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Anti-Adaptive Harmful Birds Repelling Method Based on Reinforcement Learning Approach

CHEOL WON LEE[1], (Member, IEEE), AZAMJON MUMINOV[2], MYEONG-CHEOL KO[2], HYUNG-JUN OH[3], JUN DONG LEE[4], YOUNG-AE KWON[5], (Member, IEEE), DEAYOUNG NA[6], SUNG-PHIL HEO[7], AND HEUNG SEOK JEON[2]

[1]Department of Smart Farm Application Research, Electronics and Telecommunications Research Institute, Daegu 42994, Republic of Korea
[2]Department of Software, College of Science Technology, Konkuk University, Chungju 27478, Republic of Korea
[3]Department of Computer Information, Yeungnam University College, Daegu 38541, Republic of Korea
[4]Department of Multimedia Engineering, Gangneung-Wonju National University, Wonju 25457, Republic of Korea
[5]Institute for Innovative Education, Konkuk University, Chungju 27478, Republic of Korea
[6]School of Global Leadership, Handong Global University, Pohang 37554, Republic of Korea
[7]Department of Information and Communication Engineering, Gangneung-Wonju National University, Wonju, 26403, Republic of Korea

Corresponding author: Heung Seok Jeon (hsjeon@kku.ac.kr)

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ABSTRACT To prevent crop damage from harmful birds, various repelling methods have been studied. However, harmful birds are still causing damage in the orchard by adapting to the repelling device according to their biological characteristics. This paper proposes a method called Anti-adaptive Harmful Birds Repelling (AHBR) that uses the model-free learning idea of the Reinforcement Learning (RL) approach to repell harmful birds that can effectively prevent bird adaptation problems. To prevent adaptation, the AHBR method uses a method of learning the bird's reaction to the available threat sounds and playing them in patterns that are difficult to adapt through the RL approach. We also proposed the Long-term and Short-term (LaS) policy to meet the Markov assumptions that make RL difficult to implement in the real world. The LaS policy enable learning of the actual bird's reaction to the sound of a threat. The performance of the AHBR method was evaluated in a closed environment to experiment real harmful bird such as Brown-eared Bulbul, Great Tit, and Eurasian Magpie captured in orchards. Results obtained from the experiment showed that the AHBR method was on average 43.5% better than the threat sound patterns(One, Sequential, Reverse Sequential, Random) used in commercial products.

INDEX TERMS Agricultural engineering, machine learning, intelligent systems, automation, Anti-adaptive repeller.

I. INTRODUCTION

Most orchards are located outdoors to meet the environmental and space requirements for the survival of fruit trees. Birds living around orchards naturally flock to orchards rich in food. For this reason, orchards suffer from the harmful bird around them every year. Fruits are damaged by about 30% of their total annual production, as shown in Fig. 1.

Repelling harmful birds since humans began farming is an important research topic. The various bird repeller researches for protecting farms by harmful birds have been studied from the traditional methods (scarecrow, kite, balloon) to the modern methods (sound gun, sonic repeller, sound repeller), as shown in Fig. 2 [1].

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However, harmful birds are still damaging the orchards. We think the biggest reason is the adaptation of the birds. Most methods of repelling birds work in the early stages, but they become less effective over time. Birds in the early stages of invasion run away because they feel strange to any threat. However, they repeatedly re-invade orchards for the purpose of abundant food. These repetitive invasion experiences allow them to learn and adapt to the threat. In particular, birds have biological characteristics that adapt faster than other species. Birds of the past have traveled long distances in their lives to find their habitat through their wings. So they often faced strange and unfamiliar environments, and as a result evolved to quickly adapt to the environment in order to survive [2]. Without considering the adaptation, It is difficult to prevent the re-invasion of harmful birds in the usual way.

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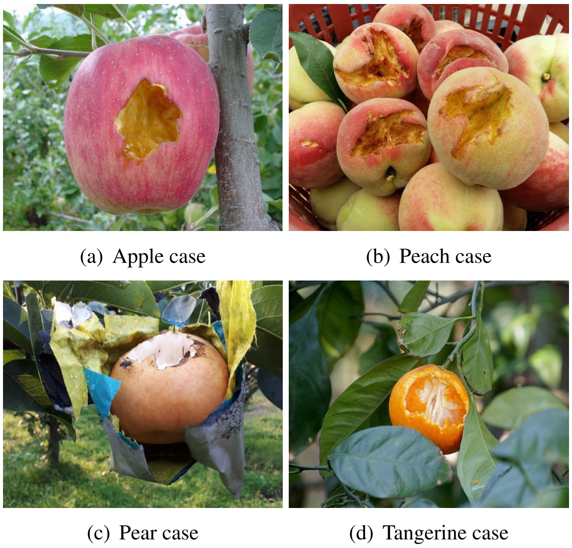
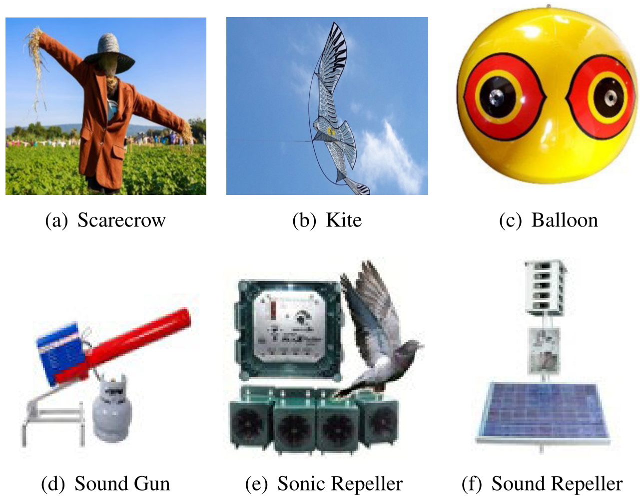


(a) Apple case (b) Peach case (c) Pear case (d) Tangerine case

FIGURE 1. Several orchard cases damaged by harmful bird.



(a) Scarecrow (b) Kite (c) Balloon (d) Sound Gun (e) Sonic Repeller (f) Sound Repeller

FIGURE 2. Variety harmful bird's repellers from traditional to modern.

To prevent the damage of harmful birds on the farm, it is important to prevent adapting to the threat for the re-invasion situation. However, to our knowledge, we have not been able to find studies focused on preventing the adaptation of harmful birds. Most studies related on repelling birds have dealt with adaptation as a small option. For example, Turner PR proposed a kite repellent method that claims that erratic wind fluctuations can prevent the adaptation of harmful birds [3]. This method relies on wind and has the limitation that a kite can be perceived as a non-threatening object when there is no wind. Lee S proposed a method to repel harmful birds by aiming them directly with a laser sensor [4]. This method is difficult to adapt, but works correctly only when it is hit by a harmful bird's eye. Simon G suggested a way to net the entire farm [5]. If the farm is covered with a net, harmful birds cannot enter. However, this method is expensive because the net needs to be replaced every year. Chemical methods have also been proposed [6]–[9]. These methods strongly prevent adaptation, but the effects of chemicals are limited by weather. Ma DF proposed a study to control wild birds using the sound of whistling through the airhole design of a telephone pole [10]. The technique introduces a variety of whistling sounds generated by the wind passing through the hole to prevent adaptation. Zhao Z tried to use natural enemy sounds to repel harmful birds on the speaker [11]. Wei Y used ultrasonic sound to defeat the bird [12].

Most of the previous methods of repelling birds use sound, as described above. This is because sound can cover a wide area relatively easily and has various features. Previous threat sound patterns used in commercial products include simple sound play methods such as one sound, sequential, reverse sequential, and random. However, birds can easily adapt to simple sound play patterns. For example, if the repeller plays the same threat sound without taking into account the bird's reaction, the bird easily learns the sound and perceives it as an environment, not a threat.

Therefore, reaction analysis of harmful birds is necessary for the repelling methods to prevent adaptation through understanding the behavior of them. However, humans are much more difficult to implement technically because it is difficult to fully understand the thoughts of animals. Nevertheless, studies to understand animals based on data are constantly being attempted. In the early days, studies were attempted to analyze animal behavior using the Support Vector Machine (SVM) technique, a kind of machine learning [13], [14]. These methods showed pretty good performance, but were not enough to be applied to the service.

Next, Deep learning (DL) was used as a tool for analyzing animal behavior data. This method requires a lot of data for learning, but it can accurately classify the animal's behavioral data [14], [15]. However, the problem is that previous methods for classifying animal behavior cannot be used for harmful birds because data collection devices cannot be attached to the invaded bird. So, we proposed the Long-term and Short-term (LaS) policy to judge the bird's reaction only with the state of the detected bird without attaching a separate device.

Previously, commercial product threats play sounds according to human-defined threat levels and play plans. We believe that the level of threat of each sound should be determined by the reaction of a harmful bird. In order to threaten based on the bird's reaction, the level for each threat sound must be defined. However, defining the level of threat sound based on a harmful bird's reaction is difficult because the bird's response is stochastic depending on environmental factors such as habitat, species, and individual characteristics. For example, when a bird's habitat is near a construction site, a bird is less sensitive to explosion sounds than a bird in a forest. Therefore, the threat level must be variable.

We use the Reinforcement Learning (RL) approach to measure the variable threat level of threat sounds. RL is an approach to learning the environment like a person by rewarding the agent for its effective behavior [16].

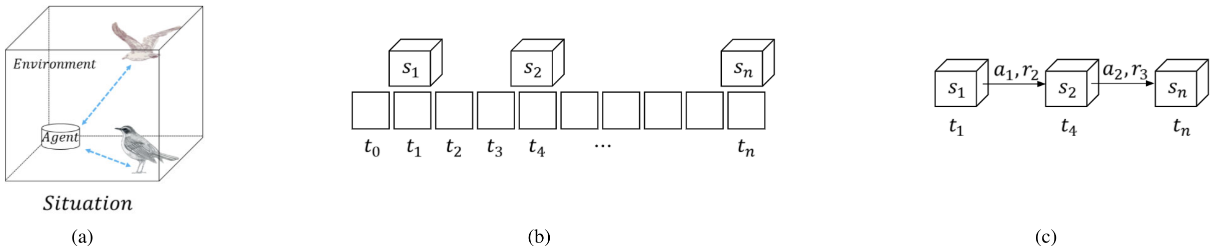


FIGURE 3. Definition of the RL elements in the AHBR method. (a) A Situation definition. (b) Situations in the time table from t_0 to t_n. (c) Relationship between Situation, Action, Reward, and Time in AHBR method.

This method works under the assumption of the Markov property that when the agent does something in its current state, it can know the next state. However, our environment for repelling birds is an environment where the next state cannot be predicted based on the agent's actions. Therefore, we used the Model-free RL method based on Monte Carlo theory. Monte Carlo theory learns only the results obtained through practical experience [17], [18]. The Model-free RL method can calculate the threat level by learning only the reaction of a bird that has occurred without depending on environmental factors.

In this paper, we propose Anti-adaptation Harmful Birds Repelling (AHBR) scheme that finds the optimal threat sound pattern that makes adaptation difficult by determining the reaction of harmful birds based on the LaS policy and rewarding according to the determined reaction using Model-free RL. In general, previous methods improve performance by adding sound that works well, while our method uses given sounds to find the optimal sound pattern. The performance is verified by comparing the previous threat sound playing method with the proposed method through real bird experiments.

The rest of this paper is organized as follows. Section II introduces the AHBR method in detail. Section III shows the experiments, such as adaptation of bird in our environment, analysis sound effect by bird reactions, and the performance of the AHBR method. Finally, Section IV and V consist of discussion and conclusion.

II. THE ANTI-ADAPTATION HARMFUL BIRDS REPELLING (AHBR) METHOD

A. DEFINITION OF ENVIRONMENT FOR USING THE RL APPROACH

The AHBR scheme's environment is defined as the RL element to learn harmful birds, such as *Agent*, *Environment*, *Action*, *Reward*, and *Situation*, as shown in Fig. 3. The *Agent* is a device that can detect harmful birds and operate the AHBR method for repelling. The *Environment* means the range in which the *Agent* can detects birds. The *Situation* is the core definition in our AHBR method. The *Situation* S_n refers to a situation which the *Agent* detected birds in the *Environment*, as shown in Fig. 3 (a). Therefore, repeated invasion of harmful birds can be expressed as S_1 to S_n between time t_1 and t_n, as shown in Fig. 3 (b). The *Agent* takes the *Action* according to the *Reward*. In the AHBR method, the *Action* is to play threat sounds to repel harmful birds. A threat sound is made up of three actions divided into three volume levels. Each volume level is 100%, 70%, and 30% of maximum volume for the speaker. The criteria for classifying volume levels were set to sections in which the repellent effect differed by more than 30% through experiments. Because too little volume difference can be perceived as the same threat. The *Reward* is a reward value for how much the threat sound played by the *Agent* suppressed bird's adaptation. Under these assumptions, if the *Situation* is s_1, the *Action* can be represented by the a_1 and the *Reward* as r_2. Finally, the *Situation* s_n, *Action* a_n, and *Reward* $r_n + 1$ is structured using the RL approach, as shown in Fig. 3 (c).

B. THE LONG-TERM AND SHORT-TERM (LaS) POLICY

Harmful birds can react differently to the same threat sound, depending on their habitat, species, and individual characteristics, as called an unknown Markov Decision Processes (MDP) environment. In an unknown MDP environment, learning is impossible because the RL can't know how the environment will behave according to actions.

We propose a Long-term and Short-term (LaS) policy that can simplify various environmental factors in order to perform the RL in a real environment. The LaS policy is criteria for determining adaptation to learn and evaluate the bird's reaction trying to adapt when they hear a threat sound, as shown in Fig. 4. The states of harmful birds observed by agents can be classified into the invasion, re-invasion, and enduring state. Invasion state means the state of s_1 in Fig. 4 (a) that harmful bird first invaded. The re-invasion state refers to the state of s_2 in which harmful birds have re-invaded after being repelled in s_1. The Enduring state means that the harmful birds endure to the threat played by the agent, as shown in S_2 of Fig. 4 (b).

We defined the adaptation as long-term and short-term through the observable state of the agent. The Long-term adaptation refers to the criteria for adaptation determination when re-invasion is detected after harmful birds are repelled. This means that repelled birds are slowly adapting to current threats. For example, if the interval between s_1 and s_2 becomes longer in Fig. 4 (a), it can be determined that it cannot adapt to the threat played in s_1. Conversely, if the interval between s_1 and s_2 is shortened, it can be determined that harmful birds are gradually adapting to the threat played.

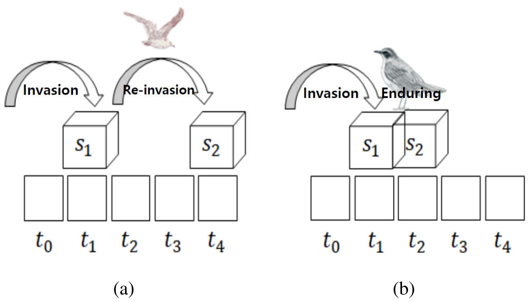


FIGURE 4. The decision criteria of harmful birds adaptation. (a) The Long-term Invasion Situation means the Re-invasion Time. (b) The Short-term Situation means the Enduring Time.

The Short-term adaptation refers to a case in which harmful birds are endured while playing threat sound s_1 in Fig. 4 (b). This means that the detected bird quickly adapts to the current threat. We use the Enduring Limitation (EL) parameter as a Short-term adaptation's decision criteria. The EL parameter is adjusted to the average value of repelling success cases. In the EL parameter 3 cases, this policy judges that the Short-term adaptation has succeeded if the bird endures to the threat sound for 3 seconds. The initial value of the EL parameter is set to 3 because we have given the approximate 3 that is the optimal value in our various experiments. This value is a setting for birds in the Republic of Korea and may vary by region and species of birds. Even if the values are not correct, our AHBR method will find the optimal value as it learns the bird.

Our AHBR method defines an adaptation by using the LaS policy, making it possible to find out which harmful birds attempt to adapt by learning the threat without complex behavioral analysis.

C. THE ANTI-ADAPTIVE METHOD UTILIZING RL POLICY

In this section, we introduce the entire framework of the Anti-adaptive Harmful Birds Repelling (AHBR) method using the RL approach, as shown in Fig. 5. The AHBR method learns the effects of threat sounds from harmful bird's reaction through grading reward using the model-free RL approach with LaS policy. The goal of this method is to play the threat sound in a form that the birds are most unadaptable.

The AHBR method updates the reward for action only through an experience like $Q(s, a)$. We use the idea of Q-learning to update action rewards through action a, state s, changed state s', and reward r as $Q(s, a)$ [16], [17]. the AHBR method basically uses most of the Q-learning concepts, the equation is the same as Q-leaning, such as

$$Q(s,a) \leftarrow (1-a)Q(s,a) + a\left[R(s,a,s') + \gamma \max_{a'} Q(s',a')\right]. \tag{1}$$

The AHBR method works when a bird is detected. The detection part is not covered in this paper. It has already been proven through various studies that it is possible to detect birds and differentiate species using vision-based deep learning [19]–[21]. We assume that we receive a result for a numerical value (0 is not detected, 1 to n are the type of birds) by the detection result. This integer numeric value is assigned sequentially from 1 according to the detection result.

When the situation in Fig. 3 (a) in which a harmful bird is detected occurs, the Initialize New Bird Data step begins, this step creates *BirdType* dataset and initializes the *Rewardtable*. If *BirdType* is not duplicated in harmful birds data *AHBRtable*, a new *BridType* is created, as

$$AHBRtable = \{BridType_1, BirdType_2, \cdots, BirdType_n\}. \tag{2}$$

A *Birdtype* is composed of returning time *RTT*, enduring time *EDT*, and reward table *RewardTable*, as

$$BridType_n = \{RTT, EDT, RewardTable\}. \tag{3}$$

The initial *RewardTable* are arbitrarily initialized to value between 0.0 and *EL*. The *EL* parameter can be set variably according to the environmental condition. This arbitrary initialization of reward allows the AHBR method to consider exploration and exploit issues of the RL [16]. While the AHBR method progresses, these rewards are changed gradually to valid values learned from practical experience. The initial value of *EL* is set to a float greater than 0, change by the average EL parameter of the repelling successful cases.

The Check Returning Time step checks the Long-term adaptation using the returning time *RTT* parameter. The *RTT* is a list to remain bird's invasion history for determining Long-term adaptation of LaS policy, it indicates how long the harmful bird has been delayed from previous invasion time to current invasion time, as

$$RTT_t = InvasionTime_t - InvasionTime_{t-1}. \tag{4}$$

The Update Delayed Reward step compensates according to the returning trend *RTTrend*. The *RTTrend* determines the Long-term adaptation of harmful birds, as

$$RTTrend_t = RTT_t - RTT_{t-1}. \tag{5}$$

A negative value of the *RTTrend* means that the played threat effect is decreased and the bird is gradually adapting to each invasion. The positive value of the *RTTrend* means that the played threat effect is increased and the bird is not adapting. This step only reduces the reward for previously played threat sound when the *RTTrend* is a negative value.

The Select Threat Sounds step only selects the best reward action a through greedy rule in *RewardTable* of *BirdType*, as

$$SelectThreat(BirdType) = \underset{a \in Action}{\operatorname{argmax}}\, RewardTable(a). \tag{6}$$

If the *RewardTable* has more than one of the biggest rewards, this step selects sequentially in the list. The Play Threat sounds step plays the threat sound selected in the previous step.

The Check Repelling Result step converts the bird's reaction to state according to the LaS policy, counts the time before the bird is repelled while the threat sound is playing. The Counted time is the enduring time *EDT*, it is a list

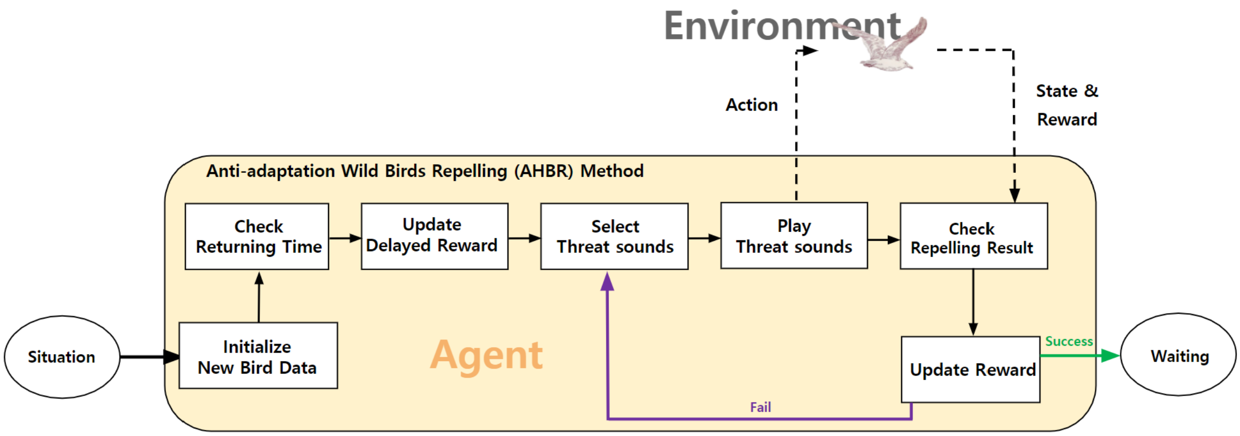


FIGURE 5. **The framework of the Anti-adaptive Harmful Birds Repelling (AHBR) method. It is designed to learn the harmful bird's reaction using the model-free RL. Each element's composition(Agent, Action, Environment, State, and Reward) follows the basic RL.**

to remain enduring history for determining the Short-term adaptation. if the *EDT* is smaller than the set *EL* value, this *Situation* has been successfully repelled in the Short-term adaptation policy.

The Update Reward step rewards for the action according to the Check Repelling Result. At this step, we consider the reward and discount factor for action. If harmful birds are repelled within set *EL* value seconds, the AHBR method perceives that this threat sound is an effective sound. Therefore, the reward value of used action *a* in the *RewardTable* is increased, this reward value is applied as

$$RewardTable(a) \leftarrow RewardTable(a) - EDT_t. \tag{7}$$

The *EDT* is also stored as a history, and trends are analyzed like *RTTrend* as

$$EDTrend_t = EDT_t - EDT_{t-1}. \tag{8}$$

The positive value of the *EDTrend* means that harmful birds were the Short-term adapting to used action. Conversely, the negative value means that the Short-term adaptation of harmful bird is prevented. Then, the reward is updated through LaS policy. The AHBR method has Model-free and On-policy features such as Q-Learning, which can lead to local optimization issues. In this case, there arises a problem of selecting only one sound that has the best effect in known range without any exploring after the passage of time. So, we use a discount factor that prioritizes the most recent reward by updating the values directly in the action reward of the *RewardTable* as

$$RewardTable \leftarrow \gamma RewardTable. \tag{9}$$

The discount factor is applied as γ, the default value is 0.99. This factor prevents the situation that repeatedly plays only the highest threat sound, makes the AHBR method more exploratory.

Finally, the AHBR method updates the reward in the *RewardTable* of each *BirdType* and checks the past *RTTrend* and *ETTrend* whenever a situation occurs, and updates the reward for the current action. Based on the updated reward, the AHBR method can select the sound that the bird feels most threatened with, and this order becomes a pattern.

If repelling fails over the *EL* parameter seconds, the AHBR algorithm adjusts the *EL* value to the average successful *EDT*. And then the process restarts the Select Threat Sounds step after updating the failure reward. The AHBR method, through the repetition of this process, finds a solution to prevent the adaptation of harmful birds like the RL [13]. The detailed flow of the process is shown in Algorithm 1.

Algorithm 1 AHBR Algorithm

procedure AHBR*BirdType*
GET integer *BirdType* when bird detected
if *BirdType* is new **then**
    INIT new *BirdType* reward in *RewardTable*
else if *RTTrend* of *BirdType* is decrease **then**
    DECREMENT reward value for last action in Delayed Reward Update Function
end if
while bird is not repelled **do**
    GET *SelectedAction* that is the best reward in *RewardTable* of *BirdType*
    while *EDT* < *EL AND* bird is not repelled **do**
        PLAY *SelectedAction* through Play Threat Sound Function
        COMPUTE *EDT* that count until the bird was repelled
    end while
    if bird repelling success **then**
        INCREMENT reward of *SelectedSound*
    else if bird repelling failure **then**
        DECREMENT reward of *SelectedSound*
    end if
    INCREMENT reward of unused all sound
    SET changed rewards in *RewardTable* through Update Reward Function
end while

III. EXPERIMENTS

A. EXPERIMENTAL ENVIRONMENTS

In order to quantitatively evaluate the performance of the proposed algorithm, we built a closed environment in which harmful birds must continuously invade for survival. Fig. 6 (a) is the appearance of the cage, and its size is $2.5 \times 4 \times 8m$. Fig. 6 (b) is the inside of the cage with a birdhouse, a model tree, and two food troughs as red box. Fig. 6 (c) is a device for experiments located inside the food trough of Fig. 6 (b). The device consists of a Raspberry Pi 3, a Pi 3 camera for detection, an external battery, and a Bluetooth speaker for playing threat sounds. The speaker is the PISnetHiFi model, the output is $8W$ and up to $16W$, and the frequency is $100Hz$ to $20KHz$.

(a) (b) (c)

FIGURE 6. The environment for the experiment. (a) The appearance of cage. (b) The inside of cage is a birdhouse, a model tree, and two food troughs marked with red boxes. (c) The experiment device for repelling in the trough.

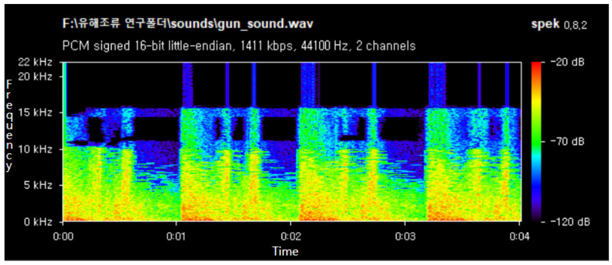
(a) (b) (c)

FIGURE 7. Harmful birds used in experiments. (a) Brown-eared Bulbul. (b) Great Tit. (c) Eurasian Magpie.

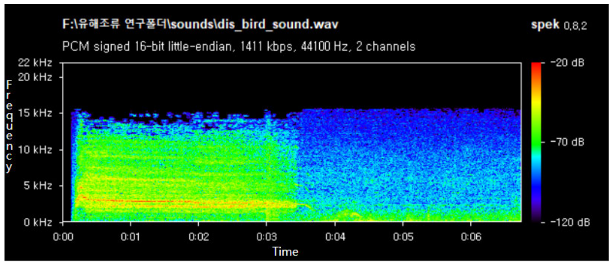
In our experiments, three types of harmful birds were used: Brown-eared Bulbul, Great Tit, and Eurasian Magpie. These harmful birds were captured by traps in the surrounding orchards and released after the experiment. This animal experiment was approved by the Institutional Animal Care and Use Committee of Konkuk University in the Republic of Korea (KU16183).

The audible frequency range of the Eurasian Magpie is $100Hz$-$21000Hz$ [22]. The audible frequencies of Brown-eared Bulbul and Great Tit are unknown, but they are classified as a sparrow species. So we assumed their hearing frequency is $250Hz$-$12000Hz$ [22].

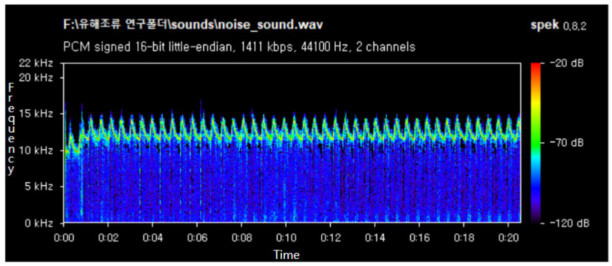
We conducted experiments with sounds commonly used to repel birds, such as explosions, natural enemies, and noise sounds. Fig. 8 is a visualization of the characteristics of each threat sound. The threat sound of an explosion consists of a periodic explosion, as shown in Fig. 8 (a), with a range of $5000Hz$-$22000Hz$. The natural enemy threat sound consists of a hawk's shout as shown in Fig. 8 (b), the range



(a) explosion



(b) natural enemy



(c) noise

FIGURE 8. The visualization of the used threat sound frequency spectrum. (a) Periodic explosion sound (4 times). (b) Hawk's shout sound (One breath). (c) Periodic noise (Radio noise).

is $2000Hz$-$15000Hz$. The noise threat sound consists of repeated noise sounds with short periods and has a range of $11000Hz$-$15000Hz$, as shown in Fig. 8 (c).

B. VERIFICATION OF HARMFUL BIRD ADAPTATION

In this experiment, we validate that they are actually adapting to the threat through food intake data from harmful bird in an stimulus/non-stimulus environments. The experimental method is to compare the apple intake of birds living in cages without any stimulus and the apple intake of birds exposed to persistent threat sounds. Non-stimulus and Stimulus cases were performed individually to avoid interference, and different individuals of the same species were used, approximately 24 cm in length. Fig. 8 (a) explosion sound was used in the stimulus case. The bird intake was measured in units of 4 hours. Fig. 9 (a) shows the experiment result, the x-axis is the average intake per hour and the y-axis is time.

In the Non-stimulus cases, harmful birds ate about 3-4g per hour up to the first 16 hours due to the unfamiliar cage environment. After adapting to the environment, it can be seen from Fig. 9 (a) that the intake amount converges to about 5g in 20 hours. At this time, It means a harmful bird had fully

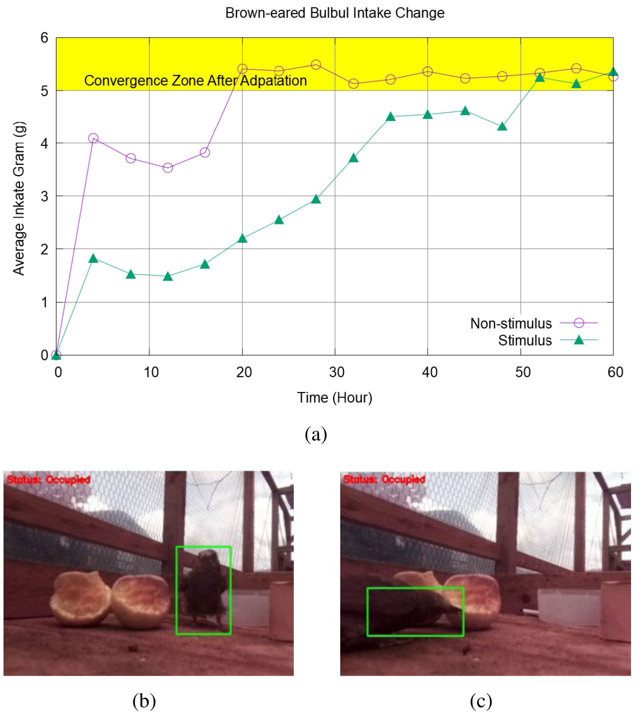


FIGURE 9. Changes in food intake of the Brown-eared Bulbul according to the simulus/non-stimulus environment. (a) Experiment result. As the bird learns and adapts to the environment, its intake converges to a certain amount (yellow box area). (b) The situation where the bird is learning the threat. (c) The situation in which the bird adapts to and feeds on the threat.

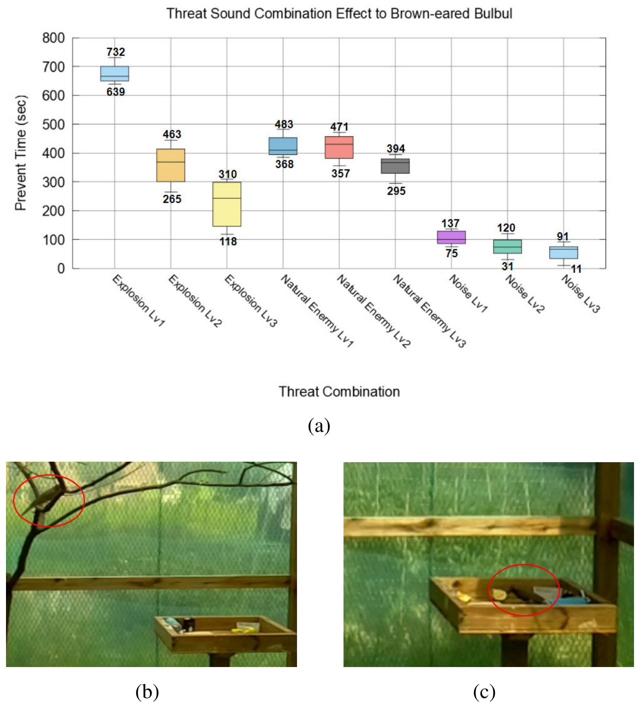


FIGURE 10. The effect of combinations of sounds and volumes to Brown-eared Bulbul. (a) Experiment result. (b) The situation where the bird is learning the threat. (c) The bird has adapted from threat.

adapted to the cage environment. Therefore, adaptation was judged based on the bird's 5g intake (same species and size), as can be seen in the yellow boxed zone in Fig. 9 (a).

The Stimulus case took 52 hours to reach the convergence zone after adaptation, which was 61.6% slower than the Non-stimulus case. Although not shown in Fig. 9 (a), it shows a converged intake of about 5g from 52 to 70 hours. Fig. 9 (b) shows a situation where a bird learns if the sound of a threat is dangerous. Fig. 9 (c) shows a situation where a bird ignores and feeds despite the sound of a threat.

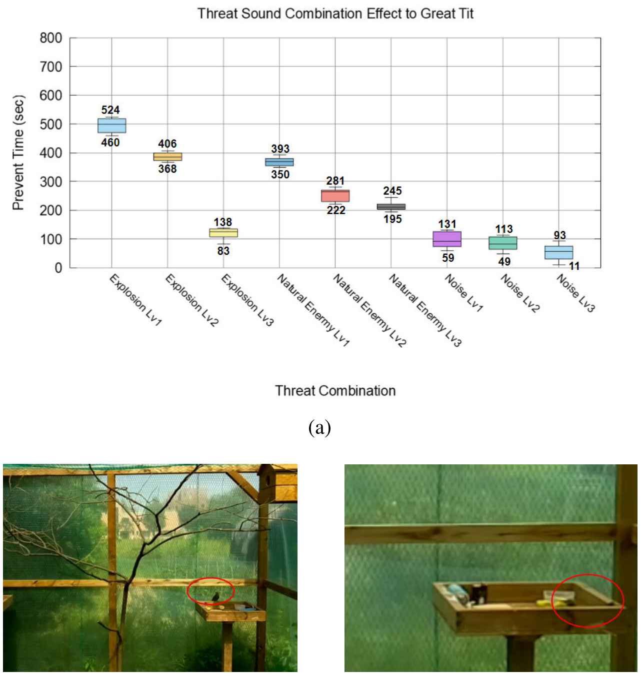
The results of this experiment showed that in both experiments, bird intake converged to an average intake over time. After convergence, the bird was not feel threatened by the sound that occurred, which proves that the bird can learn the threat.

C. COMPARISON OF THREAT SOUND EFFECTS OF DIFFERENT COMBINATIONS

In this experiment, we check two types of birds to see if factors such as the type or size of the threat sound and the species of the bird are correlated. For the experiment, an apple and a repelling device placed in a feeding container as shown in Fig. 10 (b). The only food in this environment is the apple located in front of repelling device. Then, the time from the time the bird was set in the environment to the first pecking of the apple was measured.

We conducted experiments with 5 birds, each of two kinds, Brown-eared Bulbul and Great Tit, which frequently invade Korean orchards. In these experiments, 9 types of threat sounds were used by combining the three sounds (explosion, natural enemy, noise) in Fig. 8 and the volume level (Lv1=100%, Lv2=70%, Lv3=30%) of the speaker. The volume Lv1 of the speaker used in this experiment is 130dB, Lv2 is 80dB, and Lv3 is 60dB. The experiment was measured 10 times per threat sound with a long term over 45 days. The experimental results are shown in Fig. 10-11 (a). The Y-axis of the graph is time (seconds) and the X-axis is the 9 threat sound combinations. Each data in the graph shows the maximum value, average value, minimum value, and deviation of the values of 10 times.

Fig. 10 (a) shows the effect of the threat sound combination on the Brown-eared Bulbul. The most effective threat sound to the Brown-eared Bulbul is explosion and volume Lv1 (100%). This result is related to the maximum audible frequency of Brown-eared Bulbul and the high decibels of the 22000Hz frequency of explosion threat sound. This harmful bird responded sensitively to the explosion combinations, which showed a linear protection time depending on the volume level. The difference according to the volume level of the explosion sound is 45.5 percent for Lv1 and Lv2, 27.6 percent for Lv2 and Lv3. On the other hand, the natural enemy threat sound is not affected by the volume than the explosion threat sound. In the case of a natural enemy sound, the difference between the volume Lv1 and Lv3 is only 13.7 percent, which is relatively small compared to the explosion threat sound. Then, it means the combinations of natural enemy sound threaten regardless of volume level to Brown-eared Bulbul.



(a)

(b) (c)

FIGURE 11. The effect of combinations of sounds and volumes to Great Tit. (a) Experiment result. (b) The situation where the bird is learning the threat. (c) The bird has adapted from threat.

The noise threat sound showed a low repelling effect in most cases.

Fig. 11 (a) shows the experiment result for the Great Tit. This harmful bird showed faster adaptation than the Brown-eared Bulbul in most of the cases. The best repelling performance in this experiment was the explosion threat sound and volume Lv1. The Great Tit was affected by volume level in both explosion and natural enemy combinations. The difference of threat performance between volume Lv1 and Lv3 of the explosion sound is 75.5%, and 43.8% for the natural enemy sound is 43.8%. The noise threat sound was almost ineffective.

The experiment of Brown-eared Bulbul was less affected by the volume of natural enemy threat sound, showed a large deviation in the experiment. On the other hand, the experiment of Great Tit shows the result of being affected by the volume in all cases. Here, we can see that the species of threat sound is correlated according to the species of birds, and the response according to the loudness is different. And this result means that there is an optimal sound that threatens the bird.

D. PERFORMANCE EVALUATION OF AHBR METHOD

This experiment evaluates the performance of the AHBR method to prevent adaptation through optimal threat sounds found by bird's reaction learning. To evaluate the performance, we compare the proposed method with the sound play patterns previously used to repel the harmful bird, such as One Sound, Sequential, Reverse Sequential, and Random patterns. The sound play patterns used 9 combinations of sound types and volume used in Experiment C of the previous section. The experiment was conducted by measuring the time that takes the bird to adapt to the sound pattern and peck an apple. Each pattern of threat sounds is played as the bird approaches. Each pattern was measured five times from Brown-eared Bulbul, Great Tit, and Eurasian Magpie.

Fig. 12 shows the result of the comparison by threat playing pattern. The One Sound pattern plays only one sound when detecting harmful birds, we used threat sound of explosion and volume Lv1. This pattern averaged 610 seconds of repelling performance. The Sequential patterns play sequentially from the weakest threat sound based on the results of Experiment C. For example, the order is noise and volume Lv3, noise and volume Lv2, noise and volume Lv1, natural enemy and volume Lv3, explosion and volume Lv3, natural enemy and volume Lv2, explosion and volume Lv2, natural enemy and volume Lv1, explosion and volume Lv1. In this pattern, the birds have already tended to adapt to relatively weak threat sounds before the stronger threat sounds are played. Repelling performance is averaged 431 seconds. The Reverse Sequential pattern is the reverse order of the Sequential pattern, the threat sounds are played in the strongest order. This pattern averages 714 seconds of repelling performance and is better than the One Sound pattern. The Random pattern randomly plays threat sounds, is repelling performance of 838 seconds, the deviation between the lowest and highest values is large. The results of the Reverse Sequential and Random patterns show that the unfamiliar patterns included even with relatively weak threat sound than the One Sound pattern composed of threat sound with stronger threat effects are effective in preventing harmful bird's adaptation.

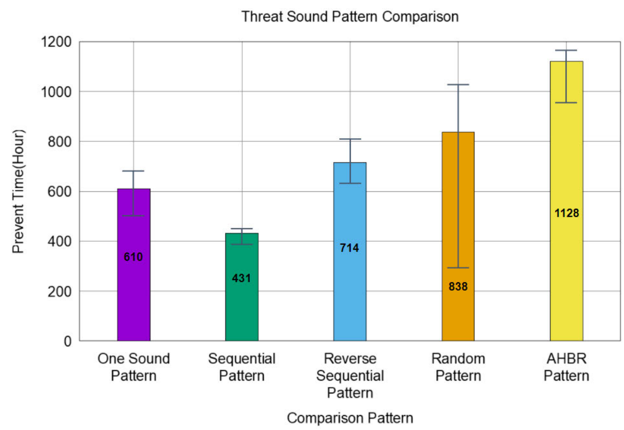
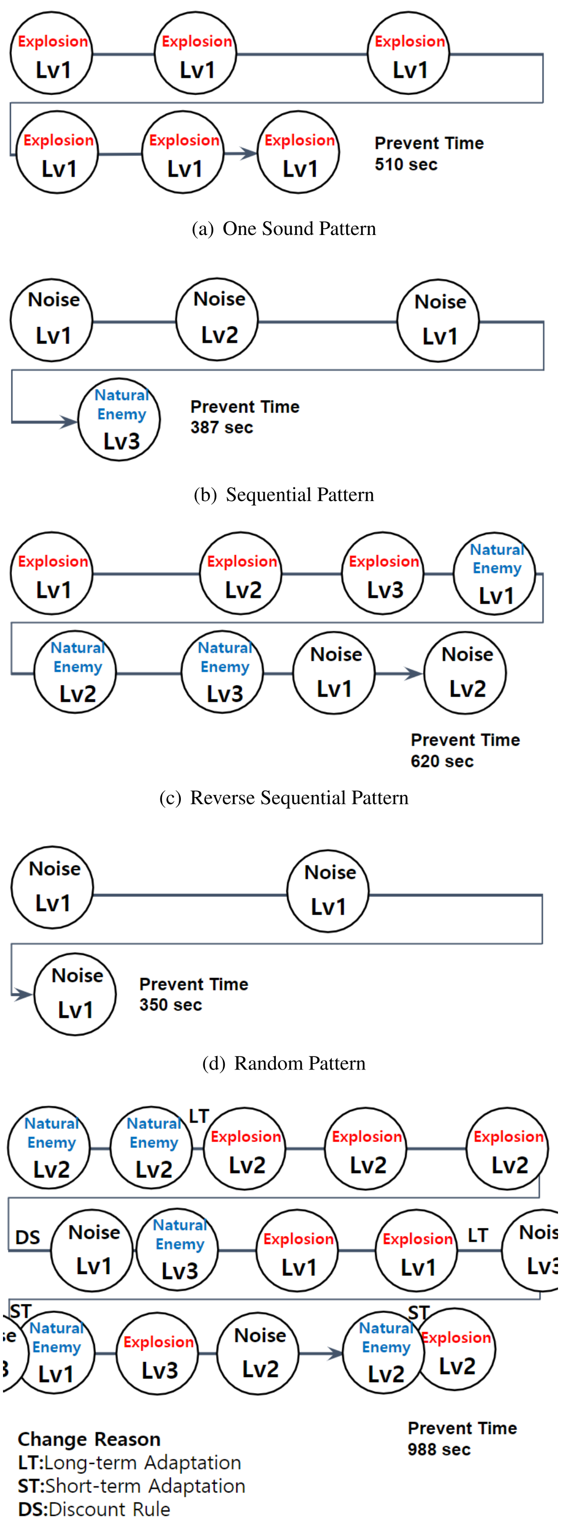


FIGURE 12. Comparison of the AHBR method and other threats playing patterns.

The AHBR pattern showed the best performance of 1128 seconds, which is 46% better than the One Sound pattern and 37% better than the Reverse Sequential pattern. This result indicates that it is more effective to consider harmful bird's reactions than to play the threat sounds regardless of harmful bird's reactions, such as the Reverse Sequential and Random pattern.



(a) One Sound Pattern

(b) Sequential Pattern

(c) Reverse Sequential Pattern

(d) Random Pattern

(e) AHBR Pattern

FIGURE 13. **The worst case of threat sound playing patterns.**

Figure 13 shows what combinations of sounds were used in what order in the worst case of each pattern used in the experiment. In fact, the reason for the large deviation of the random pattern in Fig. 12 can be seen in the case of Fig. 13 (d).

On the other hand, in the case of Figure 13 (e) using the AHBR technique, there were relatively more intrusions than in (a)-(d). Nevertheless, the AHBR method determines the bird's adaptation status based on the LaS policy and shows that it is used various combinations of threat sounds.

IV. DISCUSSION

Most orchards use harmful bird repellers, but they are still suffering enormous damage. And farmers say the problem of adaptation of harmful birds is the biggest difficulty. So, we aim to develop a method to prevent adaptation by learning the reaction of harmful birds by using artificial intelligence techniques and playing the most threatening sound.

Actually, through experiments, the adaptation of harmful birds, the correlation between the species of bird, the type of sound, and the volume was confirmed. This correlation is that each species of bird has a different sound that feels most threatened, which is why the repeller must learn the bird's reaction. In fact, from the experimental results, if the AHBR method learns the reaction of the bird and plays the threat sound that is optimal for repelling it, it can perform better than other previous methods.

However, this study is highly dependent on the combination of types of threat sounds. If a harmful bird adapts to all sounds, it can become impossible to repel. Also, the use of sound to repel harmful birds can cause noise problems. Therefore, as a follow-up study, there is a need for a study of a technique that can use artificial intelligence to generate an optimal repelling sound that is inaudible to humans at the audible frequency of birds.

V. CONCLUSION

In this paper, we proposed the AHBR method based on the RL approach. The AHBR method can delay the invasion by an average of 43.5 percent compared to the sound threat repelling method commonly used to repel birds invading orchards. Although tested in a closed environment, it means 43.5 percent prevention of harmful bird's adaptation more than previous repelling methods. We believe this method will work better in an open real orchard environment. In conclusion, this study proves that unfamiliar pattern even though they are relatively weak among other threat sound is more effective for repelling harmful birds than to play the stronger and known threat sounds.

In addition, proposed in this paper the LaS adaptation decision policy can calculate the adaptability of harmful birds based on detection status without analyzing bird's behavior. This policy can be useful to apply the RL in learning a variety of pests. In the future, we will continue research on applying the latest ideas of other RL and methods of repelling using sounds in the inaudible zone that cannot be heard by humans.

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CHEOL WON LEE (Member, IEEE) was born in Chungju, Republic of Korea, in 1987. He received the B.S., M.S., and Ph.D. degrees in computer engineering from Konkuk University, Chungju, in 2012, 2015, and 2020, respectively.

He is currently a Researcher with the Department of Smart Farm Application, Electronics and Telecommunications Research Institute (ETRI). His research interests include application of vision-related artificial intelligence technology to smart farms and autonomous driving technology of intelligent robots, such as simultaneous localization and mapping (SLAM).

AZAMJON MUMINOV received the B.S. degree in computer engineering from the Tashkent University of Information Technologies, Uzbekistan, in 2015, and the master's and Ph.D. degrees with the Department of Software Technologies, Konkuk University, Chungju, Republic of Korea.

He is also a Research Assistant with the Department of Software Technologies, Konkuk University. His research interests include artificial intelligence, machine learning and deep learning algorithms, the IoT, sensor networks, and GPS algorithms.

MYEONG-CHEOL KO received the M.S. and Ph.D. degrees in computer science from Yonsei University, in 1997 and 2003, respectively.

Since 2004, he has been a Professor of computer engineering with Konkuk University, where he directs the Advanced Visualization and Interaction Technology (AVIT) Research Group. His research interests include 3D computer graphics and human–computer interaction focusing on the design and implementation of augmented reality systems.

HYUNG-JUN OH received the B.S. and M.S. degrees in computer engineering from Hongik University, in 2002 and 2004, respectively, and the Ph.D. degree in computer engineering from Hongik University, in 2013.

Since 2014, he has been an Assistant Professor with the Computer Information Department, Yeungnam University College. His research interests include the IoT applications and information security.

JUN DONG LEE received the B.S., M.S., and Ph.D. degrees in computer science from Hongik Unversity, Seoul, South Korea, in 1990, 1993, and 2001, respectively.

From 1997 to 2007, he was an Associate Professor with the Department of Computerized Information Processing with the Wonju National College. From 2018 to 2020, he was the Vice-Chairman of the Korea Society of Computer and Information. Since 2007, he has been a Professor with the Department of Multimedia Engineering, Gangneung-Wonju National University. His research interests include programming language, the IoT, and platform.

YOUNG-AE KWON (Member, IEEE) received the M.S. degree in computer education from Semyung University, Jecheon, Republic of Korea, in 2000, and the Ph.D. degree in computer engineering from Chungbuk National University, Cheongju, Republic of Korea, in 2011.

She is currently a Professor with the Institute for Innovative Education, Konkuk University, Chungju, Republic of Korea. Her research interests include app and e-learning, Internet programming, multimedia communication, and network security.

DEAYOUNG NA was born in Gyeongju, Republic of Korea, in 1983. He received the B.S. degree in computer system, the M.S. degree in mobile computing, and the Ph.D. degree in computer engineering from Konkuk University, Chungju, South Korea, in 2006, 2009, and 2019, respectively.

Since 2019, he has been an Assistant Professor with the School of Global Leadership, Handong Global University. His research interests include the development of the IoT with artificial intelligence for smart farm with livestock and simultaneous localization and mapping (SLAM) for autonomous mobile robot.

SUNG-PHIL HEO received the Ph.D. degree in information sciences from Tohoku University, Sendai, Japan, in 2004.

From 1993 to 2014, he was a Principle Researcher, a Team Leader, and the Project Director with the Korea Telecom Research and Development Center, Seoul, South Korea. In 2014, he joined the Kumoh National Institute of Technology, where he was a Professor of the ICT Convergence Research Center. Since 2016, he has been an Associate Professor and the Department Head of the Department of Unmanned and Autonomous Vehicle Engineering, Kyungwoon University, South Korea. He is currently a Professor with the Department of Information and Communication Engineering and the General Director of the Industry-Academic Cooperation Foundation, Gangneung-Wonju National University, South Korea. His research interests include the IoT/M2M, contents based multimedia retrieval, u-healthcare, AR/VR, and next generation wireless communication technology.

HEUNG SEOK JEON received the B.S., M.S., and Ph.D. degrees in computer engineering from Hongik University, Seoul, South Korea, in 1996, 1998, and 2001, respectively. Since 2002, he has been a Professor with the Department of Computer Engineering, Konkuk University. He is currently the Director of the Institute for Intelligent Software Convergence Research. His research interest includes applying the artificial technologies to the various areas, such as smart farm, intelligent robots, and systems.