https://doi.org/10.21289/KSIC.2020.23.2.125

Autonomous Tracking of Micro-Sized Flying Insects Using UAV: A Preliminary Results

Chanyoung Ju, Hyoung Il Son*

〈Abstract〉

Tracking micro-sized insects is one of the challenges of protecting ecosystems and biodiversity. In this study, we propose an approach for the autonomous tracking of micro-sized flying insects, and develop an unmanned aerial vehicle (UAV)-based robotic system. The Kalman filter is applied to the received signal strength emitted from radio telemetry to estimate the position while reducing the measurement error and noise. The autonomous tracking strategy is a method in which the UAV rotates at one point to measure the signal strength and control its position in the strongest direction of the signal. We also design a system architecture comprising a tracking sensor system and a UAV system for micro-sized insects. The estimation and autonomous tracking of the target position by the proposed system are verified and evaluated through dynamic simulation. Therefore, in this study, we propose and validate a UAV-based tracking system for micro-sized flying insects, which has not been proposed in studies conducted thus far.

Keywords : Micro-sized flying insects, Localization, Autonomous tracking, Unmmaned aerial vehicle, Radio telemetry

* Corresponding Author, Professor, Dept. of Rural and Biosystem Engineering, Chonnam National University, 77 Yongbong-ro, Buk-gu, Gwangju 61186, South Korea
E-mail: hison@jnu.ac.kr, Tel: 062-530-2152

1. Introduction

Tracking wildlife is crucial to protecting and managing ecology and biology. The radius of action, main habitat, and the number of endangered species can be effectively recognized by monitoring the movements of animals and insects. Therefore, localization and tracking have been studied using sensor networks to identify the activities of dynamic animals [1]. Recently, mobile vehicles and robots have also been introduced to deal with environmental diversity and uncertainty and to improve maneuverability [2]. Among them, aerial robots are attracting attention to solve challenging problems, such as the active localization and flexible tracking of targets as they fly without restrictions at certain places in contrast to ground robots [3]. The objective of this study is to investigate the use of an aerial robot (i.e., unmanned aerial vehicle or UAV) system for the localization and autonomous tracking of a micro-sized target.

In the tracking of dynamic animals and small insects using a UAV, studies on the behavior of targets (not micro-size, from large to small) have been conducted [4-5]. Various localization, mapping, path planning, and autonomous tracking algorithms based on aerial robots for tracking wildlife (e.g., bird [6], yellow-eyed penguins [7], rhino [8], and bear [9]) have been proposed. However, as evaluating the impact of exotic species on the ecosystem in response to climate change is becoming increasingly important, the tracking of the movements of micro-sized insects having small weight and size is attracting attention as a significant challenge in the future.

For example, the yellow-legged or Asian hornet, also known as *Vespa velutina*, has caused tremendous damage to the beekeeping industry and ecosystem as its activities spread from Asia to Europe [10]. The Asian hornet also threatens people in urban areas; nevertheless, no robotic system has yet been reported to estimate its location or to track its trajectory autonomously. Recently, tracking methods through which humans can listen to the output of an audio signal have been used to track the Asian hornet [11]. Therefore, the tracking robotic systems for micro-sized flying insects such as the Asian hornet are effective in managing alien species, protected species, and natural ecosystems, and further have the advantage of preserving biodiversity.

Animal tracking systems mainly include (Ⅰ) visual-sensor-based system (e.g., stereo camera, thermal camera); (Ⅱ) satellite-based global positioning system or Argos system; (Ⅲ) radio-signal-based harmonic radar system, radio-frequency identification (RFID) system, or radio telemetry system~ [12]. In this study, to select a tracking method for micro-sized insects based on a UAV, we considered three conditions: (ⅰ) the weight of the sensor to be attached to the target (e.g., transmitter and tag); (ⅱ) the weight of the sensor to be attached to the UAV (e.g., receiver and camera); (iii) the traceable distance.

First, (Ⅰ) does not need to consider the condition of (ⅰ) because the visual sensor is only attached to the UAV to track the micro-sized target. However, it is not an appropriate approach owing to its limited performance of (iii). Second, (Ⅱ) sufficiently satisfies the conditions of (ⅱ) and (iii); however, this is also not an appropriate approach because tiny sensors required to be attached to micro-sized insects do not exist [13]. Finally, as (Ⅲ) adequately satisfies the conditions of (ⅰ), (ⅱ), and (iii), we approached the development of a UAV system for tracking micro-sized flying insects using this method.

However, in the method of (Ⅲ), RFID has a limited detection distance (typically within 1-5 m) and is used within specific environments [14]. Therefore, RFID is not suitable for the active tracking of micro-sized flying insects in the field. Consequently, most researchers use a harmonic radar or radio telemetry to track the behavior, movement, and evolution of wildlife or insects. Generally, a harmonic radar uses fixed radars to track targets; hence, it has a fixed detection area (less than 1 km in diameter) and uses passive tags (no battery in the tag) so that the availability of tag power is not continuous [15]. There also exists a dynamic harmonic radar system with a large vehicle, but it is difficult to develop an autonomous UAV system (the objective of this study) using this approach because the payload of a UAV is usually less than 5 kg. Most of the harmonic radar systems that track small insects are static/fixed and huge radars are used in them [16]. Therefore, a harmonic radar is not appropriate to develop an autonomous UAV system with superior maneuverability and scalability.

In the case of radio telemetry using an active transmitter, the weight of the receiver is within the payload of the UAV; hence, it is applied to a UAV-based autonomous tracking system. Nevertheless, it is used to track insects that are heavy owing to the limitations on the weight of the transmitter [15]. Furthermore, radio telemetry remains challenging for tracking micro-sized species owing to their short tracking range (typically 100-500 m) [15]. Therefore, this study aims to develop a radio-telemetry-based autonomous UAV system that can track micro-sized flying insects such as wasps [17] and beetles [18].

1.1 Contributions

In this paper, we propose an autonomous tracking strategy for micro-sized flying insects based on a UAV system. That is, the UAV autonomously tracks the estimated position of the target while receiving the signal strength emitted from a transmitter (radio telemetry). In the case of localization, the Kalman filter is applied to reduce measurement error and noise. Autonomous tracking is a strategy to generate the path of a UAV while computing the strongest direction of the measured signal. Dynamic simulations demonstrate the validity of our proposed system through tracking scenarios. In summary, our main contributions are as follows:

- We propose a systematic approach for the autonomous tracking of micro-sized flying insects.
- We implement and evaluate a UAV-based tracking system that solves the limitations (e.g., small species and short tracking range).

2. Localization and Tracking of Target

2.1 Kalman-filter based localization

In this paper, we focus on the range-based localization and the received signal strength intensity (RSSI), which is used as a representative tracking approach for the dynamic target. The Kalman filter is applied to improve the localization performance for the micro-sized flying target while reducing the measurement noise.

The Kalman filter is a recursive filter that estimates states based on measurements that contain noise or error. It is mainly applied in the area of localization and tracking. Therefore, the Kalman filter estimates the state of the dynamic system modeled as

$$x_{k=} Ax_{k-1} + w_k \tag{1}$$

where x_k is the state vector at time k, A is the state transition model which is applied to the previous state x_{k-1}, $w_k \sim N(0, Q_k)$ is a random variable that represents the process noise, normally distributed with zero mean and covariance matrix Q_k.

The observation (or measurement) term z_k of the true state x_k is defined as

$$z_k = Hx_k + v_k \tag{2}$$

where H is the observation matrix that related the current state x_k to the observed measurement z_k at time k, $v_k \sim N(0, R_k)$ is the observation noise which is assumed to be zero man Gaussian white noise with covariance matrix R_k.

The Kalman filter is a series of processes consisting of two states: time update (i.e., predict) and measurement update (i.e., correct). The phase of time update uses the state estimates from the previous step to produce an estimate of the state of the current step. This predicted state estimate is also defined as the *a priori* state, denoted by $\hat{x}_t^-$. In the phase of measurement update, the current *a priori* prediction is combined with the current observation information to update the state estimate. This improved estimation of the current state is termed the *a posteriori*, denoted by $\hat{x}_t$.

The equation for predicting the current

state and error covariance of the Kalman filter (time update) is defined as

$$\hat{x}_t^- = A\hat{x}_{t-1} \tag{3}$$

$$P_t^- = AP_{t-1}A^T + Q \tag{4}$$

The measurement update phase of the Kalman filter, which calculates the Kalman gain and updates the measurements and the error covariance, is denoted by

$$K_t = P_t^- H^T (HP_t^- H^T + R)^{-1} \tag{5}$$

$$\hat{x}_t = \hat{x}_t^- + K_t(z_t - H\hat{x}_t^-) \tag{6}$$

$$P_t = (I - K_t H)P_t^- \tag{7}$$

The terms K_t, P_t^-, and P_t represent the Kalman gain, the covariance of the *a priori*, and the covariance of the *a posteriori*, respectively. The other terms are the same terms expressed in Eq. (1) and (2).

The update process of the Kalman filter requires a model of measurement or system. In our approach, we need to define a signal propagation model as the UAV tracks the radio signal emitted from the micro-sized flying target. Therefore, we take a signal propagation model, log distance path-loss model, that is appropriate to represent RSSI measurements [19]. The log distance path-loss model used to correlate the distance between the transmitter and receiver based on the received signal strength (RSS) is defined as

$$h_\psi(x, O) = P_{d_0} - 10n\log\frac{D_\psi(x, O)}{d_0} \tag{8}$$

where $h_\psi(x, O)$ is the RSSI measurement function between the target's position $x = [x_x, x_y]$ and the observer's position $O = [O_x, O_y]$ with heading angle ψ, P_{d_0} is the received signal strength (i.e., power) at the reference distance d_0, n is an environmental factor with a range from 2 to 4 (i.e., path-loss exponent), and $D_\psi(x, O)$ is the Euclidean distance between x and O. In this equation, $D_\psi(x, O)$ can be found by substituting $h_\psi(x, O)$ for P_{D_ψ} (RSSI) calculated at any $D_\psi(x, O)$.

In field environments such as forests and

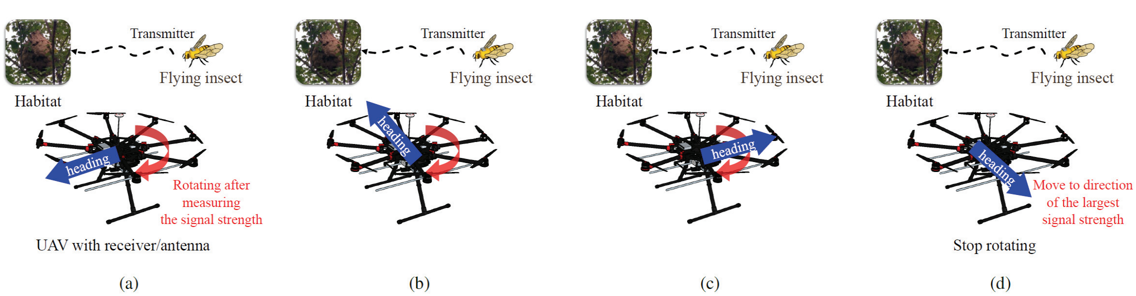

Fig. 1 UAV-based autonomous tracking strategy. (a) Step 1 (b) Step 2 (c) Step 3 (d) Step 4

non-urban areas, RSS is greatly affected by noise. Assuming these noises are white, the total RSS measurement z is defined as

$$z = h_{\psi}(x, O) + v \tag{9}$$

Algorithm 1 Tracking strategy

input: orientation $\phi_t = \{\phi_1, \phi_2, ..., \phi_t\}$, UAV current position O, UAV current heading ψ, desired distance D_o

UAV position input $O_d \leftarrow O$

UAV heading input $\theta \leftarrow \psi$

$D_{\psi}(x, O) \leftarrow D_0 + C$

While $D_{\psi}(x, O) \leq D_0$ do

  $\alpha \leftarrow 0$

  for $i = 1$ to K do

    $\theta \leftarrow \phi_i$

    Compute $h_{\psi_i}(x, O), D(\phi_i)$ by Eq. (10)

    $\alpha \leftarrow \max(\alpha, h_{\psi}(x, O))$

  end for

  for $j = 1$ to K do

    if $h_{\psi}(x, O) = \alpha$ then

      $D_{\psi}(x, O) \leftarrow D_{\psi_j}(x, O)$

      $\theta \leftarrow \phi_j$

      $O_d \leftarrow O_d + D_{\psi}(x, O) \dfrac{\vec{\theta}}{\| \theta \|}$

    end if

  end for

end while

output: $\theta, D_{\psi}(x, O)$

2.2 Autonomous tracking strategy

The tracking algorithm based on UAV is described in Algorithm 1. As the period of the signal emitted from the transmitter is very slow, it takes approximately 30 to 60 sec. to receive the signal while rotating the antenna by 10°, even if the rotation time of the UAV is excluded. As the position of the target (i.e., flying insect) varies from time to time, the rotation time must be minimized. In this study, the UAV aims to track the target while measuring the signal for only four orientations ψ_k (i.e., 0, 90, 180, and 270°). The steps are described more specifically as follows:

(1) The moving UAV stops and measures the RSS at the current position. (Fig. 1(a))

(2) The UAV rotates in place at a certain angle (e.g., 90° in clockwise direction) to measure the signal strength. (Fig. 1(b) and 1(c))

(3) The direction in which the RSS is the largest is regarded as the direction in which the target is located, and the UAV advances in the corresponding direction (Fig. 1(d)). As the UAV can be translated in a space, it is possible to reduce the rotation time by reducing one step to return to its initial direction (i.e., the direction shown in Fig. 1(a)).

(4) Although the range-based localization approach, it can move to the estimated direction and distance based on the tracking strategy as the UAV is also interested in the RSS measured in the 90° direction of the antenna (blue-colored arrows in Fig. 1).

(5) Even if the target stops at habitat, the

tracking process continues until the relative distance between the UAV and the target decreases by a certain distance. Therefore, the tracking process completes when the relative distance is close enough.

3. Aerial Tracking System for Micro-sized Flying Insects

In this study, a UAV-based tracking system is proposed to estimate and autonomously track the positions of micro-sized flying insects. The concept of the proposed system is shown in Fig. 2. The overall system is composed of the tracking sensor system and the UAV system. The radio-telemetry-based tracking sensor system mainly includes a transmitter, receiver, and Yagi antenna, and the UAV system includes a flight controller, companion computer, and various UAV sensors (e.g., barometer, gyroscope, magnetometer, and accelerometer).

An octocopter having a large payload was built to mount the radio telemetry receiver and Yagi antenna. The Pixhawk2 was used as the flight controller to control the UAV directly with various sensors, and the Raspberry Pi 3 was used as the companion/onboard computer (compute module) to mount the high-level controller. The companion computer communicates with the radio receiver via RS232 to USB communication.

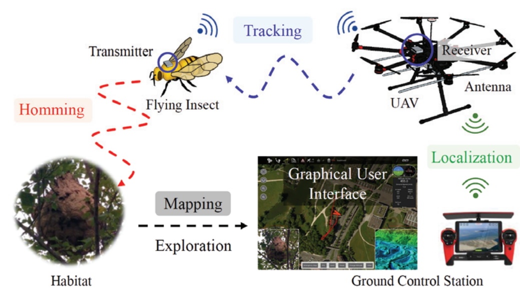

Fig. 2 Concept of the aerial tracking system for micro-sized radio-tagged flying insect

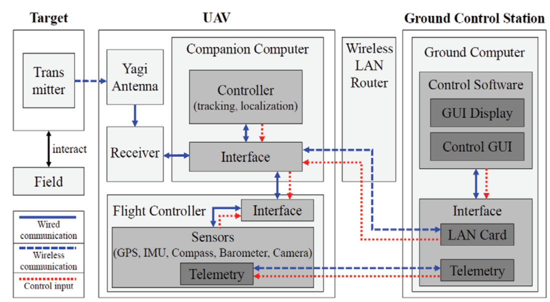

Fig. 3 Diagram of the system architecture

In particular, the voltage input for gain control can be provided directly to the receiver, which is connected to the Yagi antenna with a coaxial cable. That is, data are transmitted from the signal of the transmitter attached to the flying insect in the order of antenna, receiver, and companion computer.

Fig. 3 shows a diagram of the UAV-based tracking system architecture. The solid blue line represents wired communication, the blue dotted line represents wireless communication, and the red dotted line represents the control input signal. The information of the UAV and the estimated target position are displayed in the software of the ground control station via telemetry radio and LAN card. Each communication and controller is implemented through a robot operating system (ROS). Here, the path through which the UAV should fly is also computed by the onboard computer, and the position and velocity of the UAV can be controlled through the ROS and MAVLink protocols. Low-level commands are sent from the high-level controller to the flight controller, and the Pixhawk directly controls the motor.

4. Experiments and Discussions

4.1 Dynamic simulations

To validate the tracking strategy, a software-in-the-loop simulation was performed using the robotic simulation software program Gazebo with robot op-erating system as shown in Fig. 4. It is assumed that the speed of the flying insect is 6 m/s, and that the insect moves from the starting position (i.e., the releasing location) to the target position (i.e., habitat) along the trajectory, including the random Gaussian function. Moreover, the path of the flying insect was created to be globally straightforward according to expert

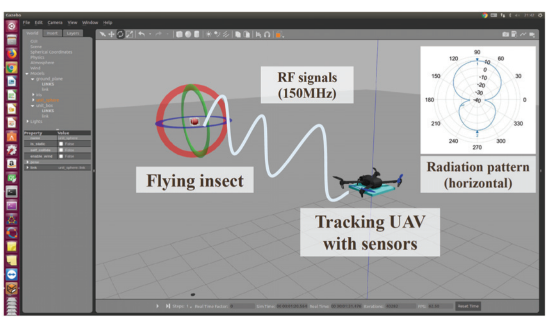

Fig. 4 Simulation environments

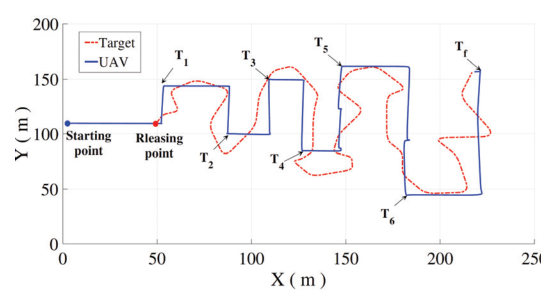

Fig. 5 The trajectory of target and UAV

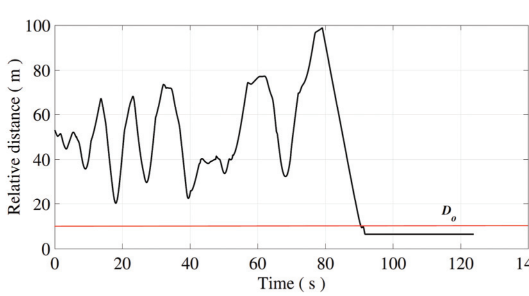

Fig. 6 Relative distance between target and UAV

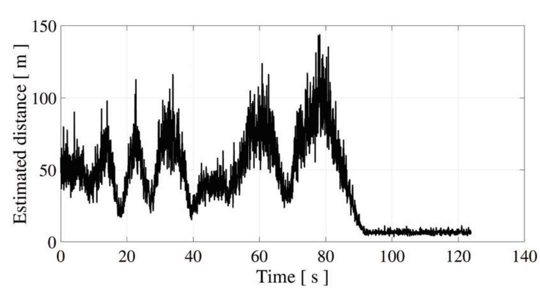

Fig. 7 Estimated relative distance

Table 1. Experimental results of simulation

time	Orientation	RSSI	Distance	Relative distance
T_1	0°	-52.500	69.263	47.958 m
	90°	-52.767	71.425	
	180°	-54.466	86.856	
	270°	-54.374	85.941	
T_2	0°	-48.234	42.384	52.611 m
	90°	-52.109	66.214	
	180°	-52.795	71.656	
	270°	-49.061	46.618	
T_3	0°	-50.952	57.955	57.986 m
	90°	-51.974	65.193	
	180°	-52.601	70.073	
	270°	-52.548	69.647	
T_4	0°	-44.398	27.252	25.145 m
	90°	-48.234	42.384	
	180°	-49.148	47.087	
	270°	-44.748	28.373	
T_5	0°	-51.304	60.353	41.771 m
	90°	-52.095	66.107	
	180°	-54.740	89.604	
	270°	-52.736	71.170	
T_6	0°	-51.967	65.140	69.545 m
	90°	-54.527	87.468	
	180°	-55.574	98.673	
	270°	-52.673	70.656	
T_7	0°	-39.776	16.007	9.790 m
	90°	-38.794	14.296	
	180°	-35.133	9.379	
	270°	-38.883	14.360	

advice. At this time, the movement of the flying insect was depicted as the dynamic movement of a sphere point. An Iris+ model of 3DR Inc. was adopted as the tracking UAV and this model has dynamic characteristics in this simulator. It was assumed that the flying insect and the UAV float at the same height (i.e., 5 m). Therefore, the transmitter attached to the flying insect generates a signal of the same intensity at a period of 1 Hz (frequency range is 150 MHz), and the mathematical model of the receiver and the antenna (calculated in Sec. 3) is implemented in the dynamic simulator. This receiver can change the gain value by adjusting the voltage input. However, in this experiment, the gain value is constant. The RSS calculated from the directivity model is transferred to the companion computer (system memory), and the UAV moves a relative distance in the direction with the largest RSS value after rotating.

4.2 Experimental results

Figs. 5-7, and Table 1 show the experimental results of localization and tracking performance based on UAV system for dynamic targets. In Fig. 5, the trajectory of the micro-sized flying insects (red line) and the tracking UAV (blue line) are presented in the $X-Y$ coordinate. In the case of the dynamic target, the flight starts from the releasing point about (50, 100) to the final point about (220,160), and the UAV tracks autonomously the radio signal emitted from the dynamic target. Fig. 5 also clearly shows that the UAV tracks the target without missing. In the simulation results, we defined the time when UAVs reach the final position as T_f, $\frac{1}{7}T_f$ as T_1, $\frac{2}{7}T_f$ as T_2, ..., $\frac{6}{7}T_f$ as T_6 to present detailed measurement.

The distance difference between the

dynamic target and the UAV over time is shown in Fig. 6. It can be observed that the distance difference between the two gradually decreases from approximately 80 sec. because the flying insect reaches the habitat and does not move anymore, and the UAV continues to move to that location. Before the target is stopped (i.e., before 80 sec.), it can be seen that the relative distance to the target decreases or increases because the UAV continues to repeat the localization and tracking process. After narrowing the distance from the flying insect, if the relative distance $D_{\psi}(x,O)$ is smaller than the desired distance D_O set in Algorithm 1, it can be confirmed that the UAV has stopped the tracking process as shown in Fig. 6 (after 90 sec.).

Fig. 7 shows the results of the localization for the dynamic target over time. That is, this value means $D_{\psi}(x,O)$ calculated from the Kalman filter-based localization algorithm. However, this value is the radius of the certain range, not distance, in range-based localization. However, in our tracking strategy, we set this radius to a scalar quantity in the ψ direction. Compared to Fig. 6, which shows the actual relative distance, Fig. 7 shows the performance with an estimated error of up to 50 m. In the case of the localization result (80 sec.), in other words, the actual relative distance is 100 m, but the estimated distance is about 150 m. This result (i.e., localization of micro-sized flying insect) tends to be less than the performance of localization for static targets as the system or measurement noise occurred. Nevertheless, it can be seen that the influence of the error can be disregarded when the distance between the UAV and the target is sufficiently close.

Table 1 describes the detailed values of the computed RSSI and estimated distance at a specific time. ψ denotes the heading angle of the UAV, $h_{\psi}(x,O)$ presents the RSSI measurement, $D_{\psi}(x,O)$ represents the estimated relative distance, and the extra value indicates the actual relative distance. That is, the UAV estimates the direction in which the target is located through the $h_{\psi}(x,O)$ function. Once the direction is determined, the UAV flies to track the flying insect based on $D_{\psi}(x,O)$. In this process, the Kalman filter is applied to the system with linear and Gaussian distribution to improve the tracking performance by reducing the measurement error.

Although the developed approach in this study is an efficient method to track micro-sized flying insects, it should not be overlooked that most systems are nonlinear dynamic systems. Therefore, if an extended Kalman filter or particle filter is applied in the proposed system, the dynamic target can be estimated and tracked more quickly and accurately. Alternatively, if an event-driven heterogeneous robot system (e.g., UAV equipped with a thermal infrared camera and radio-tracking UAV) is applied to the tracking of micro-sized targets, it is more scalable and more useful than conventional systems [20].

5. Conclusion

In this study, we proposed a UAV-based approach for tracking micro-sized flying insects. The Kalman filter is applied to the receiver signal strength to improve the performance of position localization. Based on this value, we proposed a strategy for UAVs to track flying insects autonomously, and we constructed/performed a dynamic simulation to validate the developed system. The simulation results demonstrated that the proposed method can estimate and track the position of the target. It was also confirmed that the UAV reaches the final position of the habitat without missing the object. Although the performance of position localization is not highly accurate, it can be solved sufficiently by considering a filter for a nonlinear system (e.g., particle filter and extended Kalman filter). These results validate our approach, and the system developed in this study could be used to track and manage micro-sized animals and insects in the ecosystem.

In the future, practical experiments will be conducted using flying insects and a tracking UAV carrying an antenna and a receiver. Furthermore, to reduce the tracking time and improve the tracking accuracy, (i) several antennas will be used in one UAV, (ii) several UAVs having individual antennas will be swarmed together [21-22], or (iii) extended Kalman filter, unscented Kalman filter, and particle filter are applied to the localization algorithm in our proposed system.

Acknowledgments

This work was supported by the Korea Institute of Planning and Evaluation for Technology in Food, Agriculture, Forestry and Fisheries (IPET) through the Agri-Bio Industry Technology Development Program, funded by the Ministry of Agriculture, Food and Rural Affairs (MAFRA) (316038-3).

References

[1] J. I. Huircan, C. Mũnoz, H. Young, L. Von Dossow, J. Bustos, G. Vivallo, and M. Toneatti, "Zigbee-based wireless sensor network localization for cattle monitoring in grazing fields," Computers and Electronics in Agriculture, vol. 74, no. 2, pp. 258–264, 2010.

[2] J. Kim, S. Kim, C. Ju, and H. I. Son, "Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications," IEEE Access, vol. 7, pp. 105100–100115, 2019.

[3] K. S. Christie, S. L. Gilbert, C. L. Brown, M. Hatfield, and L. Hanson, "Unmanned aircraft systems in wildlife research: current and future applications of a transformative technology," Frontiers in Ecology and the Environment, vol. 14, no. 5, pp. 241–251, 2016.

[4] H. V. Nguyen, M. Chesser, L. P. Koh, S. H. Rezatofighi, and D. C. Ranasinghe, "Trackerbots: Autonomous unmanned aerial vehicle for real-time localization and tracking of multiple radio-tagged animals," Journal of Field Robotics,

vol. 36, no. 3, pp. 617–635, 2019.

[5] O. M. Cliff, D. L. Saunders, and R. Fitch, "Robotic ecology: Tracking small dynamic animals with an autonomous aerial vehicle," Science Robotics, vol. 3, no. 23, p. eaat8409, 2018.

[6] O. M. Cliff, R. Fitch, S. Sukkarieh, D. L. Saunders, and R. Heinsohn, "Online localization of radio-tagged wildlife with an autonomous aerial robot system," in Robotics: Science and Systems, 2015.

[7] C. G. Muller, B. L. Chilvers, Z. Barker, K. P. Barnsdale, P. F. Battley, R. K. French, J. McCullough, and F. Samandari, "Aerial vhf tracking of wildlife using an unmanned aerial vehicle (uav): comparing efficiency of yellow-eyed penguin (megadyptes antipodes) nest location methods," Wildlife Research, vol. 46, no. 2, pp. 145–153, 2019.

[8] M. Olivares-Mendez, C. Fu, P. Ludivig, T. Bissyand´e, S. Kannan, M. Zurad, A. Annaiyan, H. Voos, and P. Campoy, "Towards an autonomous vision-based unmanned aerial system against wildlife poachers," Sensors, vol. 15, no. 12, pp. 31362–31391, 2015.

[9] M. A. Ditmer, J. B. Vincent, L. K. Werden, J. C. Tanner, T. G. Laske, P. A. Iaizzo, D. L. Garshelis, and J. R. Fieberg, "Bears show a physiological but limited behavioral response to unmanned aerial vehicles," Current Biology, vol. 25, no. 17, pp. 2278–2283, 2015.

[10] F. Requier, Q. Rome, G. Chiron, D. Decante, S. Marion, M. Menard, F. Muller, C. Villemant, and M. Henry, "Predation of the invasive asian hornet affects foraging activity and survival probability of honey bees in western europe," Journal of Pest Science, vol. 92, no. 2, pp. 567– 578, 2019.

[11] P. J. Kennedy, S. M. Ford, J. Poidatz, D. Thi´ery, and J. L. Osborne, "Searching for nests of the invasive asian hornet (vespa velutina) using radio-telemetry," Communications biology, vol. 1, no. 1, p. 88, 2018.

[12] C. J. Amlaner and D. W. Macdonald, A handbook on biotelemetry and radio tracking: proceedings of an International Conference on Telemetry and Radio Tracking in Biology and Medicine, Oxford, 20- 22 March 1979. Elsevier, 2013.

[13] B. Thomas, J. D. Holland, and E. O. Minot, "Wildlife tracking technology options and cost considerations," Wildlife Research, vol. 38, no. 8, pp. 653–663, 2012.

[14] S. Sarkka, V. V. Viikari, M. Huusko, and K. Jaakkola, "Phase-based uhf rfid tracking with nonlinear kalman filtering and smoothing," IEEE Sensors Journal, vol. 12, no. 5, pp. 904–910, 2011.

[15] W. Daniel Kissling, D. E. Pattemore, and M. Hagen, "Challenges and prospects in the telemetry of insects," Biological Reviews, vol. 89, no. 3, pp. 511–530, 2014.

[16] R. Maggiora, M. Saccani, D. Milanesio, and M. Porporato, "An innovative harmonic radar to track flying insects: the case of vespa velutina," Scientific reports, vol. 9, no. 1, pp. 1–10, 2019.

[17] Q. S. Le, J. Kim, J. Kim, and H. I. Son, "Report on work in progress of small insect tracking system using autonomous uav," in 2017 14th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI). IEEE, 2017, pp. 242–243.

[18] M. Negro, E. Caprio, K. Leo, U. Maritano, A. Roggero, G. Vacchiano, C. Palestrini, and A. Rolando, "The effect of forest management on endangered insects assessed by radio-tracking: The case of the ground beetle carabus olympiae in european beech fagus sylvatica stands," Forest ecology and management, vol. 406, pp. 125–137, 2017.

[19] J. B. Andersen, T. S. Rappaport, and S. Yoshida, "Propagation measurements and models," IEEE Communications Magazine, p. 43, 1995.

[20] C. Ju and H. I. Son, "Modeling and control of heterogeneous agricultural field robots based on ramadge-wonham theory," IEEE Robotics and

Automation Letters, pp. 1–1, 2019.
[21] C. Ju and H. I. Son, “A distributed swarm control for an agricultural multiple unmanned aerial vehicle system,” Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering, vol. 233, no. 10, pp. 1298–1308, 2019.
[22] C. Ju and H. Son, “Multiple uav systems for agricultural applications: control, implementation, and evaluation,” Electronics, vol. 7, no. 9, p. 162, 2018.

(Manuscript received February 27, 2020;
revised March 22, 2020; accepted April 1, 2020)