Camera Placement Optimization for Vision-based Monitoring on Construction Sites

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Abstract –

For successful vision-based monitoring, the camera placement is an important and challenging issue. However, the previous Art Gallery Problem – which is a traditional optimization problem closely similar to the camera placement problem – did not take into account characteristics of construction sites, and thus faced difficulties in placing cameras on site and collecting adequate video/image data of construction activities. To handle the drawback, this paper aims to develop a camera placement optimization framework that considers characteristics of construction sites. The framework consists of two main processes: (1) problem definition and mathematical modeling and (2) optimum camera placement. For the validation, the case study was performed. The results showed the applicability of the developed framework in finding the optimal number, locations, and viewpoints of surveillance cameras for vision-based site monitoring. In conclusion, this research can contribute to propose proper camera placement on construction sites, increase quality of collected visual data, and improve the performance of site monitoring.

Keywords –

Vision-based monitoring; Operation-level; Construction site; Camera placement; Optimization;

1 Introduction

A number of video/image data are collected on construction sites for the purpose of vision-based monitoring. Recently, Unmanned Aerial Vehicle (UAV) is extensively utilized for video/image data collection and analysis in practice [1]. However, practitioners still install surveillance cameras on construction sites for continuous operation-level monitoring. It can be explained that the UAV-based visual data has difficulties to provide the operation-level information (e.g., work time, direct work rate) while it contains more macro, project-level information (e.g., progress measurement) [2]. In contrast, cameras located at construction sites have a capability to capture video/image data involving operation and logistics of input resources such as workers, equipment, and materials [2-4].

For successful operation-level site monitoring, camera placement is a critical and challenging issue to be addressed. In practice, the camera placement is usually conducted manually based on experts' knowledge or experiences. The manual processes make the camera placement to become time-consuming and cost-ineffective. In response to this issue, many researchers have made efforts to solve Art Gallery Problem (AGP) – which is a well-studied open research area that finds the optimal locations of safety guards such that they satisfy the maximum visual coverage in an art gallery. AGP theorems and algorithms are also widely adapted and applied to optimize the camera placement in the visual sensor network domain [5-11]. In the construction domain, Albahri and Hammad [12] attempted to find the optimal camera placement in indoor buildings using Building Information Modeling (BIM).

Even though the previous works showed promising results in finding optimal camera configurations, they focused on the camera placement in controlled, arranged environments for limited purposes. Thus, it is still challenging to determine proper number, locations, and viewpoints of cameras due to various unique conditions of construction sites. To handle such limitation, this paper aims to develop a camera placement optimization framework that considers characteristics of construction sites.

2 Literature Review

In this chapter, the authors review previous works on vision-based monitoring systems on construction sites and previous approaches for solving camera placement problems including Art Gallery Problem.

2.1 Vision-based Monitoring at the Operation-level on Construction Sites

Vision-based monitoring at the operation-level is generally carried out on construction sites for the purpose of safety and productivity management. In the past, project managers directly visited construction sites for gathering operation-level information. However, the manual methods made the monitoring tasks to become expensive and time-consuming [13].

To address the problem, many studies have been performed to develop automated vision-based monitoring systems, which automatically extract safety and productivity information from video/image data. Chi and Caldas [14], for example, presented an image-based safety assessment method for earthmoving operations. In addition to the safety assessment, Kim et al. [15] applied fuzzy inference for supporting immediate risk awareness of workers. Vision-based analysis techniques were also utilized to detect workers' unsafe behavior detection. Han and Lee [16] presented a method that detects unsafe behavior from stereo images. Park et al. [17] developed a vision-based method that recognizes non-hardhat-wearing states of construction workers. Automated vision-based productivity analysis also raised attention. Many researchers focused on developing an activity recognition method for earthmoving equipment; for instance, the method proposed by Kim et al. [18] analyzed interactive operations (e.g., proximity, individual actions) between heavy equipment for recognizing earthmoving activities. Golparvar-Fard et al. [19] used spatio-temporal features and support vector machines to classify actions of earthmoving excavators and dump trucks. Gong and Caldas [20] developed a video-based analysis model for evaluating concrete pouring operations of tower cranes. Bugler et al. [21] also presented a fusion approach of photogrammetry and video analysis techniques for assessing earthmoving productivity.

2.2 Art Gallery Problem for Camera Placement

Art Gallery Problem (AGP) is the well-documented optimization problem of finding minimum number of safety guards and their locations required to cover the interior of an art gallery [8]. Because camera placement optimization has similar natures with AGP [5], AGP-based approaches have been performed to optimize camera networks in various domains.

In the camera surveillance domain, researchers primarily aim to maximize coverage of stationary cameras for indoor building. The cameras were installed to observe pedestrian and unexpected events (e.g., crime, traffic accidents) for security/traffic monitoring purposes [8-9,22-23]. Other researchers also considered Pan-Tilt-Zoom and omni-directional cameras for coverage modeling and maximization [6-7,24]. In recent years, the camera placement problems are extended to multi-objective optimization for maximizing camera coverage and minimizing installation costs simultaneously [5-6,11]. In the construction domain, a few studies have examined the camera placement problem in building environments. The work in [24] visualized and calculated the coverage of multiple cameras in public building spaces. The coverage modeling method presented in [25] used Building Information Modeling (BIM) for a simulation-based optimization and was further developed in [12].

The previous research showed promising results in camera placement optimization for indoor spaces and urban areas. However, it is still challenging to determine proper number, locations, and viewpoints of cameras to be installed on construction sites. To overcome such limitation, this paper develops a camera placement optimization framework considering characteristics of construction sites.

3 Research Framework

The research framework is composed of two main processes. First, we perform problem definition and mathematical modeling. Second, the optimum camera placement is found through site modeling, coverage simulation, and genetic algorithm.

3.1 Problem Definition and Mathematical Modeling

The goal of this research is to optimize number, locations, and viewpoints of cameras that maximizes effective coverage given site-specific constraints (e.g., installable locations). The camera coverage (without occlusions) can be represented with its effective distance and view angle as shown in Figure 1. For the spatial modeling of construction sites, a 2D grid-based matrix was used. The grid size was set as 0.5m x 0.5m based on the expert suggestions during the interview.

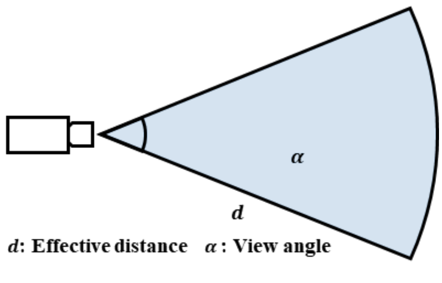

Figure 1. Camera coverage modeling

Next, the mathematical model was developed in order to manage the defined problem as follows.

Objective Functions

$$max\ \sum_{\theta}\sum_{i}\sum_{j} x_{i_1 j_1 \theta_1} e_{i_1 j_1 \theta_1 i_2 j_2} w_{i_2 j_2} \qquad (1)$$

Constraints

$$P\sum_{\theta}\sum_{i}\sum_{j} x_{ij\theta} \leq Budgets \qquad (2)$$

$$\sum_{\theta} x_{ij\theta} \leq l_{ij}\ for\ \forall i,j \qquad (3)$$

$$1 \leq i \leq n, 1 \leq j \leq m, 0 \leq \theta \leq 360 \qquad (4)$$

where

$$x_{ij\theta} = \begin{cases} 1, & if\ a\ camera, with\ viewpoint\ \theta, is\ at\ (i,j) \\ 0, & otherwise \end{cases} \qquad (5)$$

$$e_{i_1 j_1 \theta_1 i_2 j_2} = \begin{cases} 1, & if\ a\ camera\ (i_1, j_1, \theta_1)\ covers\ cell\ (i_2, j_2) \\ 0, & otherwise \end{cases} \qquad (6)$$

$$w_{ij} = spatial\ importance\ weight\ of\ cell\ (i,j) \qquad (7)$$

$$l_{ij} = \begin{cases} 1, & if\ a\ cell\ (i,j)\ is\ installable \\ 0, & otherwise \end{cases} \qquad (8)$$

The objective function plays a role in maximizing the total weighted effective coverages for vision-based site monitoring. By multiplying the spatial importance weight, possibilities in finding camera configurations that cover targeted monitoring areas can increase (e.g., work zones, travel paths, and material storages). The first constraint (Equation (2)) indicates that the total costs (i.e., number of cameras multiplied by unit prices) should be less than allocated budgets. When considering a camera dimension (around 0.5m x 0.5m) and a grid size, it is necessary to include Equation (3) to ensure that only one camera is located at each cell; however, this constraint can be released if a grid size is set sufficiently larger than a camera dimension (e.g., grid size: 3m x 3m; camera dimension: 0.5m x 0.5m). Equation (3) also explains that cameras should be placed at installable locations. The last constraints are considered for lower and upper bounds of locations and orientations.

3.2 Optimum Camera Placement

The proposed problem-solving method consists of three main modules: site modeling, coverage simulation, and genetic algorithm (GA). First, the site modeling is performed to encode spatial information of the actual construction site. Next, the performance of initial camera placement is evaluated to reproduce better coverage with simulation. GA generates new candidates for camera placement based on the evaluation. Until the terminal condition (i.e., the number of iterations is larger than the pre-determined threshold) is satisfied, the simulation-based coverage evaluation and GA-based reproduction processes are iterated.

3.2.1 Site Modeling

The site modeling creates the site-layout and spatial importance weight maps. First, the site-layout map is generated based on actual site drawings or top-view images. The next step is to create the spatial importance weight map. The spatial weights are assigned as 1, 2, and 3 for normal areas (i.e., background), travel paths and material storages, and work zones respectively. Based on the site modeling, the initialization is carried out. Among the camera-installable locations (e.g., facility boundaries) of the site-layout map, the initial number, locations, and viewpoints of cameras are randomly selected.

3.2.2 Coverage Simulation

The coverage simulation module computes the monitoring performance, total weighted effective coverage, of camera placement through coverage modeling and visibility analysis. The coverage modeling calculates camera coverage without occlusions based on the given camera type (i.e., effective distance and view angle). Next, the visibility analysis is conducted to deal with occlusion effects. Rotation angles to camera locations are primarily calculated for all cells within the coverage. It is then capable of capturing cells in the same line-of-sight when they have same rotation angles. Among the captured cells, cells located farther than any occluded cells are determined as invisible points.

3.2.3 Genetic Algorithm

GA is composed of two main steps: performance evaluation and population reproduction. First, the performance evaluation processes the calculation of objective function values: the total weighted effective coverage and total costs. By using the spatial importance weight map and the measured effective coverage, the first objective function can be determined. It is also possible to compute the total costs by multiplying the number of cameras and its unit price. Based on the acquired results, the population reproduction step is carried out as follows: selection, crossover, and mutation [5]. The selection chooses a subset of chromosomes with higher objective function values from population at the prior iteration, which may result in adoption to the best solution. Afterwards, 95% of the selected chromosomes is proceeded to the crossover and mutation; the other 5% individuals remain to secure the best solutions at the last iterations. Among the 95%, 80% and 20% were further selected for the crossover and mutation respectively. The probability-based uniform selection, the scattered method, and the adaptive feasible method were applied for each process of selection, crossover, and mutation respectively. Moreover, the authors mapped the real-world decision variables (i.e., numbers, locations, and orientations of cameras) into the chromosomes as follows. Each chromosome is composed of 2D locations and orientations. Chromosomes are also generated for all cameras to be installed, which means the number of chromosomes is same as the number of cameras.

4 Case Study

To validate the proposed framework's applicability, the authors performed a case study considering practical conditions of an actual construction site. Since the selected site already had three surveillance cameras for the purpose of vision-based monitoring, it was available to compare the performance of existing cameras and the suggestions based on the proposed method. The method was implemented using MATLAB 2017a on a laptop computer [Intel i7-5500 CPU @ 2.40 GHz, 8.00GB RAM, Windows 10, 64bit].

The case study was applied to the actual site-layout where two buildings were under construction. The site scale was 70m x 30m. There were total three cameras installed. The project manager aimed to mainly monitor work zones, travel paths, and material storages with the maximum budgets of $2,000. They purchased the surveillance cameras with the unit price of $500.

The effective coverage of both existing and suggested camera networks (with three cameras) are visualized with the red lines in Figure 2. The total weighted effective coverage rate (WVCR), calculated with Equation (10), was increased from 45.7% to 87.1% with the suggested camera placement.

$$WECR = \frac{\sum_{\theta}\sum_{i}\sum_{j} x_{i_1 j_1 \theta_1} e_{i_1 j_1 \theta_1 i_2 j_2} w_{i_2 j_2}}{\sum_{i}\sum_{j} w_{ij}} \qquad (9)$$

5 Conclusions

This research proposed a camera placement optimization framework for vision-based monitoring on construction sites. To validate the applicability of the proposed framework, the case study was carried out considering actual conditions of construction sites. The performance of existing camera networks and suggested solutions was compared. The results showed the suggested design outperformed the existing camera placement in terms of the total weighted effective coverage rates. With the proper camera placement, it is expected to collect adequate quality of video/image data and support vision-based monitoring tasks successfully.

Several research challenges remain to be improved. For instance, the proposed framework can be applied to diverse construction projects involving various unique site conditions. It is then available to identify and incorporate more various elements in the camera placement framework. Although it is a challenging issue to find proper 2D locations of surveillance cameras in practice, optimization with 3D modeling can be addressed for further studies.

Acknowledgements

This research is supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT & Future Planning (2017R1E1A2A01077468). This material is in part based upon work supported by the National Science Foundation (NSF) under CMMI Award #1635378. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NSF.

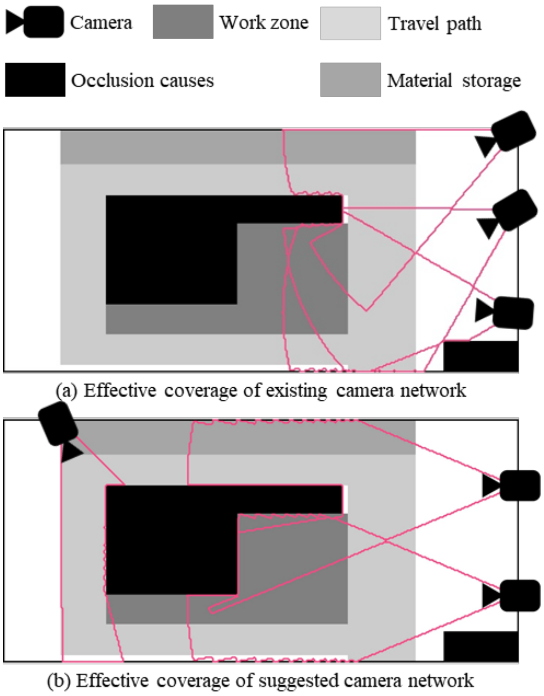

Figure 2. The coverage areas of camera networks

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