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Development of an Autonomous Situational Awareness Software for Autonomous Unmanned Aerial Vehicles

Yun-Geun Kim, Woohyuk Chang, Kwangmin Kim and Taegeun Oh†
Agency for Defense Development

Abstract

Unmanned aerial vehicles (UAVs) are increasingly needed as they can replace manned aircrafts in dangerous military missions. However, because of their low autonomy, current UAVs can execute missions only under continuous operator control. To overcome this limitation, higher autonomy levels of UAVs based on autonomous situational awareness is required. In this paper, we propose an autonomous situational awareness software consisting of situation awareness management, threat recognition, threat identification, and threat space analysis to detect dynamic situational change by external threats. We implemented the proposed software in real mission computer hardware and evaluated the performance of situational awareness toward dynamic radar threats in flight simulations.

Key Words : Unmanned Aerial Vehicle, Autonomous Situational Awareness, Radar Localization, Line-of-Sight Analysis

1. Introduction

In recent years, the unmanned aerial vehicle (UAV) market has been growing rapidly due to demand in sectors such as transportation, infrastructure management, and disaster detection including for forest fires and emergency rescue [1–3]. Moreover, UAVs are increasingly needed in the defense sector because of their advantages in 3D (Dull, Dirty, and Dangerous) missions as potential future replacements for manned air vehicles. However, because of their low autonomy levels that necessitate human supervision, UAVs can be operated only in situations where operators can control them continuously. A high level of autonomy for UAVs is crucial to overcome this limitation and allow UAVs to perform dangerous missions, such as enemy territory infiltration and reconnaissance missions independently.

The autonomous UAV technology for executing 3D missions can be mainly classified into autonomous situational awareness technology for understanding and predicting situations and autonomous decision-making technology for adaptively making decisions depending on the situation [4]. The former includes object recognition technology, context inference technology, situation representation technology, and so forth [5–7]. The autonomous decision-making technology includes path optimization technology and collision avoidance technology in dynamic situations [8–9]. Autonomous decision making requires the support of autonomous situational awareness technology for recognizing external situation changes. In the civil sector, deep learning-based situational awareness technology is actively investigated using learning data obtained from real-world situations [1–3]. However, autonomous situational awareness technology is difficult to apply in the 3D military missions because data cannot be obtained in actual situations as sufficiently as necessary for learning. Furthermore, although situational awareness technology considering external communication conditions [10] and ontology-based situational awareness technology [6] have been proposed, they cannot yet handle threat situations and has not been verified using real embedded computer for UAVs.

In this paper, we developed an autonomous situational awareness software to recognize external threat situations and validate the performance through simulated flight tests. The proposed autonomous situational awareness software comprises a situational awareness management function that manages the situational awareness procedure, a threat recognition function that recognizes external threats, a threat identification function that identifies information, such as the location of the recognized threat, and a threat analysis function that analyzes the effect of the identified threat on the mission. Here, external threats are assumed to be radars capable of detecting the UAV, and the subject UAV is assumed to be a low observable fixed-wing UAV with a built-in radar warning

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† Corresponding Author
Tel: +82-42-821-4230, E-mail: tgoh84@gmail.com

receiver (RWR) sensor that can measure the azimuth between the radar and UAV.

The autonomous situational awareness software uses the RWR sensor to detect the presence of a new radar, and a position identification flight is performed for the recognized new radar to identify its location. When the location of the new radar is identified, the threat space for the radar are calculated to analyze the effect on the mission. In this paper, the threat identification and analysis functions are activated or deactivated depending on the situation for computational efficiency. In particular, Graphic Processing Unit (GPU)-based parallel operations are applied in an embedded environment to improve the speed of analyzing the radar threat space. The performance of the developed autonomous situational awareness software was verified through repeated simulated flight tests by modifying the mission computer hardware mounted on an actual aircraft and loading the autonomous situational awareness software.

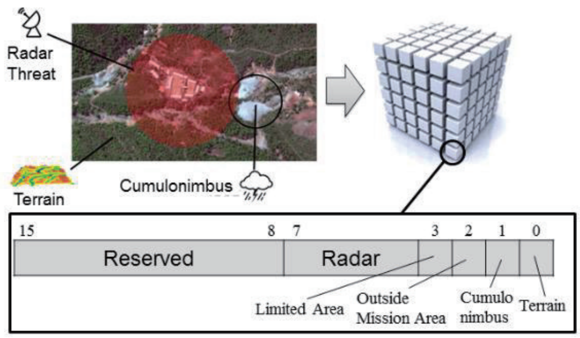

Fig. 1 Structure of Spatial Situation Information for a UAV

2. Structure of Autonomous Situational Awareness Software for UAV

2.1 Definition of Threat and Spatial Situation Information

A UAV should be capable of performing missions and flight path planning onboard to perform missions autonomously. This requires it to have the ability to distinguish between the space it can fly and the space it cannot fly. In this paper, we have defined the spatial situation information including the radar threat space and the terrain collision risk space, as shown in Fig. 1. The aim was recognizing the situation induced by the radar and the terrain, which are typical threats that can occur during performing military missions by UAVs.

A mission area is divided into three-dimensional grids, and the spatial information, such as radar and terrain information, is stored with 2 Bytes data in each grid. The spatial situation information must be updated in real-time according to the UAV status information and the data acquired from the sensors for onboard flight path and mission re-planning. Radar threats were defined with 4 bits to allow the elastic reflection of the threat radius based on the detection probability. This can be used to derive a flight path that takes the risk of detection of some probability when there is no flight path that can avoid the maximum threat radius. Restricted area, airspace, and cumulonimbus information, in addition to terrain information, are classified and defined to facilitate the flight path re-planning according to the situation considering the area intrusion.

2.2 Structure of Autonomous UAV Software

The proposed autonomous UAV software consists of an autonomous mission management unit and an autonomous situational awareness unit. The autonomous mission management unit manages the mission and the UAV, and makes decisions based on the situation recognition result. The autonomous situational awareness unit recognizes the current situation based on the sensor data and the UAV information. The autonomous mission management unit can be subdivided into the mission management function, mission re-planning function, flight path re-planning function, and so forth; however, they will not be discussed because they are not in the scope of this papaer. The autonomous situation awareness unit comprises the situational awareness management function, threat recognition function, threat identification function, and threat space analysis function. The situational awareness management function pre-processes the sensing information and the UAV status information, and delivers it to other functions in the autonomous situational awareness unit. Moreover, it activates the threat identification function and the threat space analysis function according to the current situational awareness procedure, and updates the spatial situation information based on the result. The threat recognition function is responsible for continuously monitoring the sensor data and the UAV information to determine whether a new threat exists or not. The threat identification function uses the sensor data and the UAV information (location, speed, pose, etc.) accumulated for a certain period of time regarding a new threat to identify the location of threat. Here, the flight path re-planning is requested by the autonomous mission management unit to increase the accuracy of identifying the location of threat. The threat space analysis function uses the identified threat and terrain information to distinguish the threat space and the hiding space through the line-of-sight (LOS) analysis. The proposed structure is universally applicable for a variety of threats; however, in this paper, we implemented the recognition, identification, and analysis functions for the radar threat, a typical threat, and verified their performance. A detailed description of each function will be provided, starting with the next subsection.

2.3 Situational Awareness Management Function

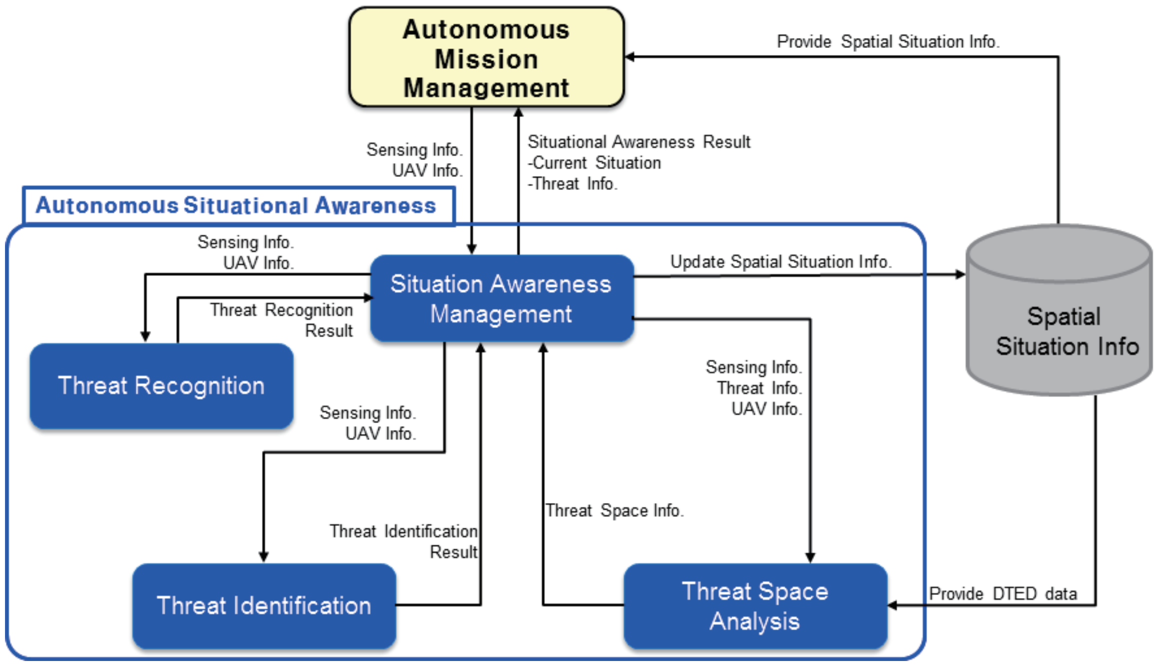

Fig. 2 Structure of the Autonomous Situational Awareness Software for UAVs

The situational awareness management function initializes the spatial situation information and other functions, and if a new threat is recognized by the threat recognition function, it activates the threat identification and spatial analysis functions according to the procedure and delivers the required information. Furthermore, it makes judgements on the emergency situation by directly analyzing the sensor data.

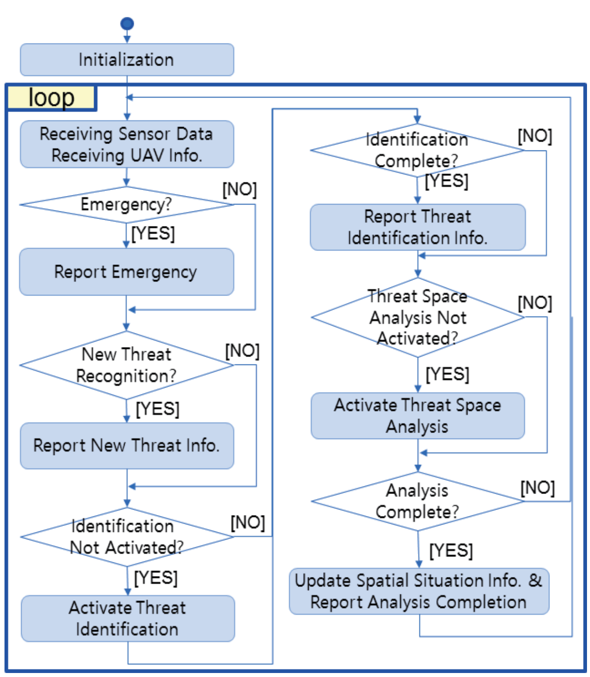

Fig. 3 Process of Autonomous Situational Awareness

The procedure of the situational awareness management function is shown in Fig. 3. First, the spatial situation information and each function are initialized. The initial spatial situation information is fetched from a file created based on the threat information at the time of pre-mission planning. Furthermore, as the threat recognition function requires continuous monitoring, it is activated in the initialization stage and the state is maintained. After the initialization, the autonomous situational awareness is performed by repeating the procedure in the loop of Fig. 3. First, after receiving the sensor data and the UAV information, it is determined whether the situation is emergency or not. If the mode of a particular radar in the RWR data is Track/Launch, then the UAV is in a situation of being detected/tracked by the radar, which corresponds to an emergency situation. Furthermore, if the current position of UAV corresponds to a radar threat space or a terrain collision risk space, it is also determined as an emergency. Once the judgment of an emergency situation is completed, it is checked from the threat recognition function whether a new threat has occurred. When a new threat occurs, the threat identification function is activated. When the threat identification is complete, the result is reported to the autonomous mission management unit, and the threat space analysis function is activated to perform the threat space analysis for the identified threat. After the threat space analysis is completed, the result is reflected in the threat space situation information, and the completion is reported to the autonomous mission management unit to perform the mission and flight path re-planning.

2.4 Threat Recognition Function

The threat recognition function determines whether a new threat has occurred based on the sensor data and the UAV's information. In this papaer, we use the RWR sensor data to perform the function of recognizing a new radar that has not been recognized in advance. Because the RWR sensor provides the type and azimuth of the radar, for which the signals have been detected at the current position, it can be used to determine whether the radar was recognized newly or not. Fig. 4 shows the algorithm for determining a new radar. First, the azimuth between the current UAV position and the pre-recognized radar is calculated. Subsequently, the calculated azimuth information and the radar type are compared to filter out the radars that are impossible to match with the RWR data. The matching is performed between the remaining radar and RWR lists, and a combination with the highest probability is selected through the maximum likelihood estimation (MLE) method. When there are a set R of m radars and a set S of n RWRs, a certain matching combination Z between the radars and the RWR can be defined as follows:

$$\begin{aligned} &\mathrm{R} = \{r_1, r_2, \cdots, r_m\}, \\ &\mathrm{S} = \{s_1, s, \cdots, s_n\}, \\ &\mathrm{R} = \{z_1, z_2, \cdots, z_n\}, where\ 0 \le z_i \le m. \end{aligned} \tag{1}$$

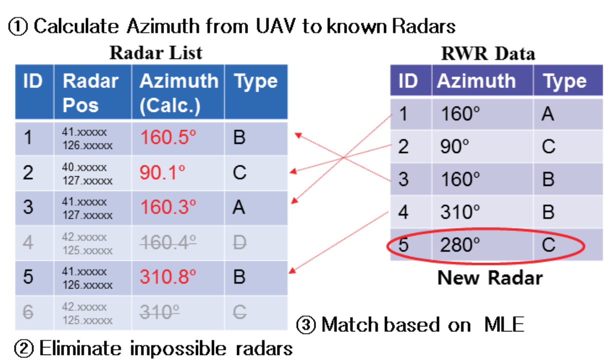

Fig. 4 Method for New Radar Recognition

For the matching combination Z, a radar list number to be matched is selected in the order of the RWR list. Furthermore, it should be allowed to select 0, which indicates a new radar because the case of a new radar should be also considered. The probability of the combination Z, created this way, is calculated as the product of the normal distribution probability of the RWR measurement error obtained by the difference between the azimuth sd measured by the RWR for each RWR, and the azimuth rd calculated using the radar's position and the aircraft's position, as expressed in Eqs. (2) and (3). Here, in the case of a new radar, because the rd value does not exist, its probability is replaced with the probability of not being any one of all radars. In this paper, a combination with the highest probability is selected by calculating the probabilities of all possible combinations to facilitate the recognition of a new radar.

$$P(Z) = \prod_{i=1}^{n} p(s_i = r_{z_i}) \tag{2}$$

$$p(s_i = r_{z_i}) = \begin{cases} f_{\mu,\sigma}(|sd_i - rd_{z_i}|),\ if\ z_i > 0 \\ \prod_{k=1}^{m}\left(1 - f_{\mu,\sigma}(|sd_i - rd_k|)\right), if\ z_i = 0 \end{cases} \tag{3}$$

2.5 Threat Identification Function

The threat identification function identifies detailed information, such as type, model name, and position of the recognized new threat. The threat identification function used in this paper monitors the azimuth of the RWR ID recognized as a new radar for a certain period, with the aim of identifying its intersection point as the position of the radar. Existing studies that use the RWR azimuth information to identify the radar's position [11–13] measured the azimuth from multiple positions while flying for a long time with a mission of identifying the radar positions. Moreover, they identified the radar's position with an error of less than 1 km through the triangulation. However, we aimed to identify the position of a radar in a short period to avoid it when a radar that was not recognized beforehand is suddenly detected. Therefore, we propose a method of identifying the approximate position by performing a flight for the position identification within 1 min. To improve the position identification accuracy of the radar, it is highly efficient to fly in a circle around the radar's position. However, it is impossible to fly in a circle because the distance between the radar and the UAV cannot be identified by the RWR alone. Furthermore, if safety is considered, it is better to fly in the orthogonal direction of the RWR azimuth; however, the signals of RWR may disappear. Hence, flying at an acute angle close to the orthogonal direction is needed. However, as the angle changes depending on the specifications of the aircraft and the detection distance of the radar, the RWR signals are collected while flying 1 min in the direction that forms an acute angle of 80° with the RWR azimuth arbitrarily, as shown in Fig. 5. The method of identifying the position using the collected RWR data was implemented based on the multiple sampling correlation algorithm (MSCA) that has excellent computational efficiency [11]. The MSCA method collects the line of bearing (LOB) fan areas reflecting the maximum direction detection error in the direction detection angle from various positions.

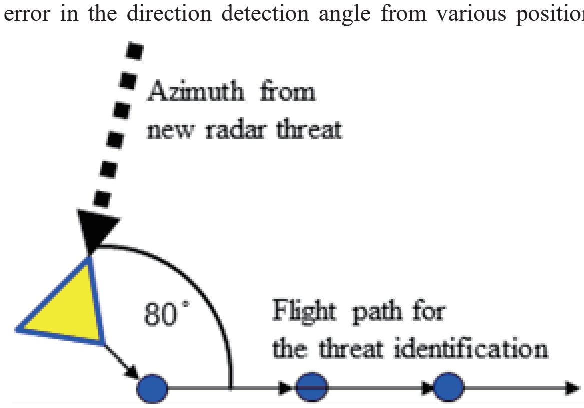

Fig. 5 Flight Path for New Radar Threat Identification

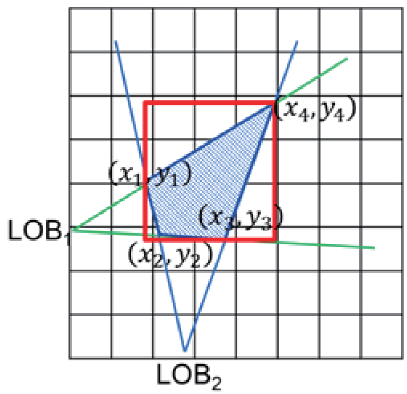

Fig. 6 Selecting Candidate Area for Radar Localization

Additionally, it determines the center point of the shape formed with its crossing area as the horizontal position of the radar. However, because the crossing section of the LOB fan areas, collected in a short time, is excessively broad to identify the radar's position, we proposed a method of estimating the radar's position considering the error characteristics of the RWR. Fig. 6 shows that it begins by setting the crossing area of two LOB fan areas as a candidate area, comparable to the MSCA method. As the actual position of the radar exists in the crossing area between the LOB fan at the time of initial measurement and the LOB fan after a certain period, the crossing area is selected as a candidate area. Considering the complexity of the calculation and desired responsiveness, we selected the crossing area of the LOB fan at the time of initial measurement and the LOB fan after 10 s as a candidate area. After selecting the candidate area, the probability of existing in each grid $P_{loc}(c_i)$ is calculated, as expressed in Eq. (4), for all azimuths collected within 50 s for each grid in the area.

$$P_{loc}(c_i) = \prod_{t=t_{init}}^{t_{end}} f_{\mu,\sigma}\left(\left|sd^t - cd_i{}^t\right|\right), \quad (4)$$

where c_i denotes the i-th grid, sd^t denotes the azimuth measured at time t, and $cd_i{}^t$ denotes the azimuth calculated with the position of the i-th grid and the aircraft position at time t. For each gird, the final probability is calculated by multiplying the probability calculated for each azimuth measured from a time-point t_{init} when the crossing area is determined to a time-point t_{end} after 50 s. Moreover, the position where the probability is the highest among the grids in the candidate area is selected as the horizontal position of the radar. The radar's altitude can be determined by the altitude value of the digital terrain elevation data (DTED) at the horizontal position. However, because of the presence of position identification error, a relatively low altitude may be misdetermined as the position of the radar, which causes an error that classifies majority of the area as hiding spaces during the spatial analysis. To solve this problem, we adjusted the altitude of the radar to the maximum altitude in the candidate area. Considering the safety of the aircraft, this is a measure for reducing the false-negative probability at the expense of true-positive probability for the threat space judgment.

2.6 Threat Space Analysis Function

This section describes the threat space analysis by a newly identified radar threat. If the position of the radar threat is estimated by the position identification algorithm, the threat space is analyzed where the LOS can reach and the nonthreat space, which is occluded by the terrain, through the LOS analysis for the adjacent space of the related position. Figure 7 shows an example of the radar's threat space analysis, and the gray and dark gray areas represent the terrain and the non-threat space, respectively. R is the newly identified radar, for which the position is estimated, and P1 and P2 indicate the top of the terrain, respectively. Suppose the straight lines passing R–P1 and R–P2 are L1 and L2, respectively. Then, the space higher than L1 and L2 becomes a threat space, which is visible to the radar, and the area between L1/L2 and the terrain becomes the non-threat space occluded by the terrain.

Many studies, such as [14] and [15] have used the analysis method of LOS by radar; however, these methods are for the optimal radar placement. Indeed, although they can derive the result through precise analysis in a static environment, they require plenty of computation time. We implemented an LOS analysis algorithm based on a high-speed algorithm introduced in [16] for prompt analysis of threat spaces regarding a newly identified threat in a dynamic situation.

The high-speed LOS analysis consisted of the procedures shown in Fig. 8. When the position of the new threat estimated by the position estimation algorithm and the sensor information are received, the terrain information around the estimated position is loaded on the memory. Here, the DTED altitude is used as terrain information. Figure 9 shows that the terrain information is divided into N groups to perform parallel computations for the threat space analysis, thereby reducing the total computation time. We applied N = 4 because the radar threat space analysis uses four central processing units on the mission computer equipped with the autonomous situational awareness software. The analysis speed of the terrain information was improved by analyzing the lowest terrain altitude in the boundary region instead of performing analysis for each altitude at each position. By using the intermediate

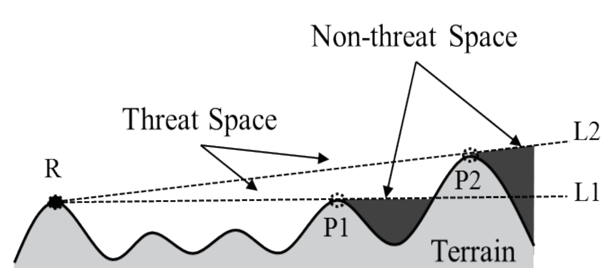

Fig. 7 Example of Radar Threat Space Analysis

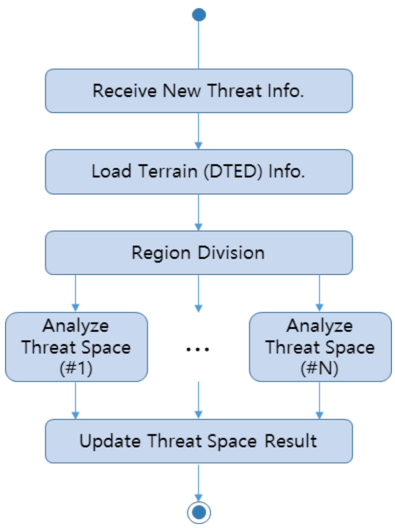

Fig. 8 Flowchart for Radar Threat Space Analysis

results in the analysis process as the threat analysis results at positions between the new radar and the boundary region, the redundant computations, and hence the required time were reduced at the computed position. Furthermore, to reduce the degradation of the parallel computing efficiency caused by the interference, the memory access was prevented for the adjacent terrain in the parallel computing process through the region division, as shown in Fig. 9.

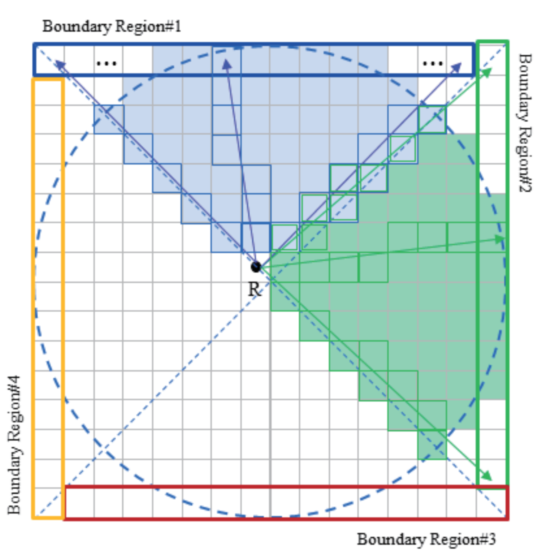

Fig. 9 Example of Region Division for Radar Threat Space Analysis

3. Validation of Autonomous Situational Awareness Software

3.1 Validation Environment of the Autonomous Situational Awareness Software

The environment for validation of the autonomous situational awareness software is shown in Fig. 10. The autonomous situational awareness software was loaded on the mission computer of an actual aircraft. In addition, the existing flight operation program was modified to interoperate with the autonomous situational awareness software. The integrated test environment is an environment where simulated flight tests are performed, interlinking with a mission computer. It consists of three main simulation functions as follows:

- Ground control equipment simulation: it comprises a mission plan and test scenario management function, a ground control equipment simulation function of the aircraft and an the integrated test environment operation function including the UAV avionics and mission environment simulations.
- UAV Avionics simulation: it simulates the communication function and the functions of onboard equipment, including the data-links and RWR loaded on the aircraft to simulate and transmit the radar threat information, the aircraft position information, and the ground control equipment's control commands to the mission computer.
- Mission environment simulation: it simulates the flight environment, other approaching aircraft, and ground-based anti-aircraft radar threat based on a dynamic model. The anti-aircraft radar threat simulation includes functions that support the determination of detection by radar and the RWR detection by reflecting the positions and characteristics of the radar and the aircraft, and display the radar threats in the ground control equipment simulation.

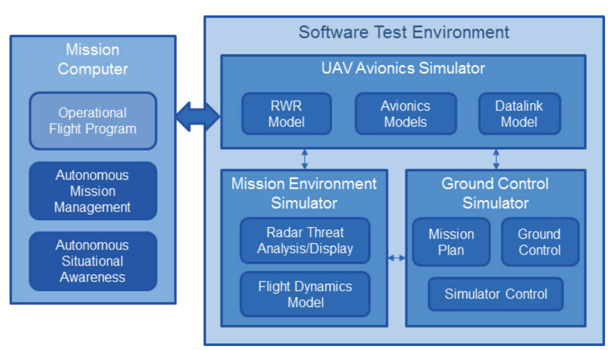

Fig. 10 Block Diagram of Evaluation Environment

In the mission environment simulation, a radar model of system tool kit (STK) [17], that was a commercial system analysis tool, was used to simulate the radar threats. When the analysis is performed to determine whether the radar has detected by reflecting the positions, characteristics, and terrain shielding of the radars and the aircraft in the radar model of STK, the results are delivered to the mission computer through the RWR model of the UAV avionics simulation. Subsequently, the mission computer uses the data to perform the recognition, identification, and threat space analysis of the new radar threat.

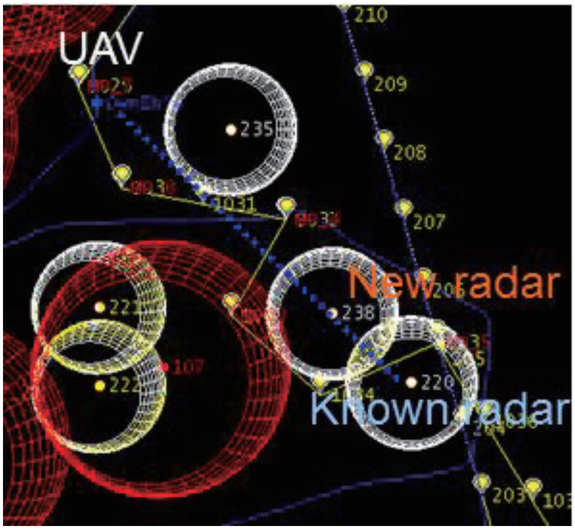

Fig. 11 Example of Confusion in Radar Detection

The hardware specifications of the mission computer equipped with the autonomous situational awareness software were as follows:

- VPX3-C1: Intel Core i7-3612QE (2.1 GHz), 8 GByte DDR3 SDRAM, 32 GB NAND Flash Drive
- GP107: NVIDIA QUADRO PASCAL GP107 GPU (768 CUDA Cores), 4 GB GDDR5 Memory

The mission area was set with a length of 749.1 km, a width of 1,223.7 km, and a height of 15.3 km for the validation of the developed software. Furthermore, the size of the spatial situation data was 495 MB. The level 2 DTED data were used after converting them into binary data in the threat analysis, whereas the size was 495 MB. For the radar threats, three radar types were assumed, and 100 radars were placed at arbitrary positions considering the terrain. When creating simulation scenarios, an arbitrary number of radars was selected and placed. The test was performed repeatedly for 100 simulation scenarios in the integrated test environment of the software configured as described above. Moreover, the new threat occurrences per scenario were set to three times.

3.2 Situation Recognition Performance

Three hundred radars were newly detected in 100 scenarios. Table 1 shows detection performance of the autonomous situational awareness software.

Table 1 Performance of New Radar Detection

Number of new radars detected	Detections	Misses	Confusions	False alarms
300	294	0	6	0

Detection refers to accurately identifying the presence of a new radar and the corresponding RWR ID, and miss is the number of times of missing the detection. Confusion is the number of times of a new radar being detected but identified with an incorrect RWR ID. False alarm refers to a case of false-detecting a new radar even though it does not exist. The autonomous situational awareness software detected 294 out of 300 new radars. Although there was no false alarm, the RWR ID was incorrectly determined for six radars. Fig. 11 shows that a new radar (no. 238) was recognized with an existing radar (no. 220) simultaneously on the same line, but they were impossible to distinguish based on the direction detection accuracy of the RWR. However, when flying for position identification, they are sufficiently distinguishable because the UAV deviates from the same line as it moves. Therefore, we are planning to add a function to check for confusion during a position identification flight in the next study.

3.3 Threat Identification Performance

We used the position identification accuracy of new radars to analyze the threat identification performance of the autonomous situational awareness software. As the radar position identification error is proportional to the distance between the radar and the UAV, we calculated the mean identification error for each distance by dividing the distance between the radar and the UAV in 10 km units, as shown in Fig. 12. As expected, the identification error increased as the distance increased. The reason for the large error at 140 km is that the number of samples is small because the number of radars in the corresponding distance is four. By flying for 1 min, the position

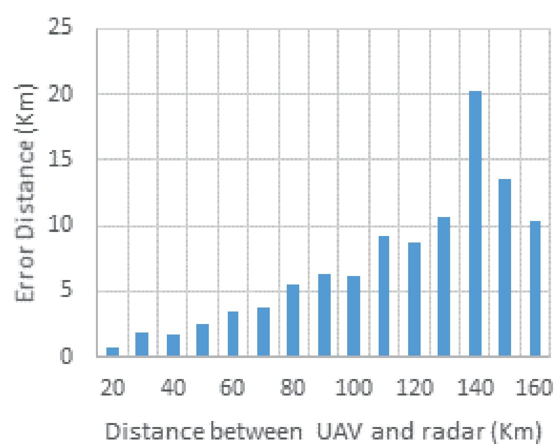

Fig. 12 Radar Localization Error according to Distance between UAV and Radar

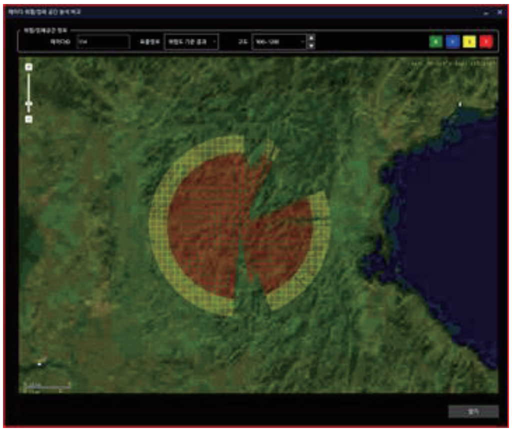

Fig. 13 Example of New Radar Threat Analysis Result

identification could be performed with a mean error of 6.2 km for the radars at 100 km distance.

Because of performing a flight path re-planning based on the threat space analysis, the radar threats were avoided in all scenarios.

3.4 Performance of the Threat Space Analysis

Figure 13 shows an example result of the radar threat space analyzed using the developed algorithm for radar threat space analysis. The red and yellow areas represent a detection rate of 80% and 60%, respectively. Furthermore, the analysis results show that there are areas occluded by the terrain.

Table 2 shows the analysis time and accuracy of the developed radar threat space analysis algorithm. The developed algorithm was implemented to parallelize using four threads on the CPU and 768 CUDA cores on the CPU. The analysis time shows the time duration that the threat space was analyzed by receiving the information, including the estimated position. In addition, the accuracy was calculated by comparing to the radar threat simulation results obtained using the radar model of STK [17]. First, the analysis time shows that it was improved by approximately 48% through the GPU parallelization compared to the CPU parallelization. Although the analysis was performed for 656 ms (CPU) and 335 ms (GPU) on average, the threat space analysis algorithm, implemented in the embedded environment, showed an average accuracy of 94.94% and 95.20%, respectively, compared to the radar simulation results of the STK, which takes more than 20 min on average. Therefore, the developed software can be used in dynamic mission environments.

Table 2 Time and Accuracy of Radar Threat Analysis for CPU/GPU Implementation

Type	Measurement	Average	Worst Case	Std. Dev.
CPU	Time (ms)	656	897	213
	Accuracy (%)	94.94	87.16	2.99
GPU	Time (ms)	335	401	33
	Accuracy (%)	95.20	87.17	2.56

4. Conclusion

UAVs are becoming increasingly important for executing dangerous military missions, such as enemy territory infiltration and reconnaissance on future battlefields. Furthermore, autonomous situational awareness technology allows UAVs to recognize the situation autonomously. It is essential to reduce the workload of operators and handle sudden situational changes. In this paper, we proposed a structure for the autonomous situational awareness software that performs threat recognition, identification, and analysis to recognize dynamic situational changes. That is, we proposed a structure, in which the threat recognition, identification, and analysis functions are activated according to the procedure under the control of the situational awareness management function to recognize the situation. We loaded the autonomous situational awareness software on a mission computer with the hardware specifications appropriate for an actual UAV and interlinked it with the integrated simulation environment to test the situational awareness performance for radar threats. The recognition, identification, and analysis were performed for radar threats in 100 scenarios. The results proved that situational awareness could be executed to avoid the radar threats, and re-plan the mission and the flight path. Furthermore, the parallelization method using the GPU was applied to shorten the threat analysis time. As the proposed software has a general-purpose structure, it can be used for a variety of threats, and the follow-up study will implement recognition, identification, analysis functions, and verify their performance for not only radar threats but also aerial threats, such as enemy manned/unmanned aerial vehicles or enemy ground threats, identified by image-based object recognition.

References

[1] J. Kim and J. Lee, “Drone Technology and Market Report,“ *S&T Market Report*, vol. 67, August 2019.

[2] D. Tsouros, S. Bibi, and P. Sarigiannidis, “A Review on UAV-Based Applications for Precision Agriculture,” *Information*, vol. 10, no. 349, pp. 1–26, 2019.

[3] C. Yuan, Z. Liu and Y. Zhang, “Fire Detection using Infrared Images for UAV-based Forest Fire Surveilence,” *Proc. Int. Conf. Unmanned Aircraft Syst. (ICUAS)*, pp.

567–572, June 2017.
[4] M. Endsley, B. Bolte and D. G. Jones, “Designing for Situation Awareness: An Approach to Human-centered Design,” *Taylor & Francis*, 2003.
[5] J. Lee, S. Lee, D. Kim, S. Hong and S. Yang, “Trends on Object Detection Techniques Based on Deep Learning,” *Electronics and Telecommunications Trends*, vol. 33, No. 4, pp. 23–32, August 2018.
[6] M. Jeon, M. Lee, H. Park, Y. Park, H. Yoon and Y. Kim, “Ontology and CNN-based Inference of the Threat Relationship Between UAVs and Surrounding Objects,” *The Korean Institute of Information Scientists and Engineers*, vol. 47, No. 4, pp. 404–415, April 2020.
[7] T. Oh and H. Yoon, “A method of Real-time Radar Masking Area Analysis,” *KSAS 2018 Fall Conference*, pp. 1305~1306, November 2018.
[8] S. Oh, “Research Trends of Multi-objective Optimal Path Planning for UAVs,” *Current Industrial and Technological Trends in Aerospace*, vol. 18, No. 1, pp. 65–74, 2020.
[9] Z. Zhou, X. u and X. Peng, “UAV Collision Avoidance Based on Varying Cells Strategy,” *IEEE Trans. on Aerospace and Electronic Systems*, vol. 55, no. 4, pp. 1743–1755, August 2019.
[10] O. Anicho, P. Charlesworth, G. Baicher and A. Nagar, “Situation Awareness and Routing Challenges in Unmanned HAPS/UAV based Communications Networks,” *2020 Inter. Conf. on Unmanned Aircraft Systems*, Athens, Greece, pp. 1175–1182, September 2020.
[11] H. Vieira, “Modified Multiple Sample Correlation Algorithm for Electronic Target Localization,” *IEEE Aerospace and Electronics Systems Magazine*, vol. 23, no. 8, pp. 1–8, August 2008.
[12] J. Jeon, S. Kim, D. Lee, and S. Lee, “Performance Comparison of Bearing-only Position Location Algorithms,” *11th Conf. Commun. Electron.*, pp. 124–129, September, 2007.
[13] B. Park, S. Kim, J. Ahn, Y. Kim, “Stationary Emitter Geolocation Based on NLSE Using LOBs Considering the Earths Curvature,” *The Journal of Korean Institute of Communications and Information Sciences*, vol. 42, no. 3, pp. 661–672, March 2017.
[14] H. Lee, "LOS Analysis Algorithm for Mid-range Guided Weapon System," *Journal of the KIMST*, vol. 13, no. 4, pp. 642–649, August 2010.
[15] K. Baek, Y. Lee, and, H. Jang, "Study on the Optimal Location of Low Altitude Air Defense Radar," *Journal of the KIMST*, vol. 17, no. 2, pp. 248–257, April 2014.
[16] W. Franklin and C. Ray, “Higher isn’t necessarily better: Visibility algorithms and experiments,” *Advances in GIS Research: Sixth International Symposium Data Handling*, vol. 135, pp. 18–27, May 1994.
[17] System Tool Kit (STK), “*https://www.agi.com/products/stk*”