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INTELLIGENT SCHEDULING AND MOTION CONTROL FOR HOUSEHOLD VACUUM CLEANING ROBOT SYSTEM USING SIMULATION BASED OPTIMIZATION

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ABSTRACT

This research considers overall scheduling of a vacuum cleaning robot that includes multi cleaning cycles. Even though there are research studies for generating paths for a device, the paths in each cycle tend to be similar from the fact that the motion planning is based on one tour of a target space. This paper suggests a new and effective simulation based optimization (SO) framework for generating an overall schedule and an effective path for each cycle. In the simulation stage, a dust prediction model is generated using absorbed dust data and floor information. This process uses a multi-modal Gaussian mixture model as a basic model. The generated prediction model provides the needed constraints for different mathematical programming models in the optimization stage. The proposed framework is considered as an efficient scheduling method in terms of minimizing redundant paths while maintaining tolerable dust levels during multi cleaning cycles.

1 INTRODUCTION

The technologies supporting the Internet of Things (IOT) have been developing steadily and is being applied to a wide range of applications. IOT has influenced the realm of electronic household appliances such as refrigerators, televisions, washing machines and cleaners. The most common application is to link household appliances to handheld devices such as mobile phones or tablets and to control them remotely. There have been several ongoing research studies for embedding intelligence into their controls and applications. This integration of intelligence contributes to improvement in the usability of the appliances as well as to increase their lifecycle. This paper focuses on a vacuum cleaning robot (Figure 1 (a)) as an application and explores simulation based optimization methods for embedding intelligence.

According to the *WinterGreen research study* (WinterGreen Research 2014), it is predicted that the market share of the household vacuum cleaning robot industry will increase from $1 billion to $2.6 billion in 2020. While vacuum cleaning robots remove dust autonomously making it comfortable and time-saving for customers, most of the existing robot cleaners have several limitations such as lack of intelligence, insufficient removal of dust, heavy dependency on floor environment and difficulty of overall cleaning scheduling. These limitations can adversely affect their autonomous cleaning movements. In order to overcome these limitations, this paper suggests an intelligent scheduling method for a robot cleaner. The method is based on simulation based optimization (SO) methods with a goal of removing dirt within a tolerable particulate matter (ξ $\mu g/m^3$; ξ PM-10).

The following section explains the related background knowledge and provides the relevant literature review. Section 3 summarizes the outline of the proposed approach using SO methods. Section 4 shows the effectiveness of the suggested framework with an exemplary numerical experiment.

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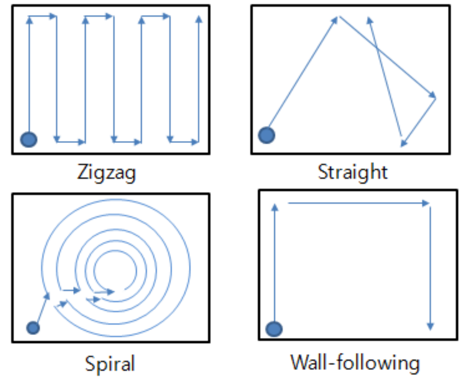
(a) Several robot cleaners (Siegel 2014)



(b) several predefined cleaning patterns

Figure 1: Several robot vacuum machines and their cleaning patterns.

2 BACKGROUND AND LITERATURE REVIEWS

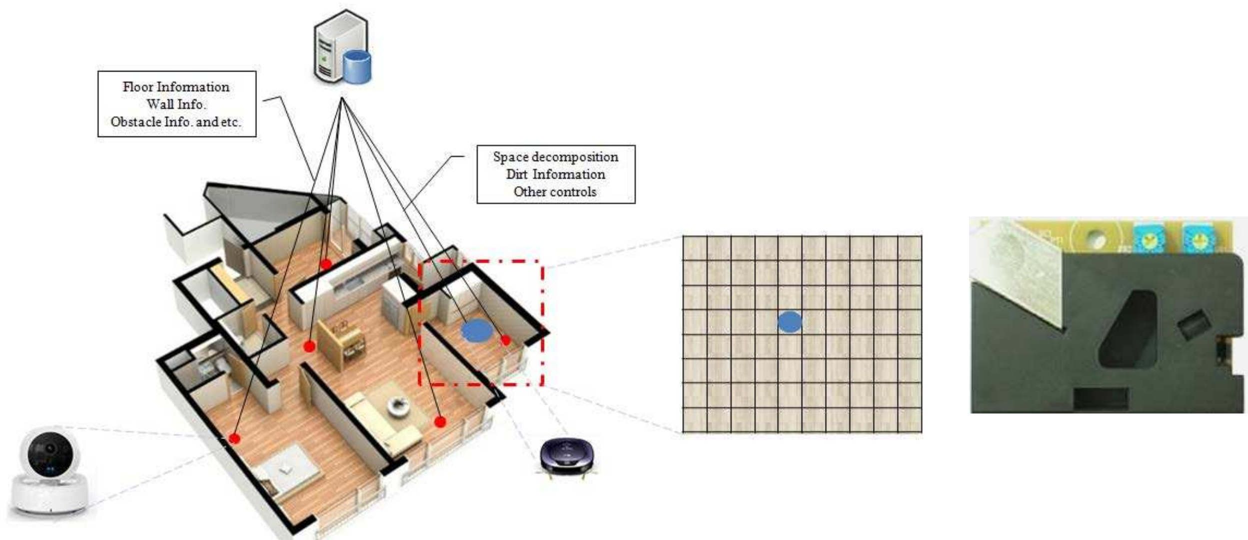
Traditional research studies in robotic vacuum cleaner have focused on its motion planning and path strategies. In general, the overall path is generated using a preprogrammed motion pattern (zigzag pattern, straight pattern, spiral pattern, wall-following pattern, combined pattern) or a random pattern. As an example, the *Philips* robot vacuum cleaner FC8802/01 uses three patterns (Philips 2014): straight, spiral and wall-following patterns. Figure 1 (b) shows several predefined cleaning patterns. The main input for the self-navigation is the real-time data gathering using several sensors such as optical sensors, ultrasound sensor, proximity sensors, surface sensors, laser, magnetic, and/or cameras. For instance, infrared sensor is a type of optical sensor that is used for detecting obstacles or walls. The robot vacuum cleaner's embedded path generation algorithm using the measured sensory data generates the motion path for a range of spaces. The machine subsequently returns to the predefined position for recharging its battery. This process is called as an one cleaning cycle. Many research studies have focused on how to effectively generate the motion planning for a cleaning cycle. The cleaning strategies for a cycle are classified into three types of strategies: 1) The strategy using cell map, 2) The template based strategy, and 3) Artificial Intelligent (AI) based method. The cell map based approaches divide a target space into several cells and the paths are planned using evaluation of adjacent cells with a choice of several available objective functions (e.g. shortest path, obstacle-free path, and/or energy saving path). Oh et al. (2004) suggest a more effective triangular-cell map than a traditional rectangle map, while Myung, Jeon, and Jeong (2009) use a Generalized Voronoi Diagram (GVD) for a cycle path. The template based path planning uses the predefined matching relations between sensory measurements and related patterns which are shown in Figure 1 (b). AI based planning methods introduce several learning techniques and generate adaptive paths. Soltero, Schwager, and Rus (2014) generate a gradient descent method-based adaptive path. These path generation techniques need information about a cleaning environment. While many related applications assume the incomplete information about the cleaning environment, it is possible to assume that complete information is known for the development of IOT techniques. Vaussard et al. (2014) generate their motion paths using a home ecosystem, where a camera(s) transmits the space information to a robot cleaner. This paper uses the assumption that a vacuum cleaning robot knows the space information.

While there are many related methods concentrating on cleaning cycles, there are few research studies for scheduling a robot's overall schedule or for planning among multi-cycles. Most of the current real robot cleaners use a user/producer-predefined schedule for a fixed time period. It implies that each cycle might have a similar trajectory and could be inefficient by generating redundant paths. This paper suggests a new and efficient overall scheduling algorithm using SO techniques. SO methods have been applied for solving NP-Complete problems. When a problem displays NP-Complete complexity, the simulation process approximates the complexity using estimated probability models. Subsequently, the models are used in the following optimization stage as parts of a set of constraints or the objective function. The repetition of these stages makes it possible to change the problem's characteristics from NP-Complete complexity to a set of pseudo-polynomial complexities. Osorio and Bidkhori (2012) improve a traffic network using Bayesian model based SO methods. This paper applies SO techniques for scheduling overall cycles while controlling the dirt degree within a tolerable particulate matter. The following section describes the proposed framework in detail.

3 INTELLIGENT SCHEDULING FRAMEWORK USING SIMULATION BASED OPTIMIZATION

3.1 Home Ecosystem and Related Sensor Module

The suggested scheduling method is based on a home ecosystem (Figure 2(a)) which consists of a main controller, several optical cameras and household appliances. The role of the ecosystem is to let the robot have sufficient information (e.g. size of space and location of walls/obstacles) about the environment. The installed cameras capture the shapes of floor, wall and obstacles, and transmit the information to the main controller. The main controller assimilates the information and transmits it to the vacuum robot. Then, the robot decomposes the target space into several cells and sets up an overall cleaning schedule and the related cycle path for each cell.



(a) Home ecosystem for controlling a vacuum robot

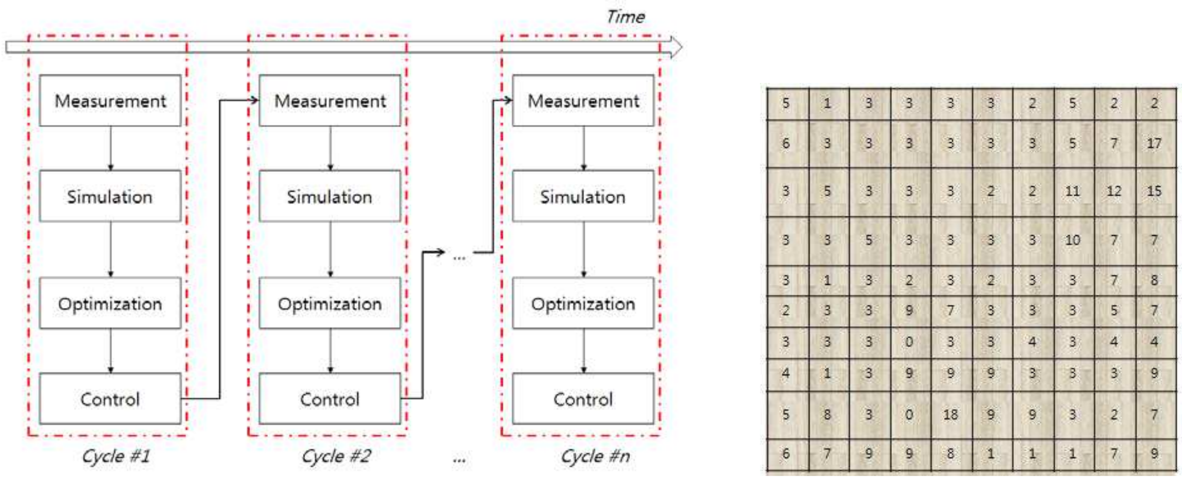
(b) An example of dust sensor (DSM501 2015)

Figure 2: Home ecosystem and installed dust sensor on a cleaning robot.

The cleaning vacuum robot has a dust sensor (Figure 2 (b)) which is used for measuring amount of dirt per each cell (Unit : PM-10). The measured amount of dust is used for approximating the probability of dirtiness of the floor and for generating an overall cleaning schedule using the following simulation-optimization processes.

3.2 Simulation based Optimization Framework for Overall Cleaning Schedule

As shown in Figure 3 (a), the overall cleaning schedule consists of several cycles. A motion path is generated in each cycle using four sub-stages: measurement, simulation, optimization and control sub-stages. The first sub-stage measures the absorbed dirt level per cell through which the robot passes and updates the information during a fixed time interval. Figure 3 (b) illustrates a dust map showing the gathered dust information during a time period. The second sub-stage uses the dust map. The dust map is transmitted from the vacuum robot to the main controller in the home ecosystem. The main controller analyzes the accumulated dust information and uses the information in several simulation techniques such as Bayesian framework (Gelman et al. 2004) or Time-series based method to predict the dust probability distribution.



(a) Overall scheduling procedure with four sub-stages (b) An exemplary dust map

Figure 3: Overall scheduling procedure and a dust map.

The multimodal probability is generated using a bivariate Gaussian distribution ($f_X(i,j)$) and Gaussian mixture method, as shown in (1) and (2). (i,j) is the cell index in the i, j^{th} cell in (1). And, μ_i and σ_i indicate the mean and the standard deviation of the i^{th} row (column), respectively. ρ is the correlation coefficient between the i^{th} row and the j^{th} column. $\Sigma_{i,j}$ indicates the covariance matrix of the i, j^{th} cell in (2). Figure 4 shows an exemplary dust probability from the simulation sub-stage. The generated dust probability $G_X(i,j)$ is transmitted from the main controller to the cleaning robot for generating overall schedule and cleaning path for each cycle.

$$f_X(i,j) = \frac{1}{2\pi\sigma_i\sigma_j\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}\left(\frac{(i-\mu_i)}{\sigma_i^2}+\frac{(j-\mu_j)}{\sigma_j^2}-2\rho\frac{(i-\mu_i)(j-\mu_j)}{\sigma_i\sigma_j}\right)} \tag{1}$$

$$G_X(i,j) = \sum_{i=1}^{N} f_{X_i}(i,j \mid \mu_i, \mu_j, \Sigma_{i,j}) \tag{2}$$

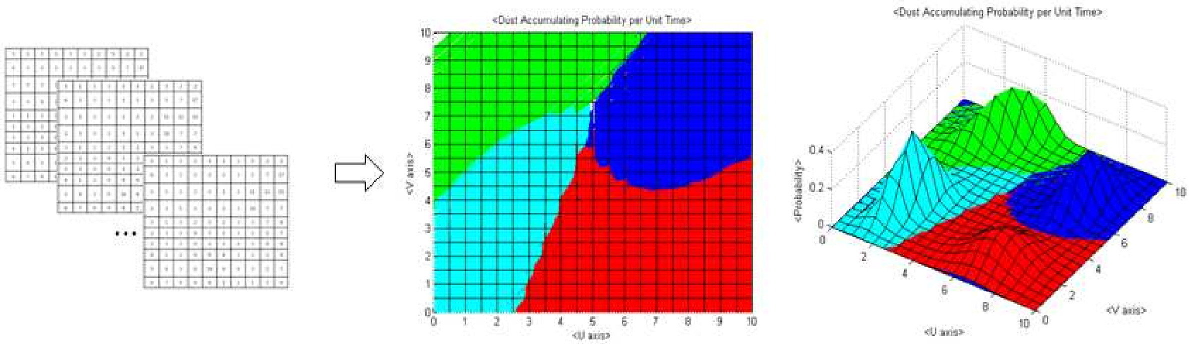


Figure 4: An simulated multi-modal dust probability distribution.

The dust probability is then used for predicting potential dirt in each cell and the overall cleaning schedule is set up considering several objective functions in the third sub-stage: the optimization sub-stage. This optimization process is called as the ε·T-tolerable cleaning stage. Since ε PM-10 signifies the absorbed dust particle during one unit time, ε·T (Unit : μg/m^3/T times) indicates the dust particles for T time units. When a customer has a target for keeping the degree of cleanness in a unit cell under ε·T for a fixed period (T), the dust level in each cell is predicted and quantized using the simulated multi-modal distribution ($G_X(i, j)$). Each cell (with a higher value than ε·T) is then sorted in descending order with respect to the predicted dust level and categorized into several groups (the number of groups = N) using several nonparametric methods. The value of N can be calculated by considering the robot's power consumption rate and the size of space. Figure 5 shows the grouping process into N groups. As shown in Figure 5, $d_{i,j}$ represents the predicted dust level of cell (*i* ,*j*) and $D_i (= \sum_{j=1}^{n_i} d_{i,j})$ is the total dust amount in the *i*th group. $D_i \cdot T$ indicates the total dust amount in the *i*th group for the time period T.

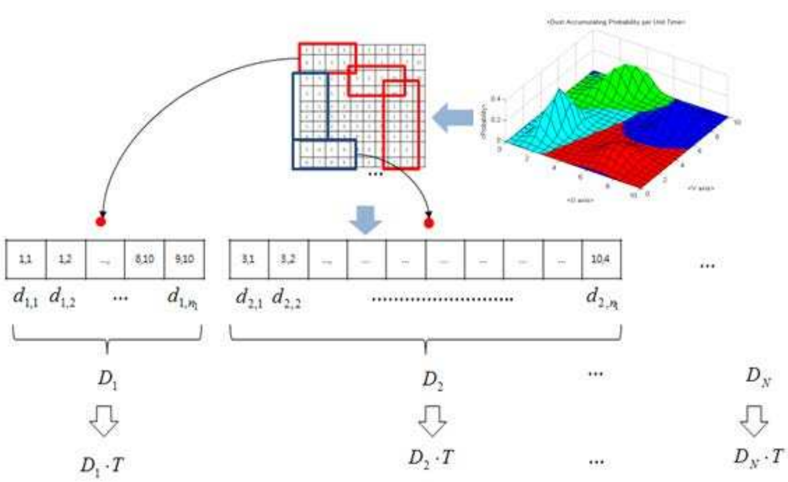


Figure 5: Sub-grouping using the simulated multi-modal distribution.

The overall schedule is calculated using the mathematical programming model in (3). As shown in (3), x_i indicates the cleaning cycle number for the i^{th} group and n_i is the total number of cells in the i^{th} group. When cleaning capacity in a cell is assumed as α in the robot, the given optimization model calculates the numbers of cycles in each group.

$$\begin{aligned} & \min \sum_{i=1}^{N} R_i \\ & s.t. \quad k_i = \alpha \cdot n_i \\ & \qquad R_i = D_i \cdot T - x_i \cdot k_i \ , \forall i \in N \\ & \qquad R_i \geq 0, \quad \forall i \in N \\ & x_i = \text{integer} \ , |\, x_i \,| \geq 0 \end{aligned} \tag{3}$$

Each detailed motion path is generated considering predefined path strategies. When a straight pattern is applied among the embedded pattern (Figure 1 (b)), each cycle path is determined using (4).

$$\begin{aligned} & \min \sum_{i=0}^{n_t} \sum_{\substack{j=0 \\ j \neq i}}^{m_t} c_{i,j} \cdot P_{i,j}^{t} \\ & s.t. \quad \sum_{\substack{i=0 \\ j \neq i}}^{n_i} P_{i,j} \geq 1 \\ & \qquad \sum_{\substack{j=0 \\ j \neq i}}^{m_t} P_{i,j} \geq 1 \end{aligned} \tag{4}$$

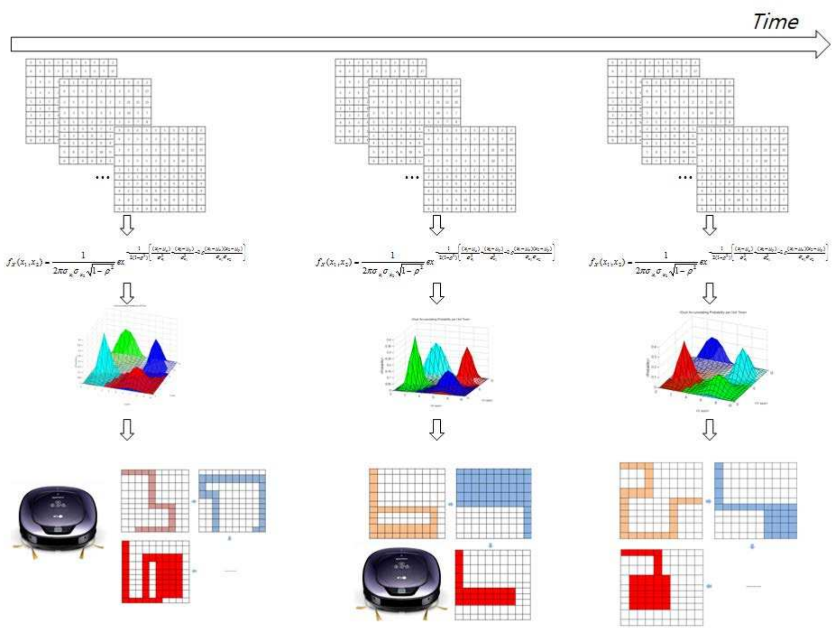


Figure 6: The outline of SO based scheduling framework and an experimental result.

The given mathematical model minimizes the overall traveling path, where $p_{i,j}^{t}$ is a binary variable indicating the existence of a trajectory from the i^{th} cell to the j^{th} cell and $c_{i,j}$ is the power consumption amount from the battery while moving from the i^{th} cell to the j^{th} cell. This model generates the best energy-consuming paths in each cycle. Finally, overall scheduling with each cycle path is generated using the provided SO framework. Figure 6 summarizes the overall SO based scheduling framework for a vacuum cleaning robot.

4 CASE STUDY AND NUMERICAL EXPERIMENTS

This section shows a numerical experiment and the analysis using the SO based scheduling framework. Table 1 shows the detailed conditions, the methods applied and the parameters used.

Table 1: The detailed parameters and methods in the numerical experiment.

Parameters & Methods	Experimental Condition	Parameters & Methods	Experimental Condition
Number of cells	100 (10 by 10 squared space without obstacles)	N	4
Dust in a cell	Random number from $N(10,5^2)$ per each cell, unit time	α	20 (PM-10)
ε	5 (PM-10) / 10 PM-10 per cell	Simulation model	Bayesian framework based Gaussian mixture model (2)
T	50 time units	Path planning methods	Straight pattern based planning and scheduling ((3) & (4))

This numerical experiment is compared to the method using a zigzag pattern and the fixed-time interval (*Discrete interval based Cleaning and Charging*) based schedule for the same space and dust levels. Table 2 shows the comparison between two case studies: the proposed framework based simulation and the fixed zigzag pattern based path planning. This comparisons are based on 20 simulation iterations and the computed averages.

Table 2: Comparisons between the proposed framework and a zigzag-fixed schedule based path plan.

Comparisons*	The proposed SO framework	Zigzag – fixed schedule based path plan
The number of cycles per T time units	6 (ea)	10 (ea)
Overall path lengths	216 movements	715 cell movements
Total remaining dust level	0.85 PM-10 per cell	3.55 PM-10 per cell

*: average of 20 simulation iterations.

As shown in Table 2, the SO based framework is more effective than a fixed schedule in terms of total number of cycles, overall path lengths and the total remaining dust level. While the provided comparison might be different with different parameters and conditions, the suggested framework is considered as a more efficient scheduling method from the fact that it handles multi-cycles in a scheduling time period and minimizes redundant paths using the dust distribution.

5 CONCLUSION AND FUTURE STUDIES

The development of IOT technologies has made control of household appliances easier and convenient. While many IOT-related appliance techniques have focused on their remote and intelligent controls, this paper considers a vacuum cleaning robot and its cleaning schedule using a SO approach. Most research studies in robotic vacuum cleaning devices focus on generating paths with specific objectives, such as energy-saving paths and/or obstacle-free paths. These studies have developed solutions for effective paths in a cleaning cycle, but have not addressed the objective of decreasing overall path considering multi cleaning cycles. This study focuses on the problem of scheduling of overall cleaning as well as path generation in each cycle.

This paper shows the use of a SO based scheduling method for solving the problem. With the assumption that the cleaning device possesses adequate information of the floor surface using a IOT based ecosystem and the detection of the absorbed dust amount using related sensor systems, it constructs a multivariate distribution and estimates the extent of the dirty environment considering the probability distribution and parameter estimates for a time period. A multi-modal based multivariate distribution is generated using the simulation stage. The generated model is used as a prediction model for scheduling the paths in the subsequent epochs. This stage is referred to as the optimization stage as the scheduling and path planning use several mathematical models. The repeating of the simulation stage and the optimization stage generates the minimized paths with the objective function within the specified tolerable dust level.

As part of future studies, a broader uncertainty-based control can be considered. While this paper controls the scheduling and paths from the fixed tolerable dust level, it can be represented using fuzzy logic or other probabilistic models. The incorporation of these uncertainties based control will make the overall control more flexible and intelligent. In addition, the use of a few meta-heuristic methods can be explored in the optimization stage. As the problem in the optimization stage is a NP-Complete problem, the use of meta-heuristics could possibly facilitate controlling the device in real-time.

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