Dynamic Path Planning for QoS Improvement in Multiple Automated Guided Vehicles

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***Abstract*—This paper studies the trajectory optimization of an automated guided vehicle (AGV) for a smart factory where material handling with high wireless communication quality is required. This design aims to maximize the sum of spectral efficiency under complex continuous-value constraints on movement and combinatorial constraints on cooperative movements. To tackle the NP-hard optimization problem, this paper proposes a hybrid algorithm that combines global and local optimization, where global optimization meets the constraints with relaxation and local optimization considers all constraints on movements. Specifically, the AGVs travel by local path planning based on dynamic window approach (DWA), given the globally optimal trajectory that is solved using dynamic programming (DP). Finally, simulation results provide the high communication quality achieved by the proposed algorithm compared to the benchmark algorithms.**

***Index Terms*—Radio resource allocation, Trajectory optimization, Automated guided vehicle**

I. INTRODUCTION

Cyber physical system (CPS) integrates control, wireless communication networks, Internet-of-things (IoT), digital twin, computing technology, and artificial intelligence (AI). With the rapid shift of companies to digital transformation (DX) in recent years, CPS has become important in the manufacturing industry to take competitive advantage [1]- [4]. CPS can learn optimal control in a digital world created by real-time monitoring of factory systems and feed it back to the physical world. This optimal control achieves the simultaneous high-mix, low-volume production necessary to ensure competitive advantage, and realizes a smart factory with improved manufacturing flexibility, productivity, and profitability [5] [6].

In a smart factory, there are different types of devices, including assembly machine and automated guided vehicle (AGV), which transports products and materials. The optimal control is applied to these devices. Material handling is the transportation of products and materials in an indoor factory. The logistics business process, including material handling, is vital in a smart factory [7] [8] [9].

In material handling, it is necessary to assign appropriate paths and tasks to each AGV to transport products and materials to the storage position designated by the system [8]. Therefore, several existing studies have investigated path planning based on the A* algorithm and task assignment based on multi-agent reinforcement learning [8] [10]. Most existing studies rely on the global shortest trajectory to reduce the transportation time or appropriate task allocation to increase the utilization of AGVs to improve the system's operational efficiency.

In Industry 4.0, smart factories require flexibility and scalability to cope with a frequent dynamic reorganization of systems, and wireless communication networks are expected to play an essential role in achieving these requirements. However, a harsh propagation environment in an indoor factory may cause severe performance degradation in wireless communication [5]. Therefore, there is an urgent need for a material handling system that also considers communication quality, which has not been considered in existing research [8] [10]. Path planning considering communication quality has been discussed in many studies for unmanned aerial vehicle (UAV) networks. In [11], UAV trajectories and radio resource allocation is optimized to maximize the channel capacity per unit energy consumed by UAVs. In [12], UAV trajectories and radio resource allocation are optimized to achieve required data rate and avoid collision between UAVs. In many existing studies, global trajectory optimizations and radio resource allocation have achieved physical collision avoidance and improved communication quality. However, global optimization requires simultaneous optimization of the trajectories of all UVs and lacks scalability and flexibility [6]. The scenario for AGVs traveling on the ground has relatively more obstacles than in the air. Thus, joint optimization of all AGV trajectories with collision avoidance in mind is computationally challenging. In addition, the motion equations and energy consumption constraints for UAVs and AGVs are generally different, making it difficult to directly apply the schemes proposed for UAV networks to AGV path planning. Therefore, it is necessary to propose a new AGV path planning that considers communication quality.

This paper proposes a hybrid algorithm that combines global and local optimization for AGVs' trajectories. The proposed hybrid algorithm considers improving wireless communication quality in material handling. Specifically, a trajectory optimization problem that maximizes the sum of spectral efficiency during the execution of each allocation task for each AGV is formulated, which is NP-hard. To tackle NP-hardness, the problem is reformulated into a computationally

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simple global optimization problem with the relaxation of complex continuous-value constraints on movement and combinatorial constraints on cooperative movements. It is solved using dynamic programming (DP) [13]. For a computationally simplified move that meets the constraints, the AGVs travel by local path planning based on the Dynamic Window Approach (DWA) [14], given the global optimal trajectory.

The rest of this paper is organized as follows. Section II describes the system model and Section III explains the proposed method. Section IV describes the simulation results and the conclusions are provided in Section V.

II. SYSTEM MODEL

Figure 1 shows a material handling system for an indoor factory considered in this paper with a square area of $D^{\text{area}}\,[\text{m}]$ on one side having multiple obstacles (such as walls, shelves, pillars, etc). The communication system consists of a single BS multiple AGVs, which are indexed by i, where $i \in \mathcal{I}$ and $\mathcal{I} = \{1, 2, \ldots, I\}$. BS and multiple obstacles are fixed and placed as shown in Fig. 1. The two-dimentional location of BS is expressed by $\boldsymbol{u}^{\text{bs}} = [x^{\text{bs}}\,[\text{m}], y^{\text{bs}}\,[\text{m}]]^\top$ and the height of BS antenna is denoted by $H^{\text{bs}}\,[\text{m}]$. The two-dimensional locations of multiple obstacles are represented by a set $\mathcal{U}^{\text{obs}}$. Each AGV travels to its allocated destination to transport materials and goods during a simulation time T^{sim} [sec]. The two-dimensional location of AGV i at time t, where $t \in [0, T^{\text{sim}}]$, is represented by $\boldsymbol{u}_i(t)$ and the antenna height of AGV i is denoted by H_i [m]. This paper assumes AGV i follow the motion equation given as follows [14]:

$$x_i(t) = x_i(0) + \int_0^t v_i(t) \cdot \cos\theta_i(t) dt, \tag{1a}$$

$$y_i(t) = y_i(0) + \int_0^t v_i(t) \cdot \sin\theta_i(t) dt, \tag{1b}$$

$$v_i(t) = v_i(0) + \int_{t_0}^t \dot{v}(\hat{t}) d\hat{t}, \tag{1c}$$

$$\theta_i(t) = \theta_i(0) + \int_0^t \left(\omega_i(0) + \int_0^{\hat{t}} \dot{\omega}(\tilde{t}) d\tilde{t} \right) d\hat{t}, \tag{1d}$$

where $v_i(t)\,[\text{m/sec}]$, $\omega_i(t)\,[\text{rad/sec}]$, $\theta_i(t)\,[\text{rad}]$ are the linear and angular velocities and the heading direction of AGV i at time t. Furthermore, the velocity and acceleration are constrained as follows:

$$-V \le v_i(t) \le V, \tag{2a}$$

$$-\Omega \le \omega_i(t) \le \Omega, \tag{2b}$$

$$-A^{\text{v}} \le \dot{v}_i(t) \le A^{\text{v}}, \tag{2c}$$

$$-A^{\omega} \le \dot{\omega}_i(t) \le A^{\omega}, \tag{2d}$$

where $V\,[\text{m/sec}]$, $\Omega\,[\text{rad/sec}]$, $A^{\text{v}}\,[\text{m/sec}^2]$, $A^{\omega}\,[\text{rad/sec}^2]$ are maximum velocities and accelerations.

This paper assumes that each AGV communicates with BS, i.e., transmits sensing information and images as it travels to its destination for material handling.

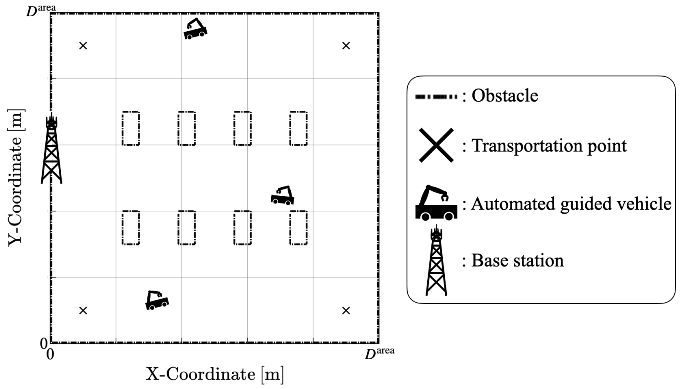

Fig. 1. Indoor factory environment.

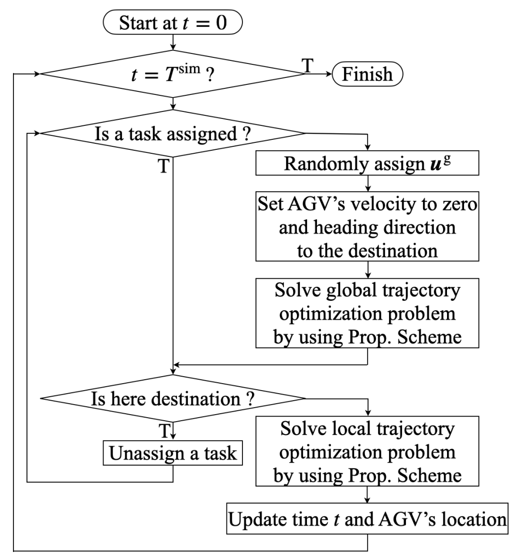

Fig. 2. Task assignment and path planning in material handling.

A. Task assignment

For material handling, a task operation model is illustrated in Fig. 2. The tasks are assigned to AGV i with instructions to arrive at random destination represented by $\boldsymbol{u}_i^{\text{g}}(t)$, where $\boldsymbol{u}_i^{\text{g}}(t) \in \mathcal{U}^{\text{g}}$ and $\mathcal{U}^{\text{g}}$ is denoted as a set of transportation points showed in Fig. 1. Each AGV travels according to its assigned task by local path planning, given a global optimal trajectory.

B. Uplink communication

All AGVs communicate with BS over one available channel with bandwidth $B[\text{Hz}]$ for transmitting information. In order to avoid signal interference among AGVs, time division multiple access (TDMA) is applied.

The distance between AGV i and BS at time t is denoted by $d_i(t) = \sqrt{\|\boldsymbol{u}_i(t) - \boldsymbol{u}^{\text{bs}}\|^2 + (H_i - H^{\text{bs}})^2}$. For simplicity, AGV-to-BS channel is dominated by NLoS paths [15], so that the channel gain is described as $\gamma_{i,\text{dB}}(t) = -10a \log_{10} d_i(t) - b - 10c \log_{10} f - \xi_{\text{dB}}\left(\boldsymbol{u}_i(t)\right)$, where a, b, c, f [GHz] denotes path loss coefficient, reference offset, carrier frequency factor, and carrier frequency, respectively, and ξ is the shadowing component with spatial correlation [16]. Then, the signal-to-noise ratio (SNR) is given by

$$\Gamma_i(t) = \frac{P_i \gamma_i(t)}{\sigma^2}, \tag{3}$$

where P_i [W] is the transmit power of AGV i and σ^2 [W] is the additive white Gaussian noise (AWGN) power.

C. Problem formulation

The aim of this paper is to maximize the achievable spectral efficiency in each task operation time by optimizing the trajectory. Thus, the optimization problem for AGV i can be formulated as follows:

$$\text{(P1):} \quad \underset{\{\boldsymbol{u}_i(t), \forall t \in (t_0, t_0+\tau_{t_0}]\}}{\text{maximize}} \int_{t_0}^{t_0+\tau_{t_0}} \log_2\left(1+\Gamma_i(t)\right) dt \tag{4a}$$

$$\text{s.t.} \quad \boldsymbol{u}_i(t_0+\tau_{t_0}) = \boldsymbol{u}_i^{\mathrm{g}}(t_0) \tag{4b}$$

$$v_i(t_0) = 0, \tag{4c}$$

$$\omega_i(t_0) = 0, \tag{4d}$$

$$\theta_i(t_0) = \arg\left(\boldsymbol{u}_i^{\mathrm{g}}(t_0) - \boldsymbol{u}_i(t_0)\right), \tag{4e}$$

$$\|\boldsymbol{u}_i(t) - \boldsymbol{u}\| \geq D^{\mathrm{hit}}, \forall \boldsymbol{u} \in \mathcal{U}^{\mathrm{obs}} \tag{4f}$$

$$\|\boldsymbol{u}_i(t) - \boldsymbol{u}_j(t)\| \geq D^{\mathrm{hit}}, \forall j \in \mathcal{I} \backslash i \tag{4g}$$

$$(1a) - (2d)$$

where t_0 [sec] and $(t_0+\tau_{t_0})$ [sec] are the start and finish time of each task operation, and D^{hit} [m] is the minimum distance to ensure collision avoidance. Here, (4b) constrain the arrival at the destination within the travel time, (4c)-(4e) indicates that the velocities and heading are initialized when a task is assigned, (1a)-(2d) constraints motion, and (4f)-(4g) constraints collision avoidance. Note that (P1) is NP-hard and difficult to solve due to the non-convex (4a), nonholonomic movement (1a)-(1d), and combinatorial restrictions (4g), which needs to be transformed and relaxation of restrictions.

III. Proposed Algorithm

To solve (P1), this paper proposes a hybrid algorithm for local path planning given the global optimal trajectory, which mainly includes a) global optimization through problem transformation and constraint relaxation, b) local planning that considers all constraints along the global optimal trajectory.

A. Global optimization

To transform (P1) as an optimal control problem to which DP can be applied, time and position of AGV are discretized by dividing travel time τ_{t_0} into $N = \lceil \tau_{t_0}/\Delta^{\mathrm{dp}} \rceil$ time slots indexed by $n \in \{1, \ldots, N\}$ and $[x, y]$ coordinates with a step of Δ^{area} [m]. In order to reduce complexity, moreover, the motion and combination constraints are relaxed by ignoring collisions with other AGVs and nonholonomic motion. In contrast, (4g) is tightened to stabilize the local path planning considering all constraints. Then, (P1) is reformulated as follows:

$$\text{(P2):} \quad \underset{\{\delta \boldsymbol{u}_i[n], \forall n\}}{\text{maximize}} \sum_{n=1}^{N} \log_2\left(1+\Gamma_i[n]\right) \tag{5a}$$

$$\text{s.t.} \quad \boldsymbol{u}_i[n+1] = \boldsymbol{u}_i[n] + \delta \boldsymbol{u}_i[n], \forall n \in \mathcal{N} \backslash N \tag{5b}$$

$$\|\delta \boldsymbol{u}\| \leq V \Delta^{\mathrm{dp}}, \forall \delta \boldsymbol{u} \in \mathcal{U}^{\mathrm{diff}} \tag{5c}$$

$$\boldsymbol{u}_i[1] = g\left(\boldsymbol{u}_i(t_0)\right), \tag{5d}$$

$$\boldsymbol{u}_i[N] = g\left(\boldsymbol{u}_i^{\mathrm{g}}(t_0)\right), \tag{5e}$$

$$\|\boldsymbol{u}_i[n] - \boldsymbol{u}\| \geq D^{\mathrm{hit}} + D^{\mathrm{safe}}, \forall \boldsymbol{u} \in \mathcal{U}^{\mathrm{obs}} \tag{5f}$$

where $\delta \boldsymbol{u}_i[n]$ is the control action of AGV i at slot n, $\delta \boldsymbol{u}_i[n] \in \mathcal{U}^{\mathrm{diff}}$, $\mathcal{U}^{\mathrm{diff}}$ is calculated by (5c), $g(\cdot)$ is the discrete position, and D^{safe} [m] is the distance for stabilizing local path planning. Here, (5b) constrain the movement to meet the state equation, (5c) is movable control actions within one time slot, (5d) and (5e) represents moving from the starting position to the destination within the travel time, and (5f) represent collision avoidance with multiple static obstacles.

(P2) can be solved by using DP presented in Algorithm1. For a given the sequential control actions $\pi_i = \{\delta \boldsymbol{u}_i[1], \ldots, \delta \boldsymbol{u}_i[N]\}$, the corresponding cost of π starting at the initial state $\boldsymbol{u}_i[1]$ is given by

$$J_{\pi_i}\left(\boldsymbol{u}_i[1]\right) = J\left(\boldsymbol{u}_i[N]\right) + \sum_{n=1}^{N-1} \log_2\left(1+\Gamma_i[n]\right), \tag{6}$$

where the terminal cost $J(\boldsymbol{u}_i[N])$ is $-\infty$ if $\boldsymbol{u}_i[N] \neq g(\boldsymbol{u}_i^{\mathrm{goal}}(t_0))$, and 0 otherwise. Then, an optimal policy π_i^* that maximizes the cost for the initial state is represented by

$$\pi_i^* = \underset{\pi_i \in \Pi_i}{\operatorname{argmax}} \, J_{\pi_i}\left(\boldsymbol{u}_i[1]\right), \tag{7}$$

where $\Pi_i = \left\{\delta \boldsymbol{u}_i[n],\, n = 1, \ldots, N \mid \delta \boldsymbol{u}_i[n] \in \mathcal{U}^{\mathrm{diff}}\right\}$. The optimal cost function can be calculated recursively using Bellman's equations by proceeding backwards in time $n = N-1, \ldots, 1$ as follows

$$J(\boldsymbol{u}_i[n]) = \underset{\forall \delta \boldsymbol{u} \in \mathcal{U}^{\mathrm{diff}}}{\text{maximize}} \log_2(1+\Gamma_i[n]) + J(\boldsymbol{u}_i[n+1]). \tag{8}$$

B. Local planning

In local planning, real-time knowledge of the surrounding environment in the vicinity using sensors enables flexible collision avoidance with dynamic obstacles in addition to static ones. Additionally, the trajectory that meets the equation of motion can be obtained with a simple calculation, since only a short-term movement is always planned. Therefore, to travel along the global optimal trajectory that maximizes the sum of achievable data rate, each AGV moves according to the local path planning based DWA algorithm, which needs to meet the nonholonomic motion, avoid collision, and reach the destination. The motion to be met is considered in the constraints, and the other two conditions to be met are considered in the objective function in DWA.

Algorithm 1 Global optimization using DP

Require: $\boldsymbol{u}_i(t_0), \boldsymbol{u}_i^{\mathrm{g}}(t_0), N, D^{\mathrm{area}}, \Delta^{\mathrm{area}}, \mathcal{U}^{\mathrm{diff}}$
Ensure: $\pi_i^* \leftarrow \{\delta \boldsymbol{u}_i^*(\forall n)\}$
$M = (D^{\mathrm{area}}/\Delta^{\mathrm{area}})^2$
Initialize matrix $\mathbf{A}$ of size $N \times M$ to 0 for the destination $g(\boldsymbol{u}_i^{\mathrm{g}}(t_0))$ in slot N, $-\infty$ otherwise
for $n \leftarrow N-1$ *to* 1 **do**
  for $m \leftarrow 1$ *to* M **do**
    if there are not obstacles around position m **then**
      Set $\mathcal{M}'$ to the neighbor positions differ from position m by $\forall \delta \boldsymbol{u} \in \mathcal{U}^{\mathrm{diff}}$
      Calculate spectral efficiency $(rate)$ at position m
      $\mathbf{\Pi}[n][m] \leftarrow \mathrm{argmax}_{m' \in \mathcal{M}'}(rate) + \mathbf{A}[n+1][m']$
      $\mathbf{A}[n][m] \leftarrow \mathrm{maximize}_{m' \in \mathcal{M}'}(rate) + \mathbf{A}[n+1][m']$
    end if
  end for
end for
Set m to the starting position $g(\boldsymbol{u}_i(t_0))$
for $n \leftarrow 1$ *to* $N-1$ **do**
  Calculate $\delta \boldsymbol{u}_i^*(n)$ by the difference between position m and position $\mathbf{\Pi}[n][m]$
  $m \leftarrow \mathbf{\Pi}[n][m]$
end for

If a sampling time Δ^{t} [sec] is sufficiently short, the equation of AGV's motion can be approximated as follows:

$$x_i(t+\Delta^{\mathrm{t}}) = x_i(t) + v_i(t)\left(\sin(\theta_i(t)+\omega_i(t)\Delta^{\mathrm{t}}) - \sin\theta_i(t)\right)/\omega_i(t), \tag{9a}$$
$$y_i(t+\Delta^{\mathrm{t}}) = y_i(t) - v_i(t)\left(\cos(\theta_i(t)+\omega_i(t)\Delta^{\mathrm{t}}) - \cos\theta_i(t)\right)/\omega_i(t), \tag{9b}$$
$$\theta_i(t+\Delta^{\mathrm{t}}) = \theta_i(t) + \omega_i(t)\Delta^{\mathrm{t}}, \tag{9c}$$

and the control pairs (v, ω) to be optimized is given under (2a)-(2d). Each of the control pairs is evaluated with respect to the evaluation function is:

$$G(v_i(t),\omega_i(t)) = \alpha \cdot prog(v_i(t),\omega_i(t)) + \beta \cdot stob(v_i(t),\omega_i(t)) + \epsilon \cdot dyob(v_i(t),\omega_i(t)), \tag{10}$$

where α, β, ϵ are three-term weighting coefficients, and three term $prog(\cdot)$, $stob(\cdot)$, $dyob(\cdot)$ are given as follows:

$$prog(v_i(t),\omega_i(t)) = -\|\boldsymbol{u}_i(t+\Delta^{\mathrm{t}}) - \boldsymbol{u}_i^{\mathrm{dp}}\| / \underset{\forall v_i(t), \forall \omega_i(t)}{\mathrm{maximize}} \|\boldsymbol{u}_i(t+\Delta^{\mathrm{t}}) - \boldsymbol{u}_i^{\mathrm{dp}}\|, \tag{11a}$$

$$stob(v_i(t),\omega_i(t)) = \min\left(1, \underset{\forall \boldsymbol{u} \in \mathcal{U}^{\mathrm{obs}}}{\mathrm{minimize}} \|\boldsymbol{u} - \boldsymbol{u}_i(t+\Delta^{\mathrm{t}})\| / D^{\mathrm{safe}}\right), \tag{11b}$$

$$dyob(v_i(t),\omega_i(t)) = \min\left(1, \underset{\forall j \in \mathcal{I}\setminus i, \forall k \in \mathcal{K}}{\mathrm{minimize}} \|\boldsymbol{u}_j(t+k\Delta^{\mathrm{t}}) - \boldsymbol{u}_i(t+k\Delta^{\mathrm{t}})\| / D^{\mathrm{safe}}\right), \tag{11c}$$

TABLE I
EVALUATION PARAMETERS.

Parameter	Value	Parameter	Value
Simulation area	50×50 [m^2]	Number of BS	1
Gridline spacing Δ^{area}	0.5 [m]	BS height	15 [m]
Simulation time	1 [hour]	Transmission power	20 [mW]
Number of trials	10^3	Carrier frequency	6 [GHz]
Number of AGVs	3	Bandwidth	100 [MHz]
AGV height	1 [m]	Noise power	-94 [dBm]
Min. inter-AGV distance D^{hit}	1 [m]	Parameters of path loss	[19]
Safety margin D^{safe}	2 [m]	Shadowing standard deviation	5.9 [dB]
Max. velocity and acceleration	[18]	De-correlation distance	20 [m]
Sampling time Δ^{t}	1 [sec]	Slot length for DP Δ^{dp}	$1/\sqrt{2}$ [sec]

where $\mathcal{K} = \{1, \ldots, K\}$, K is a period considering inter-AGV dynamic distance, and $\boldsymbol{u}_i^{\mathrm{dp}}$ is one of the positions in the global optimal trajectory. Then, an optimal control $(v_i^*(t), \omega_i^*(t))$ of AGV i at time t is given by

$$(v_i^*(t), \omega_i^*(t)) = \underset{\forall v_i(t), \forall \omega_i(t)}{\mathrm{argmax}} \; G(v_i(t), \omega_i(t)), \quad \text{s.t. } (2a)-(2d). \tag{12}$$

IV. SIMULATION RESULTS

This section provides the numerical performance evaluations of the proposed algorithm. The simulation parameters are listed in Table I. The proposed algorithm is labelled as "Proposed" and the benchmark algorithm, A* algorithm [17], as "A* algorithm". The time slot N must be greater than or equal to the number of grid points that form the shortest path, which in this paper is set to 1.3 times the number of points. The weights α, β, ϵ are set to $0.2, 1.0, 0.25$ respectively that are found by the preliminary evaluation to work well for stability to prevent from falling into local optimization. However, note that about one sampling time cannot meet (4f) and (4g), which is due to the simplified collision avoidance in the local planning to stabilize the solution for destination arrival and static and dynamic collision avoidance.

Fig. 3 shows the time of operating each task normalized in the travel time τ_{t_0} given by global optimization problem. In "A* algorithm", it can be seen that the CDF also takes values other than 0 or 1, even though the shortest path is given in the local path planning. This is because nonholonomic motions and collision avoidance with other AGVs, which are not considered in the given shortest path, are taken into account in the local planning, resulting in acceleration time and detours, which increase the time. Furthermore, CDF takes two different values, since whether collision avoidance with obstacles works in local planning depends on whether the initial location and destination are diagonally opposite. In addition, the normalization time for "Proposed" is longer than that for "A* algorithm", which is caused the optimal path given by using DP that takes longer than the shortest path.

Fig. 4 presents the average achievable spectral efficiency per AGV versus total sampling time. "A* algorithm" shows that the average spectral efficiency at all sampling time is approximately equal to the achievable spectral efficiency at any location, i.e., at $t = 0$. On the other hand, "Proposed" increases

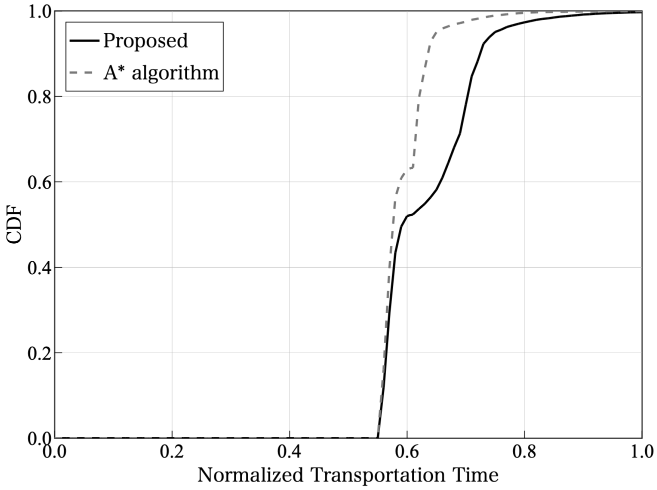

Fig. 3. Normalized time required to move for each task operation.

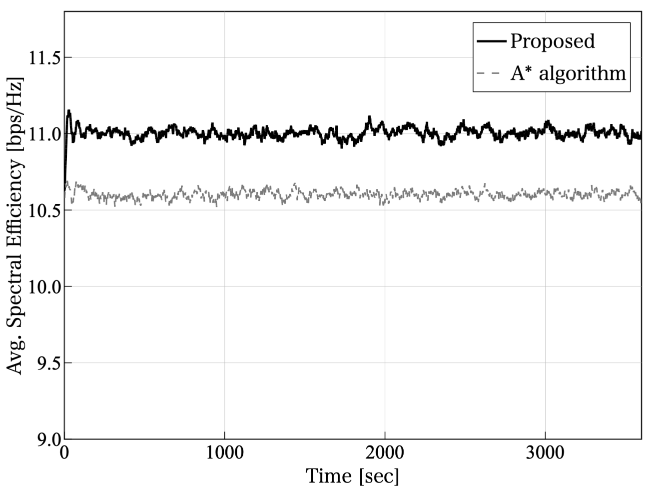

Fig. 4. Average spectral efficiency per a AGV versus total sampling time.

the average spectral efficiency for $t > 0$, and can improve the spectral efficiency by about 5% compared to "A* algorithm". This reason is that the local paths in "Proposed" are planned along the globally optimal trajectory that maximizes the sum of the spectral efficiencies.

V. CONCLUSION

This paper proposed a hybrid algorithm that combines global and local optimization for AGVs' trajectories to improve its communication quality. Specifically, the AGVs travel by local path planning based on DWA, given the globally optimal trajectory that is solved using DP. The simulation results have shown that the proposed algorithm can improve the average spectral efficiency by 5% compared to the benchmark algorithm at the cost of slightly longer trannsportation time.

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