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Original article

A Genetic Algorithm to Solve the Optimum Location Problem for Surveillance Sensors

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Abstract

Due to threats caused by social disasters, operating surveillance devices are essential for social safety. CCTV, infrared cameras and other surveillance equipment are used to observe threats. This research proposes a method for searching for the optimum location of surveillance sensors. A GA (Genetic Algorithm) was used, since this algorithm is one of the most reasonable and efficient methods for solving complex non-linear problems. The sensor specifications, a DEM (Digital Elevation Model) and VITD (Vector Product Interim Terrain Data) maps were used for input data. We designed a chromosome using the sensor pixel location, and used elitism selection and uniform crossover for searching final solution. A fitness function was derived by the number of detected pixels on the borderline and the sum of the detection probability in the surveillance zone. The results of a 5-sensor and a 10-sensor were compared and analyzed.

Keywords : Surveillance, Genetic Algorithm, VITD Map, Optimum Sensor Location

1. Introduction

Threats caused by social disasters, especially terrorism, are globally on the rise. Since 2000, terrorist attacks and deaths from terrorism have radically increased (the Institute for Economics & Peace, 2015). The importance of surveillance devices has come to light worldwide because of the increased terrorist threats. Monitoring major infrastructures, such as nuclear power plants, airports, and docks, is especially emphasized due to their social influences. Unlike common monitoring, major infrastructure monitoring for tactical purposes should observe wide areas and thus, multiple monitoring devices are needed to fulfill that purpose.

Not only are the number of surveillance equipment increasing, but also the optimum location of surveillance equipment has to be determined to prevent infiltrations of invaders. Finding the optimum location of one surveillance equipment is not a complex problem, however, the optimum location problem of multiple equipment is a dynamic and representative NP-hard (non-deterministic polynomial-time hard) problem (Mittal and Davis, 2004).

Due to such difficulties, heuristic approaches and mathematical models are usually applied to solve the multiple facility location problem. Cooper (1964) is a leader in the field of location-allocation problems, suggesting a number of heuristic algorithms. Murray's work addressed sensor placement for security monitoring in 3D urban cases (Murray *et al*., 2007). They modeled the MCLP (maximal covering location problem)

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and the BCLP (backup coverage location problem) to find the optimal location of security cameras. This article concluded that using the BCLP can acquire more feasible and economical results compared to using the MCLP. Yabuta *et al.* (2008) presented an all-region observation algorithm and weighted region observation algorithm to find the optimum security camera location. They set the object and subject function to solve the problem. Their algorithm can decide the position, direction, and visual angle of cameras for monitoring purposes. Mittal and Davis (2004) tried to minimize the cost function of sensor planning, but they found that the function is non-linear and non-differentiable. They reduced the parameter number from 9 to 2 for reducing non-linearity and non-differentiability, with the function having several global and local minima. They held the view that minimizing the cost function using gradient-based methods is impossible, and applied a simulated annealing algorithm to solve the problem.

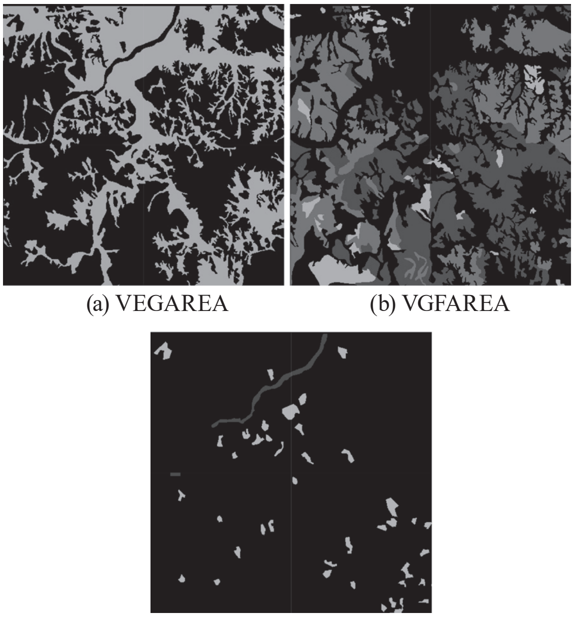
Even with much on-going research, the optimum location problem still remains hard to solve due to its complexity. To overcome these troubles, our approach is based on a GA, which is known for is powerful method to solve complex non-linear problems. A GA is a helpful algorithm for the case as it uses few initial entity solutions to evaluate various solutions (Holland, 1992). In this paper, we attempted to solve the sensor problem using a GA. A TOD (Thermal Observation Device) is chosen as the surveillance sensor in this study. An imaginary borderline and surveillance zone were set in the study area to apply the GA algorithm.

2. Input Data

2.1 VITD map

VITD is a digital vector map, made by NGA (the National Geospatial-Intelligence Agency), to be used in military operations. It contains attribute data of geographic features (NGA, 1995). This map provides six types of coverage; OBS (obstacles), SLP (slope/surface configuration, SMC (soil/surface materials), SDR (surface drainage), TRN (transportation), VEG (vegetation), as shown in Fig. 1.

VEG coverage, which has the most influential factor for a sensor's detection level, is the main input source among various types of coverage (Lee *et al.*, 2006; Kong *et al.*, 2012). VEG coverage is composed of three layers; VEGAREA, VGWAREA, VGFAREA. The VEGAREA layer shows land-uses, such as barren ground, cropland, grassland, land subject to inundation, rice fields, and scrub/brush. The VGFAREA layer contains information on species and the density of trees, and the VGWAREA layer contains information on built-up and common-open areas. In this research, a sneak-probability map model was produced using a DMT (Density Measure: % of Tree/Canopy Cover), which is contained in the VGFAREA layer.



(a) VEGAREA (b) VGFAREA

(c) VGWAREA

Fig. 1. VITD map

2.2 SRTM (Shuttle Radar Topography Mission)

On February 11, 2000, the SRTM was launched by the Space Shuttle Endeavour. NASA and NGA participated in this project to create the first ever near-global land elevation data. Endeavour orbited the Earth 16 times per day during 11 days mission. SRTM generated data for over 80% of the Earth's surface between 60°N to 56°S. The product resolution is 30 meters. ROKA (Republic of Korea Army) is using 30m resolution SRTM-Level 2 DTED (Digital Terrain Elevation Data) to create Digital Surface Models (Eo *et al.*, 2008). The 30m resolution SRTM DTED data was utilized to perform visibility analysis in this study.

Table 1. Specification data of TAS-815k

Equipment	Specification data	
	Thermal Infrared Camera	• Operation frequency: 3-5μm • Resolution: 640×480 (60Hz)
	CCD Camera	• Resolution: 1024×768 (30Hz)
	Display	• 6.5in TFT-LCD • Resolution: 1024×768 • DV in/out: RGB in, RS-170 out
	GPS	• Public/military GPS
TAS-815k	DMC	• Digital map coordinate

2.3 TOD

In this paper, we selected the TOD as the tactical monitoring sensor because of its wide use for monitoring purposes. A TOD is an imaging device that measures thermal infrared radiation. It is used as a powerful tactical monitoring device because it can detect an object during day and night. It detects infrared energy that is emitted by warm objects. It is not only used in military applications, but also the industry, building management, transportation, and crime prevention. ROKA has used TODs for night surveillance and reconnaissance since the mid-1990s. It has achieved substantial results by detecting invader infiltration several times. In this paper, we simulated the use of a TAS-815k TOD, used in ROKA, however, some specification data is confidential. For this reason, the detection range of the TOD is assumed to be 15km. Other available specification data is listed in Table 1.

3. GA to Searching Optimum Location of TOD

A GA, which is based on the law of inheritance, is a heuristic algorithm used to find the optimum solution by encoding characteristics of the solution to the chromosome. A GA does not get fixed result, but it can provide a near optimal solution for a non-differentiable and nonlinear problem (Schaffer, 1985). Another characteristic of the GA is that genetic representations and operators have to be designed for each optimization problem, since there is no common method. Genetic representations and operators proposed in this study are described in the following section.

3.1 Problem definition

There are several methods used to define object functions in sensor location problems. Murray *et al*. (2007) defined an object function as the coverage and the weighted coverage of an interest area. Mittial *et al*. (2004) used the density function of people to define the object function. In the case for the surveillance equipment location problem, the optimum location has to satisfy multiple conditions. The device should observe wide areas with as high a detection probability as possible. At the same time, the equipment should not have any missing area. To satisfy both conditions, we used two variables to define object function; pixels on the borderline and the probability in the surveillance zone.

We consider the following conditions to find the optimum location of the TOD:

condition 1: maximize : detecting pixel on borderline
condition 2: maximize : detecting probability in surveillance zone
condition 3: subject to : situating TOD in installation zone

The first condition is set to fill the blank area of the borderline where the invader can infiltrate. The second condition is set to increase the detection probability in the surveillance zone. Further details are described at section 3.5.3.

3.2 Schematic flowchart of selecting the optimum location

Fig. 2 shows the flowchart for solving the problem in this study. A common GA flow was used, even though some details were modified to fit the suggested algorithm. Before running the suggested algorithm, parameters are set up and initial solutions are selected by conditions. Initial solutions are evolved by iterative processes, including the processes of selection, crossover, and mutation. Each solution is evaluated by visibility analysis, based on a sneak probability map, which is generated by a VITD map. The result of the evaluation is applied to the selection process, and selected solutions produce next generations by crossover, and mutation processes. If solutions satisfy the termination criterion, the algorithm terminates the whole process and provides a final solution.

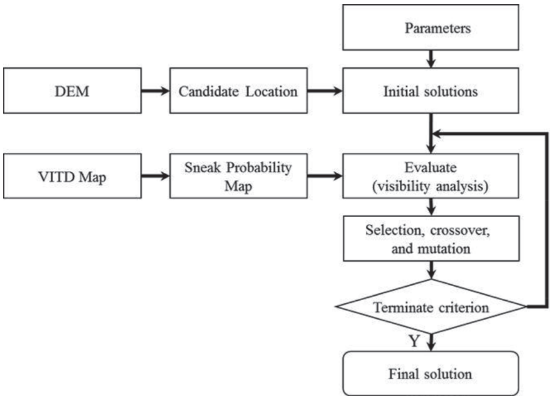


Fig. 2. Flowchart of selecting the optimal location of TOD

3.3 Coding

To perform the GA, the way solutions are represented have to be designed. This process is called the coding process. It depends on the user judgment, since there is no fixed method on coding. In this study, we coded the chromosome using

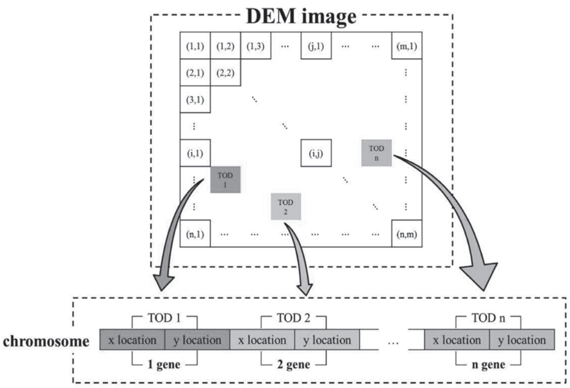


Fig. 3. Chromosome design

TOD pixel locations, (x, y). Fig. 3 shows the coding method of our problem. One chromosome is composed of *n* TOD locations. The length of each node is two, and the total length of the chromosome is two times that of the TOD number.

3.4 Initial solution

Initial solutions are randomly generated with two constraints. Firstly, the TOD must be installed in the area where the sensors can be installed. Secondly, to reduce running time, candidate pixels were selected before running the genetic algorithm. A pixel which has a higher value than double the average height value becomes the candidate pixel. As it is highly probable that the TOD which is located in the low area cannot have a large visible area (Song *et al*., 2011), we selected candidate pixels using the DEM pixel value. Eq. (1) gives the criteria for selecting the candidate pixel.

$$
\begin{aligned}
&\text{if } D(x_{ij}) > \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij}}{m \times n} \times 2.0 \\
&\quad C(x_{ij}) = 1 \\
&else \\
&\quad C(x_{ij}) = 0
\end{aligned}
\tag{1}
$$

where,

$D(x_{ij})$: pixel value of (i, j)

$C(x_{ij})$: indicator for candidate pixel

m, n: the number of row and column

3.5 Evaluation

The evaluation is a sub-process that evaluates the fitness value of each chromosome. This process is needed to determine the parent chromosomes, which will be inherited to the next generation. In this paper, we generated the detection probability map using the sneak probability map and visibility analysis to set fitness values. Two variable parameters were set to the block invader infiltration using the pixel value of the detection probability map and fitness function, using a combination of the two variables.

3.5.1 Sneak probability map

Generating a sneak probability map is essential for visibility analysis. In this paper, 3 layers, which are included in the VITD

VEG coverage (VEGAREA, VGFAREA, VGWAREA), were utilized to make the SPM (sneak probability map). According to the former study by Eo *et al*. (2008), the sneak probability model is made by the DMT attribute and the VGFAREA. The DMT attribute value is divided into categories; 0-25%, 25-50%, 50-75%, 75-100%. The VEGAREA coverage and the VGWAREA coverage are not defined sneak probability, but it cannot say that sneak probability of those layer are 0%. Bang *et al*. (2010) defined the VGFAREA layer's sneak probability as the average value of each category, and for the VEGAREA and VGWAREA case, used the lowest value of the sneak probability of VGWAREA. In this study, we adapted a setup of previous studies and defined the sneak probability as shown in Table 2.

Table 2. Sneak probability of each layer

VEGAREA	VGWAREA	VGFAREA			
0.125	0.125	0.125	0.275	0.625	0.875

Fig. 4 shows the sneak probability map. Each pixel's value is defined as the sum of VEGAREA, VGWAREA, and VGFAREA's sneak probability. The value of each pixel is above 0 and below 1.

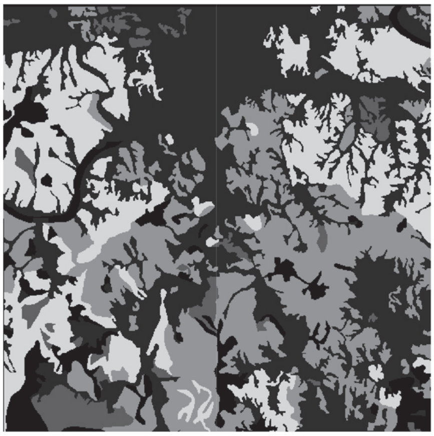


Fig. 4. Sneak probability map

3.5.2 Visibility analysis

In this study, visibility analysis was used to evaluate the TOD location. Visibility is influenced by terrain elevation, the performance of the observation device, trees coverage and other environmental factors (Kong *et al*., 2012). For visibility analysis, we perform viewshed analysis to create the detection probability map.

Viewshed analysis, also called line-of sight, is a method that determines if the human eyes or observation equipment are able to see the earth, water areas, or other environmental elements. This algorithm should be based on the elevation model of the target area (Eo *et al*., 2008). The TOD height and DEM were used as input data to perform viewshed analysis. To perform viewshed analysis, we used the Matlab viewshed program.

It is also assumed that the TOD detection probability is linearly decreased by distance. The equation of the assumption is shown as Eq. (2). Detection pixel values are made using Eq. (2), using pixel resolution and pixel distance. The maximum value of the detection pixel value is 1, and the minimum value is 0.

$$f(x_{AB}) = \begin{cases} 1 - \frac{1}{r/p} \times d_{AB} & when\ d_{AB} \leq detection\ range\ (pixel) \\ 0 & when\ d_{AB} > detection\ range\ (pixel) \end{cases} \tag{2}$$

where,

$f(x_{AB})$: Detection pobability value

r : TOD A's detection range (km)

p : DEM pixel resolution (km)

d_{AB} : Distance between TOD A and pixel B

The final equation for generating the detection probability map is shown as Eq. (3). Each pixel's adjusted visibility value and sneak probability pixel value are multiplied to make the final detection probability map.

$$F(x_{ij}) = f(x_{ij}) \times (1 - s(x_{ij})) \tag{3}$$

where,

$F(x_{ij})$: Detection probability map pixel value of (i, j)

$f(x_{ij})$: Detection probability pixel value of (i, j)

$s(x_{ij})$: Sneak probability map pixel value of (i, j)

3.5.3 Fitness function

We defined the fitness function using two variables. Firstly, the number of detected pixels on the borderline. Secondly, the sum of the detection probability pixel values in the surveillance zone. The first criterion is set with the purpose of filling empty spaces within the borderline. This criterion has importance because an empty space for the borderline can allow invader infiltration through that space. The second criterion is set for observing large areas for as far as possible, aiming to increase the detection probability of the surveillance zone.

To set up the fitness function of the multi-variable problem, Murata and Ishibuchi (1995) adopted the weight concept. The fitness function can be modeled by multiplying a weight to each variable. Eq. (4) shows the fitness function of this study.

$$F = w_1 f_1 + w_2 f_2 \tag{4}$$

where,

F: Fitness function

f_1: The number of detected pixel on the borderline

f_2: Sum of detection probability pixel value in surveillance zone

w_1, w_2: Weight value

Eq. (5) is defined to set the weight values of Eq. (4). The weight is designed for standardizing variables. After applying the weight, the maximum value of $w_1 f_1$ and $w_2 f_2$ will have the same values. This makes that our algorithm's searching path consider two variables equally.

$$\begin{aligned} w_2 &= 1 \\ w_1 &= \frac{SA}{BL} w_2 \end{aligned} \tag{5}$$

SA: Surveillance zone Area (# of pixel)

BL: Borderline Length (# of pixel)

Fig. 5 shows an example of our simulation results. The bold solid line is the borderline, and the bold dotted rectangle is the surveillance zone. The dark pixel's value is 1, the bright pixel's value is 0.5, and white pixel's value is 0. In this figure, f_1 is 5 and f_2 is 13.5. BL is 10, and SA is 30. In this case, $w_1 = 3$, $w_2 = 1$.

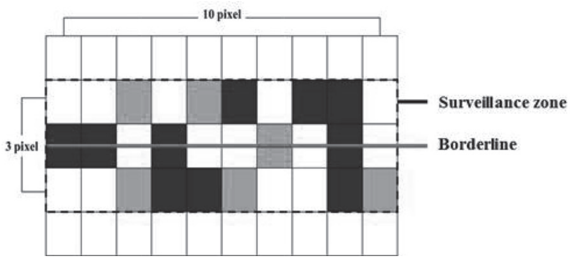


Fig. 5. Example of borderline and surveillance zone

3.6 Selection

The selection is a process that selects the parent chromosomes that are passed to the next generation. There are several selection methods; roulette wheel selection, rank selection, elitism selection, etc. In this paper, we adapted the elitism selection to quickly find an optimal solution. Elitism selection chooses chromosomes which have the highest fitness value. The number of parents is chosen and the next step is performed.

3.7 Crossover

The chosen parent chromosomes undergo the crossover process to generate the next generation. The crossover process also includes several methods; the single point crossover, the two point crossover, cut and splice, uniform crossover, etc. (Moon, 2008). To make each TOD location's inheritance do not have a correlation, we choose uniform crossover method. The random binary mask, which has the same number of TODs, was generated for uniform crossover. If the mask node value is 0, child 1 gets the node from the 1st parent and child 2 gets the node from the 2nd parent.

Fig. 6 shows how the crossover was performed in this study. The blue parent is the 1st parent, the red parent is the 2nd parent, and (011010) is the mask value. As stated above, the first, forth, and sixth node are taken from the 1st parent, and the second, third, and fifth node are taken from the 2nd parent. The 1st child will be derived by this method and the 2nd child will have the opposite node to the 1st child.

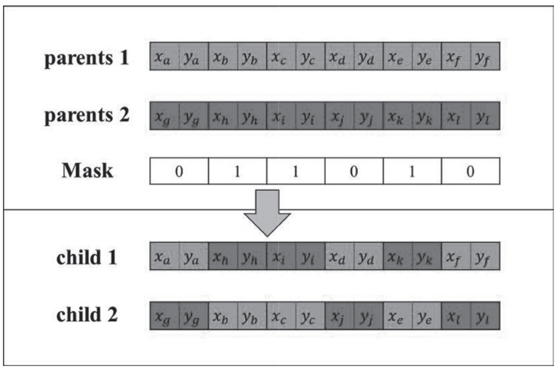


Fig. 6. Uniform crossover method

Table 3. Parameters and conditions

Parameters		Setting	
The number of population	100	Number of TOD	5 / 10
		Detection range	15km
The number of parents	5	Height of installation	5m above from ground
		Installation zone	301~500 row
Probability of mutation	10%		
		Borderline	250 row
Termination criteria	Generation > 200	Surveillance zone	225~275 row

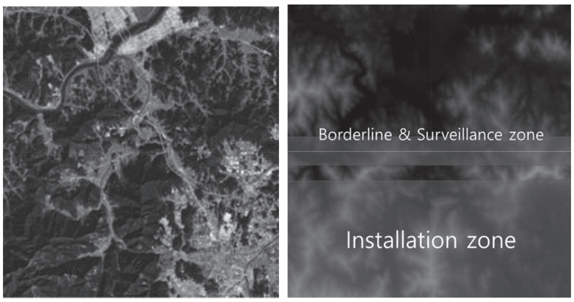
3.8 Mutation

In nature, creatures can suffer mutation. Mutation is a change in the chromosome, causing diversity in species. In a GA, the mutation process changes a chromosome's nodes. This process can create diversity within a solution, which diverges the results from the local optimum. Setting the mutation ratio entirely depends on user's skill.

4. Experiment and Result

4.1 Study area and experiment setting

In this study, we set an imaginary border, where South Korea confronts North Korea. The imaginary surveillance zone, installation zone, and enemy area were set on Daejeon province to check our algorithm (Fig. 7(a)). The horizontal line in Fig. 7(b) is the borderline, the red area is the surveillance zone, and the blue area is the installation zone, which is the candidate area of TOD location.



(a) Satellite view (Google Map) (b) Borderline, surveillance zone, and installation zone

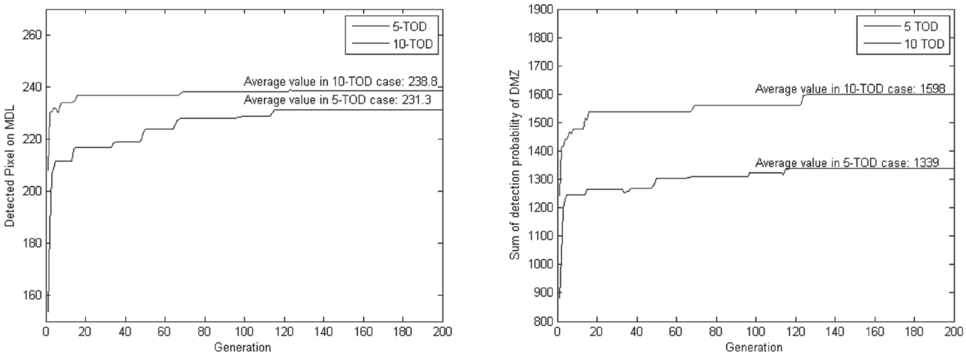
Fig. 7. Study area

Parameters and settings are given below in Table 3. For species diversity, enough numbers of the population, i.e. the number of chromosomes, was set. The number of the TOD is changed at each test as it is an important parameter in locating the TOD problem. We analyzed the performance of our algorithm by changing the number of TODs. In our experience, 200 iterations were able to find the optimum location of the TODs.

4.2 Experiment result

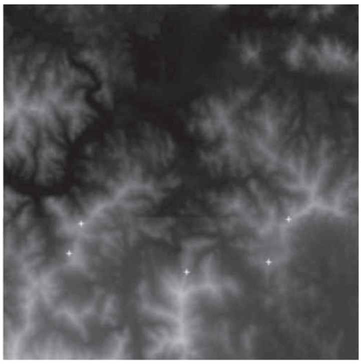
Fig. 8 shows the GA results of the 5-TOD and the 10-TOD cases, respectively. Each case is performed 10 times, and the graphs show the results of the average values of the experiments. Fig. 8(a) shows the number of detected pixel on the borderline in each case, and Fig. 8(b) shows the sum of the detection probability in the surveillance zone. The number of detected pixels on the borderlines increased by 50.49% and 14.71%, compared to the initial value of the 5-TOD case and 10-TOD case, respectively. The sum of the detection probability in the surveillance zones also increased by 51.55% and 28.78%, compared to the initial value of the 5-TOD case and the 10-TOD case, respectively.

There were slight differences between the number of detected pixels on borderline for the 5-TOD case and the 10-TOD case. The 10-TOD case produced improved results compared to the 5-TOD, but there was a minor difference between the results. The number of detected pixels by the 5-TOD was 231.3 pixels and the number of detected pixel by 10-TOD was 238.8 pixels. The difference was only 7 pixels, and it was only about a 3% improvement. In contrast to the

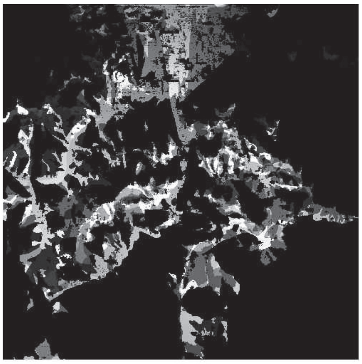


(a) The number of detected pixel on borderline (b) Sum of detection probability in surveillance zone

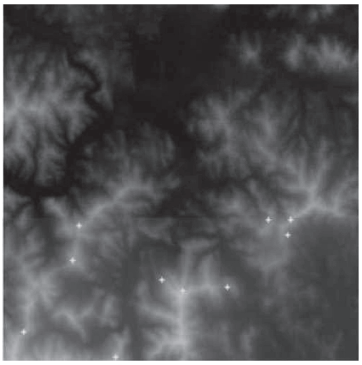
Fig. 8. GA result in 5-TOD case and 10-TOD case



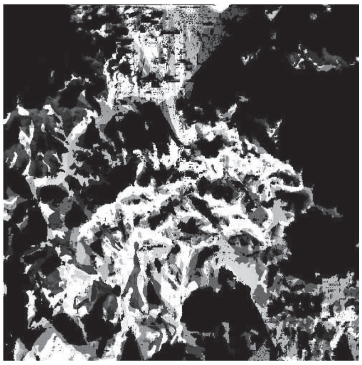
(a) Optimum location, 5-TOD case



(b) Detection map, 5-TOD case



(c) Optimum location, 10-TOD case

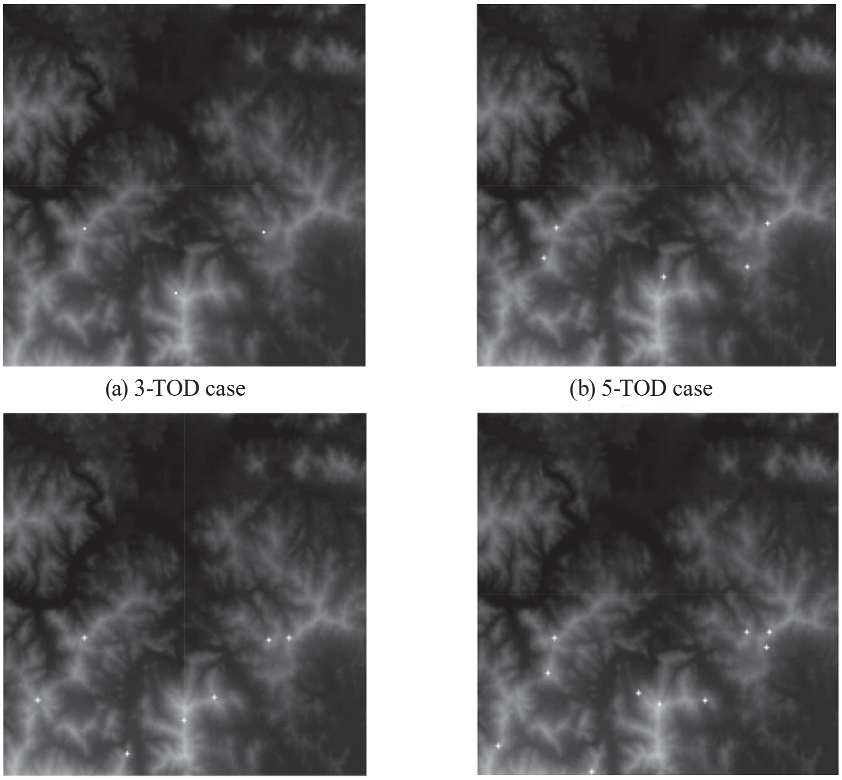


(d) Detection map, 10-TOD case

(e) Detection map; zoom in surveillance zone, 5-TOD case

(f) Detection map; zoom in surveillance zone, 10-TOD case

Fig. 9. Optimum location, detection map results



(a) 3-TOD case (b) 5-TOD case

(c) 7-TOD case (d) 10-TOD case

Fig. 10. The result of each cases

number of detected pixel, there was a significant difference in the sum of the detection probability for the surveillance zone. The sum of the detection probability by the 5-TOD was 1338.714 and the sum of the detection probability by 10-TOD was 1598.192.

Fig. 9 shows the optimum location results obtained using the GA. The optimum location of the TOD is shown in Fig. 9(a) and (c), and the detection map is shown in Fig. 9(b) and (d). For a detail comparison, the enlarged surveillance zone is given in Fig. 9(e) and (f). The black area in both cases is the nonvisible area, even if the TODs were allocated in every candidate pixel, due to terrain characteristics such as high lands or mountains. Yellow dots printed on the DEM are TOD locations. Clusters of TODs located in the upper right and middle areas were found in 10-TOD cases, compared to the 5-TOD case. The clusters observe almost the same area, thus the number of pixels on the borderline did not increased, however the sum of the detection probability significantly increased. Thus, perhaps the 5-TOD case already reached its optimum solution, and the 10-TOD case helps increase detection probability in the surveillance zone.

The TOD number affects the total detection probability. However, the number of monitoring devices can increase visibility, but the rate of increase decreases at a particular number of devices (Lee *et al*. 2006). Hence, in spite of the general notion that more TODs provide a greater detection probability, increasing the TOD number may not bring about an improved solution. Also, given that the economic feasibility must be considered in locating the monitoring device, it is important to balance between the TOD number and the increasing detection probability. The TOD number can be a variable of the fitness function; however, setting a weight value is a difficult problem.

To check for the appropriate number of TOD, we tested 3-TOD, 5-TOD, 7-TOD and 10-TOD cases. Fig. 10 shows the results of each case. For the 3-TOD and 5-TOD case, each of the TODs are distributed evenly in the installation zone. However, if more than 5 TODs are used, some TODs are concentrated in the top of the mountains. Based on our result, 5 is the most appropriate number of TODs in this study area. More TODs can improve the fitness value, however some TODs are over-positioned and the results are not cost-effective.

5. Conclusion

This paper suggested a GA to find the optimal location of the TOD. For designing the fitness function, the number of detected pixel on the borderline and the sum of detection probability in the surveillance zone were used. The final solution was attained by elitism selection, uniform crossover, and mutation.

The proposed algorithm was tested in the Daejeon province, and an imaginary borderline, surveillance zone, and TOD installation zone were set in the area. The 5-TOD case and the 10-TOD case were tested to analyze the performance of the suggested algorithm by changing the number of TODs. Results showed that optimum solutions effectively converged and showed a strong performance compared to random solutions. For the 5-TOD case, the average increasing rate of the number of detected pixels on the borderline was 50.49% and average increasing rate of the sum of the detection probability in the surveillance zone was 51.55%. For the 10-TOD case, these numbers were 14.71% and 28.78%, respectively. The number of detected pixels on the borderline was almost the same in the 5-TOD and 10-TOD case. However, the sum of the detection probability in the surveillance zone showed a significant difference between the two cases. Our results matched with previous studies in that increasing the number of sensors cannot increase the detection probability linearly. Moreover, economic feasibility must be considered in the sensor locating problem.

This paper suggests using a heuristic algorithm to solve the sensor locating problem. This approach can be used in other locating monitoring device problems, such as guard posts, cameras, and CCTV. It is recommended that the balance between increasing the total detection probability and the economic feasibility should be considered in future studies.

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