work has not done until every M_i finishes its pollination;
- *step 5:* the assessment of the MPrs' pollinating work will be carried out by the CCS system using the updated field data of pollinating area A_i. Specifically, performance criteria are employed to assess the pollinating results, and then decide whether the MPrs should continue and move to step 6 (*Yes*), or the pollination should be repeated and move to step 2 (*No*);
- *step 6:* The MPr swarm moves to the pollinating area A_{j+1};

TABLE 1. Criteria for MPr Efficiency Evaluation [18], [29].

No.	Criteria	Index
1	*Abundance*	C_1
2	*Per-visit efficiency*	C_2
3	*Activity patterns*	C_3
4	*Visitation rate*	C_4
5	*Inter specific influence*	C_5
6	*Direct pollinator efficiency index*	C_6
7	*Pollen removal efficiency index*	C_7
8	*Pollinator specificity index*	C_8
9	*Pollen transportation specificity index*	C_9
10	*Visitor Activity Index*	C_{10}
11	*Community Pollination Index*	C_{11}

IV. PERFORMANCE ASSESSMENT

A. PERFORMANCE INDICES

Similar to other agricultural activities, MPrs' pollinating in agricultural ecosystems require a set of criteria to performance assessment, thus, evaluating a pollinator's performance is an essential step in attributing pollination services and predicting how do the MPrs bring impacts on those services and strategies. As listed in Table 1, a few criteria have been summarised to evaluate MPrs' performance, which also can be taken as the pollinating optimal design objectives, optimal control objectives and pollination management strategies.

- 1, *Abundance* (C_1) *[13], [14]:* Number of actively foraging NPrs in an agroecosystem, in this case, which is the total number of MPrs assigned to the pollinating job per working area A_j.
- 2, *Per-visit efficiency* (C_2) *[15]–[17]:* Per-visit efficiency is a measure of an MPr's contribution to the stigmatic pollen load or to the plant's reproductive success in terms of seed production following a single visit, which is the number of pollen grains provided by an MPr in a single visit to a flower. In this case, the per-visit seed set (rather than pollen deposition) are taken as

the measure of per-visit efficiency [18]; In some other cases, seed set cannot be evaluated immediately after pollination, but may just be measured weeks or even months after pollination has occurred; also, seed set is not of relevance in several crops, which keep us working on further specific situations.

- 3, *Activity patterns (C_3) [19]–[24]:* pollinating activity under environmental uncertainties, which may be dependent on weather, seasonal phenology, and spatial aspects of pollinating behaviours (e.g. temperature, wind speed and solar radiation).
- 4, *Visitation rate index (C_4) [25]:* As given in Equation (6), taking into account both frequency of visits and activity rate, C_4 measures visitation rate in a relative way, where N_1 is the number of pollinating MPrs relative to the total number of MPrs involved in the pollinating activities, and AR is the activity rate, i.e. number of flowers that an MPr visited per minute.

$$C_4 = N_1 \times AR \tag{6}$$

- 5, *Inter specific influence (C_5) [26]–[28]:* Interactions between MPr groups that may reduce or enhance per-visit efficiency C_2, activity patterns C_3 or visitation rates index C_4, such as, frequency of bee encounters, foraging events, and flower inspections, and floral handling time per trial.
- 6, *Direct pollinator efficiency index (C_6) [29]:* Relying on seed set, as given in Equation (7), it measures the relative efficiency of a MPr group, where Z is the mean number of seeds set per flower by a plant population in the absence of pollinator visits; U is the mean number of seeds set per flower by a plant population with unrestrained visitation. P is the mean number of seeds set per flower by a plant population receiving a single MPr visit.

$$C_6 = \frac{P-Z}{U-Z} \tag{7}$$

- 7, *Pollen removal efficiency index (C_7) [30]:* It is a modification of C_6, which measures the relative efficiency of an MPr group, as given in Equation (8), where R_i is the mean number of pollen grains removed per flower by a plant population receiving a single visit from MPr group i; N_2 is the mean number of pollen grains removed per flower by a plant population receiving no visitation; and V is the mean number of pollen grains removed per flower by a plant population exposed to unrestricted visitation.

$$C_7 = \frac{R_i - N_2}{V - N_2} \tag{8}$$

- 8, *Pollinator Specificity Index (C_8) [31]:* As given in Equation (9), where N_3 is the number of flowers visited by the MPrs, it estimates the specificity of particular MPrs group, but does not consider the presence of pollen loads. If pollen loads are taken into account, C_9 then will be introduced.

$$C_8 = \frac{1}{N_3} \tag{9}$$

- 9, *Pollen Transportation Specificity Index (C_9) [31]:* As given in Equation (10), it considers the pollen loads placed on the same site of the MPr, where N_4 is the different pollen loads number remain on the same site of the MPr.

$$C_9 = \frac{1}{N_4} \tag{10}$$

- 10, *Visitor Activity Index (C_{10}) [32]:* It estimates the status as pollinator of each floral visitor species using Equation (11), where D_1 to D_5 are five qualitative criteria utilised to distinguish floral visitors from NPrs, the first part of the expression (D_1 D_2 D_3) indicates pollen transference, while the second part (D_1 D_2 D_4 D_5) indicates flower-visitor adaptation, attractiveness and constancy. D_1 and D_2 act as compensatory factors dropping to zero the value of C_{10} when D_4 and D_5 are one and there is no pollen transference. C_{10} varies from 0 to 1; visitor species are considered as pollinators when the values of C_{10} are significantly different from zero. D_1 - presence and abundance of pollen from the visited flower, coded as 1 for abundant, 0.5 for scarce, and 0 for no pollen; D_2 - part of the body where pollen was located and its relationship with the position or orientation of the sexual organs in the blossom during the pollination process, coded as 1 if the criterium is fulfilled and 0 otherwise; D_3 - Pollen load on the body of the vector can make contact with the stigma during a visit, coded as 1 if the criterium is fulfilled and 0 otherwise; D_4 - relationship between the blossom size and floral visitor size, coded as 1 is fulfilled and 0 otherwise; D_5 - number of visits per unit time.

$$C_{10} = \frac{(D_1 D_2 D_3) + (D_1 D_2 D_4 D_5)}{2} \tag{11}$$

- 11, *Community Pollination Index (C_{11}) [31]:* It estimates the proportion of pollinator sharing as Equation (12), where, N_5 is the number of MPrs recorded on the crop flowers in this working area, and x_i is the number of the crop flowers visited by MPr group i.

$$C_{11} = \frac{N_5}{\sum_{i=1}^{n} x_i} \tag{12}$$

B. INTELLIGENT POLLINATION MANAGEMENT

Intelligent pollination management (IPM) is an AI-driven pollination management of autonomous pollination for intelligent horticultural practices in precision agriculture, which is able to enhance pollination of a crop and to improve yield or quality, by an understanding of the particular crop's pollination needs, and by the knowledgeable management of pollenisers (the plant that provides pollen), pollinators, and pollination conditions. The IPM provides supervisory functionality as well as pollination service, in which, smart sensor network to measure the incoming and outgoing data stream of a pollinating process as well as intermediate parts of the process.

Intelligent path planning is one of the most essential features in the autonomous pollination of MPrs provided by the IPM system, and become especially crucial when MPrs is to be integrated into a national or international unmanned aerial vehicle (UAV) management system for multi-disciplinary applications, such as NASA's Unmanned Aircraft Systems Traffic Management (UTM) [33]. For autonomous pollination, path planning is often seen as a global optimisation problem, in which the feasibility of the candidate path depends on the mission, environment and MPrs' physical constraints. As shown in Figure 8, coupled with intelligent analysis of data stream, managerial events and operational actions are optimised so that the practical errors are minimised for the pollinating process, and then, the efficiency of MPrs, which is due to the numbers, the physique and the behaviour of pollinating on a given crop flower at one time, can be centrally managed and supported by CIAD [3], [12].

V. ETHICS AND REGULATORY ISSUES

The autonomous pollination using MPrs proposes a host of benefits that are compelling and imaginative for future farming, but as with other intelligent technologies, they also come with risks and new questions that human society must confront, which is not unexpected, given the disruptive nature of technology revolutions.

A. SAFETY

Similar to other agricultural robots, the micro- electromechanical MPrs may be assigned to arduous pollinating works under uncertain environment (even dangerous) and requiring work sometimes in 24 hours and 7 days a week, in which, the safety issues are with the (1) hardware and (2) software.

Typically, the software system of a robotic system can be built by thousands even millions of lines of codes by a group of programmers, in which bugs, errors and vulnerabilities likely exist. In office work, office software applications may lose data if users do not periodically save their work (which arguably is their own fault), but a tiny software flaw in complex mechatronic systems, such as a car, space robotics and MPrs, could lead to fatal results, such as collision and mechanical damage to flowers.

As for the increasing complexities of robotic structures, MPrs' body, in this case, it requires more critical and complex designs under uncertainties, such as: loads, geometry, material properties, manufacturing processes and operational surroundings, which may cause more possible faults.

Briefly, the more complicated a system is, the larger and more difficult it will be to achieve higher reliability. Reliability assessment techniques powered by computational intelligence assisted approaches help to develop initial guidance for MPrs' designs, for example, Monte Carlo sampling, the first and second-order reliability methods with genetic algorithms, swarm wolfpack algorithms, etc.

B. ETHICAL REGULATIONS

Linked to the safety issues of MPrs, it may be unclear who is responsible for any resulting harm [34]. Product liability regulations (or laws) are largely untested in MPrs, even in other robotics. It is the right to continue to evolve in a direction that releases manufacturers from responsibility, for example, end-user license agreements in software and hardware. With MPrs, for instance, there is a list of characters throughout the supply chain that may be held accountable: the programmer, the manufacturer, the environmental legal review team, the procurement officer, the field officer, the MPrs' operator, etc.

As MPrs become more autonomous, it's more possible to assign responsibility to the MPrs themselves. For example, if they can extract the features that typically define specifically given flowers, and to tell real flowers and plastic flowers. Also consider that there is ongoing work in integrating evolutionary algorithms, artificial intelligence and MPrs with biological brains.

One natural way to minimise the risk of potential harm from MPrs is to programme them to obey our regulations(laws) or follow a code of ethics. Programming aside, the use of MPrs must also comply with regulations(laws) and ethics, and again those rules and norms may be unclear or untested on such issues. For example, the use of MPrs on opium poppy flowers (Papaver Somniferum) should raise legal and ethical questions that we have yet to consider fully.

Potential questions include, but are not limited to:

1) If we could programme a code of ethics to regulate MPrs' behaviours, which ethical theory should we use?
2) Are there unique legal or moral hazards in designing MPrs that can autonomously kill people or other species, such as: bees, butterflies or animals?
3) Should MPrs merely be considered tools, such as guns and computers, and regulated accordingly?
4) Do we have any other distinctive moral duties towards MPrs and other robots?
5) Would the MPrs be handled by an operator with a 'driving licence'?

VI. SOCIAL, ECONOMIC AND ENVIRONMENTAL IMPACTS

Considering existing regulations, such as Ethical regulations on robotics in Europe [35], and allowing for analogical inferences, one could raise the objection that this MPrs might result in a fundamental change regarding our idea of MPrs for future farming and human society, and that existing regulations must be criticised for being too 'human-centred', that is able to cause a primary change in a distant future.

A. SOCIAL IMPACT

As one of the participants of the intelligent agriculture together with the 4th industry revolution (industry 4.0), the MPrs' autonomous pollination for future farming might lead a loss of jobs. Likewise, manufacturing industry had been starting to replace legions of workers by robotics, which are more efficient in processes of automation with less operating expenses, regardless of whether the workforce is growing or declining.

The standard response is that farming workers, whether replaced by other human works or robotics, could then focus more on where they can make a more significant impact and can perform higher-value jobs. Further, the demand for robots itself creates additional jobs, such as MPrs system maintenance. Another problem is, the farming system will be more MPrs dependent, which would be fewer human practitioners. and become more fragile.

B. ECONOMIC IMPACT

From an economic perspective, MPrs provide higher efficiency and better quality of pollination, which will potentially lead to an improvement of crop productivity.

The MPrs system will have a direct impact on food production to improve the future farming efficiency, for example, in 2009, CCD has affected crops represented 24% (£1.27 billion) of total UK crop sales. In 2013, $40 billion worth of products in the USA. This research proposes a conceptual framework to this CCD related back effects.

Also, MPrs robotic products will enrich a few industrial products, such as an advanced motor, MEMS system, advanced material and industrial engineering manufacturers or suppliers.

C. ENVIRONMENTAL IMPACT

Some species of plants and NPrs have developed a close interdependence in connection with pollination. Such a mutual adaptation and interdependence between a plant and pollinator is a result of a long co-evolutionary relationship. There is no need for the MPrs to develop such relationship, which might lead to a reaction chain of de-coupling between human and other species.

MPrs as embodied computers will increase pressure on rare-earth elements needed today to build computing devices and energy resources needed to power them. Networked MPrs would also increase the amount of ambient radio frequency radiation, in addition to human health problems.

VII. CONCLUSION AND FUTURE WORK

In this research, a conceptual theoretical roadmap of autonomous MAV pollinating has been proposed for food production reduction caused by the population shrinking of natural pollinators, which provides an intelligent solution to high efficient pollination for future farming.

An initiative of theoretical investigation on the autonomous MPrs pollinating system associating with a few multi-disciplinary sub-systems, such as flower recognition by computer vision techniques and robotic MPrs system, has been addressed. An architecture of an MPr, which is categorised into 6 configurations, has been presented to perform the autonomous artificial pollination. Further, the 'intelligent pollination management' has been applied to manage and assess the performance of the autonomous artificial pollination.

Underscoring the importance of evaluating MPrs' performance via multiple criteria, our results show that MPr groups contribute to pollination in different ways. These differences may provide functional complementarity and stability of pollination services to agricultural systems.

This research provides new insights into autonomous design and manufacture and into possible ways to increase the production efficiency which shortens the time from lab to market. This research would make a step change in smart design capabilities for MPrs in Industry 4.0, and help turn creative ideas into innovative products, services or processes timely and competitively. In particular, the CIAD enabled smart design system will help smart manufacturing achieve: 1) Virtual product verification and rapid product realisation; 2) On-demand mass customisation of low-cost products; 3) Distributed production; 4) A digitised manufacturing value chain; 5) Integration with product lifecycle management, complete from the conceptual design through to the product's end-of-life.

By providing the conceptual integrated framework to spatial recognition and autonomous operations of MPr systems in the era of Industry 4.0, unmanned autonomous systems and self-directed, manoeuvrable and interactive MPrs will help us to reach where no one has gone before, an event potentially to space farming.

Our future research will focus on the following aspects: (1) the implementation of experimental verification and validation for the autonomous pollination using MPrs; (2) the development of operational strategy of high efficient pollinating; (3) high efficiency and reliability design for the MPrs' flapping wings; (4) to develop a CIAD framework for the smart MPrs pollination effectiveness, as one of the components of cyber-physical system (CPS) for Industry 4.0 applications in future farming, using cutting-edge technologies, such as augmented reality/virtual reality techniques; (5) the autonomous robotics of MPrs are integrating into a CPS of future farming; (6) autonomous pollination using MPrs under micro-gravity environment for space farming, on space shuttle, international space station, also the Moon, Mars and deeper space explorations; (7) quantitative models need to be proposed to further demonstrate the social-economic environmental coupled impacts; (8)reliability-based design optimisation integrating experiment-based model validation [36]–[44]; (9) the development of new AI algorithms, such as the heredity algorithm (HA), the artificial fish swarm algorithm, the artificial wolf pack algorithm, the firefly swarm algorithm, the swarm dolphin algorithm and their hybrid derivatives (10) we will go on with our work on more complicated working condition, such as (a) if cross-pollination is needed: the flowers of different plants may be far away. Thus, at first a lot of pollen should be collected (which may be very difficult at some flower types to automatically collect pollen); then the robot would have enough pollen to pollinate various flowers in a row; (b) in most apple varieties: pollen must come from plants of another variety, otherwise, no fruit is set.

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YI CHEN (M'10–SM'17) received the B.Sc. degree in automotive engineering from the Chongqing University of Technology, in 2000, the M.Sc. degree in automotive engineering from Chongqing University, in 2004, and the Ph.D. degree in mechanical engineering from the University of Glasgow, in 2010. He has a high-level output of research publications in leading international journals and presentations at international conferences, which related to the research area of robotics, digital manufacturing, and industry 4.0, which demonstrates significant research and grant potential in engineering and cross-disciplinary applications. He is a member of IET, AAAI, AIAA, and ASME, a Fellow of HEA, and a Fellow of IMechE. He is also a Chartered Engineer. He has published over 100 academic articles in both high-impact international academic journals and international conferences and has been selected as a Publons' top 1% of reviewers in computer science and engineering. He has been actively involved in both academic research and KTP projects as a PI and a CoI funded by EPSRC, U.K., Horizon2020 (EU), NSFC, China, the National Key Research and Development Program of China, and industrial funding bodies. One of the co-organizers of the WCCI'16 Special Session on Computational Intelligence for Industry 4.0 and the CEC'19 Special Session on Evolutionary Computation for Creativity, Manufacture and Engineering Management in the Industry 4.0 Era. Besides, he is an Editorial Board Member, and he has been a Guest Editor for five special issues.

YUN LI (S'87–M'90–SM'17) received the B.S. degree in electronics from Sichuan University, in 1984, the M.E. degree in electronic engineering from the University of Electronic Science and Technology of China, in 1987, and the Ph.D. degree in parallel computing and control from the University of Strathclyde, in 1990.

In 1989, he was a Control Engineer with the U.K. National Engineering Laboratory. In 1990, he was a Postdoctoral Research Engineer with Industrial Systems and Control Ltd., Glasgow. From 1991 to 2018, he was a Lecturer, a Senior Lecturer, and a Professor with the University of Glasgow and served as the Founding Director of the University of Glasgow Singapore. He is currently a Distinguished Professor with the Dongguan University of Technology, China, where he is also the Founding Director of the Industry 4.0 Artificial Intelligence Laboratory. He has published 260 articles, one of which is seen the most popular article in the IEEE TCST every month and another is the third most popular article in the IEEE TSMC-B. Since 1991, his research interest has been computational intelligence and its applications.

Dr. Li is an Associate Editor of the IEEE TEVC, TNNLS, and TETCI. He is an FRSA and chaired the U.K. funding council's first Industrial Systems in the Digital Age conference "Looking Beyond Industry 4.0" in Glasgow, in 2017.