Interaction-Based Task Group Scheduling for a Scalable and Real-Time Self-Driving Simulation

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Abstract: We developed a self-driving test environment based on Virtual Machine (VM) technology. Our test environment enables us to test multiple types of self-driving Artificial Intelligences (AIs) in one simulation and import their self-driving software to an actual car without modification. Our test environment divides a map into several segments and assigns a physical machine to each segment. If a vehicle crosses a border, the VM that embodies the vehicle is moved to another physical machine. However, VM movement causes a load imbalance on the physical machines. We suggest a novel approach to assign high-priority processing to a group of vehicles. The group of vehicles consists of one target vehicle that we would like to test and other vehicles that may interact with the target vehicle. We create such a group by identifying interactions using a " pre-simulation". Our approach reduced the processing time of the jobs created by the self-driving AIs by more than 90 percent under an ideal condition . This result indicates that our approach contributes the real-time processing when the CPU was in an overcommitted state.

1 INTRODUCTION

Many serious accidents occur during trials of self-driving systems. The website (Sel, 2023) lists serious incidents during self-driving. AI takes a long time to learn the appropriate behavior with many scenarios. To prevent an actual driver in a self-driving vehicle from having a serious accident, many precise computer simulations should be performed before a field trial. A computer simulation can create many scenarios that are too difficult and dangerous to run in reality; thus, it reduces serious accidents before trials on public roads.

Many self-driving vehicle simulators exist, such as CARLA (Dosovitskiy et al., 2017), Udacity Self-Driving Car Simulation (uda, 2017), and Microsoft's AirSim (air, 2017). These self-driving vehicle simulators have several problems related to "flexibility." CARLA, Udacity Self-Driving Car Simulation, and AirSim were developed as monolithic applications; hence, essentially, they cannot be modified as parallel applications on a cloud computer. Consequently, they lack scalability. They have "fixed" APIs to access data inside the applications. When we require additional data that their APIs do not provide, we cannot acquire such data. if we requested additional APIs to the developers, it would take a long time to implement.

It would be ideal if we could run many scenarios with many types of simulated cars and export self-driving AI from a simulation environment to a real vehicle without any modifications. To accomplish these requirements, the self-driving simulator would clearly not be as described in previous studies. Self-driving simulators require more flexibility to achieve scalability and improve their ability to access data.

Our objective is to develop a flexible and scalable test environment for self-driving AI. Figure 1 shows an overview of the suggested environment. Our simulation environment consists of VMs, a driving simulator, a 3D map simulator, and simulation middleware. In the figure, a driving simulator and 3D map simulator are connected to virtual devices in a VM via simulation middleware and share information. The 3D simulator creates a virtual space and continuously sends pictures as a camera view to a virtual camera device on a VM. The driving simulator receives the rotation angle from the steering wheel and the ac-

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celeration value from a virtual steering wheel (and virtual acceleration pedal and brake) in a VM. The driving simulator calculates its direction and velocity from the rotation angle and acceleration value received, and sends them to the 3D map simulator to update the vehicle's location. Developers of self-driving AI can execute any task they develop in a VM, their own AI, and any libraries and runtimes. In Figure 1, ROS (Quigley et al., 2009) is used at the runtime environment in a VM.

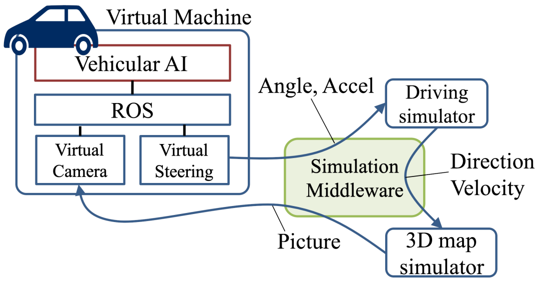
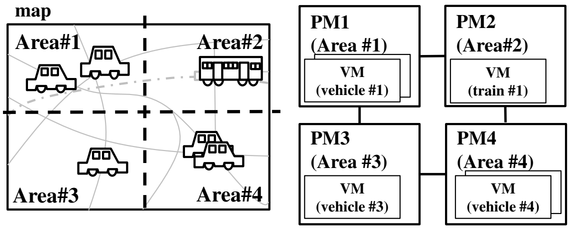


Figure 1: VM-based simulation environment.

The data transaction in the suggested type of self-driving simulation has "geographical locality". The geographical locality of a data transaction means that the data transaction often occurs between objects that are geographically close to each other in a simulation. In the case of a traffic simulation that has two self-driving vehicles that are about to encounter each other at a blind corner, they would perform a data transaction via a wireless ad hoc network to avoid a traffic accident. At the point of computation, VMs that are geographically close to each other in the simulation should be placed on a same physical machine to eliminate the data transaction over a physical network in a data center, otherwise network congestion would occur.

Figure 2 shows the VM deployment mechanism in our environment(Kohiga and Shinoda, 2020). The left side of the figure describes a traffic simulation, and the right side describes a simulation cloud. In this example, the simulation map is separated into several segments and, at least one physical machine is assigned to each segment of the map. A VM represents a self-driving vehicle.

For example, in Figure 2, there are two vehicles in Area #1 and the Physical Machine 1(PM1) is assigned to Area#1. Two VMs are executed on PM1. If a self-driving vehicle moves over the boundary of the two areas, the VM representing this self-driving vehicle moves to another physical machine. In the case of Figure 2, when a self-driving vehicle in Area#1 moves to Area#2, the VM that represents its vehicle on PM1 also moves to PM2.



("PM" stands for "Physical Machine")

Figure 2: Division of the simulation map into several areas and assignment of them to each physical machine.

Our simulation environment has more scalability and flexibility, compared with the previous works.

2 CHALLENGES

The biggest problem in our simulation environment is how to maintain real-time processing when there are several spontaneous increases of VMs in one segment described in Figure 2.

The simulation clock synchronization of all simulation objects is the most important task in a loosely coupled simulation environment. All simulation objects must maintain a simulation clock that is synchronized with the others, otherwise the simulation would lose credibility. In the case of a traffic simulation, a car crash that should occur does not occur because of the clock skew. Several techniques exist for the synchronization of the clock in an agent-based simulation. The most obvious technique is to have "global virtual time" (GVT) (Fujimoto, 2001). GVT is a clock system that is shared by all processing objects that appear in a simulation. Once GVT is set, all processes should obey this time.

There is a case in which the lack of CPUs spontaneously occurs during a simulation in our environment. Figure 3 shows a typical case in which a part of the simulation in a VM is delayed. The left side of the figure describes a simulation map and vehicles. The right side of the figure describes task scheduling with a timeline. We explained the deployment mechanism of our simulation environment in Figure 2. As the simulation proceeds, the number of vehicles in an area varies. At a certain moment, a number of vehicles exceeds a number of CPUs assigned in the segment. There are four vehicles on the left-hand side of the figure; hence, four VMs should be executed on the physical machine assigned to this segment. This physical machine has only two CPUs; hence, the execution of these VMs are delayed because of the lack of a CPU. In this case, the time lapse is twice as fast as that for the clock inside the VMs (when the real clock is $T = 2$, the VMs execute task A and task B at

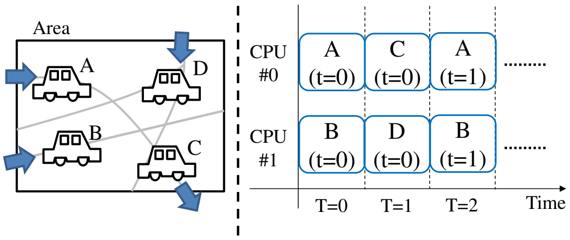


Figure 3: A influx of vehicles in one segment induces the lack of CPUs in our simulation environment.

$t = 1$).

The simulation delay in one segment propagates to all VMs in our simulation environment if they have a time synchronization mechanism like GVT. Consequently, the end of a simulation gets behind because of spontaneous increase of VMs on only one segment. Therefore, we would like to suggest how to maintain real-time processing when there are several spontaneous increases of VMs in a segment.

3 RELATED WORKS

High Level Architecture(HLA)(Dahmann, 1997) is the most famous middleware that federates independent simulators in one simulation. Compared with our simulation environment, HLA processes a federated simulation with smaller time, but forces each simulator to embed APIs to access the HLA functions. We are considering how to utilize the functionality of HLA (ex. time synchronization, data exchange) in virtual machine mechanism and it would be good step for next federation.

Many studies also have been conducted that are related to task scheduling for cloud computing, which is essentially used to reduce the turn around time (TAT) of a request from outside a data center. Its technique is based on how many requests are assigned to each computer with a certain criterion (request priority, energy aware, high CPU utilization, etc.). Task scheduling-related studies were categorized by Mathew et al. (Mathew et al., 2014). The unique feature of our simulation environment is the spontaneous movement of VMs. According to the explanation in Figure 2, if a self-driving vehicle moves over the boundary of the area, the VM that represents the self-driving vehicle also moves to another physical machine. This deployment mechanism uses the "geographical locality" of the data transaction between the VMs and simulators, but the spontaneous movement of VMs occurs. A load balancing mechanism cannot control such spontaneous movement. This feature occurs a load imbalancing and has not been studied in previous work in this field.

4 INTERACTION-BASED TASK GROUP SCHEDULING

4.1 Basic Concept

A feasible solution is to choose a minimum set of VMs to which high priority is assigned to avoid the lack of resources. We define a minimum set of VMs as the VMs that consists of one target VM and the others which interact with the target VM. A developer who is creating a self-driving AI running on the target VM must test whether the self-driving AI smoothly negotiates with other self-driving AIs when they encounter each other in a critical scenario (e.g., negotiation at a blind corner). In such tests, if we choose a set of VMs that interact with the target self-driving AI, we can ignore synchronization with the other VMs.

Figure 4 shows the image of vehicles grouped in a simulation. There are five vehicles (VehicleA to VehicleE) in the figure and they have a direction to move in (depicted by an arrow). VehicleA is moving down a road and VehicleB is moving up the same road. Finally, they pass each other somewhere on this road. If they have cameras for object recognition, then these cameras must capture the opposite vehicle (the camera on VehicleA captures VehicleB, and vice versa). Similar to VehicleA and VehicleB, VehicleC, VehicleD, and VehicleE pass each other on the right-hand side of the area; hence, they are captured by each other's cameras. We refer to VehicleA and VehicleB as "GroupA" and VehicleC, VehicleD, and VehicleE as "GroupB." In the figure, vehicles that belong to GroupA have never encountered the vehicles that belong to GroupB; therefore, we can set different priorities for each group. If we have to observe the behavior of VehicleA, we can set a high priority for vehicles that belong to GroupA. By contrast, we must ignore the behavior of vehicles that belong to GroupB.

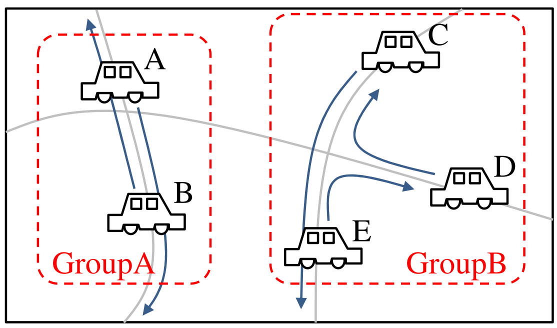


Figure 4: Basic concept is to compose the vehicles which interact with each other in a group and observe one group's behavior.

Figure 5 indicates the relationship between the elapsed time and the vehicle's position. The rectangle on the left-hand side indicates the positions of two vehicles for a certain time ($t = 0$) and the rectangle on the right-hand side indicates the positions of two vehicles for another time ($t = 1$). The two vehicles are about to interact somewhere on a road at $t = 0$ and then they move in their own directions at $t = 1$. Until the two vehicles pass each other, they belong to the same group and we must assign the same priority to them. However, after they have interacted and are moving in different directions, they are independent from each other and we no longer assign the same priority to them. To acquire the relation between the elapsed time and the vehicle's position, we must predict the interactions before we run a self-driving simulation.

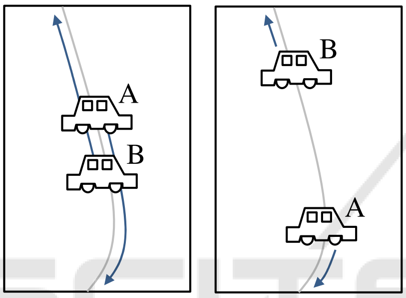


Figure 5: Two vehicles are not in one group after they pass each other.

"Interaction" refers to a scenario in which a vehicle is visible to another vehicle's sensor. Many types of sensors exist and common feature of these sensors is that they have an "effective range". For example, a camera has a range of dozens of meters that shapes sector in front and LiDAR has a range of several meters that shapes circular. If a vehicle moves into the range of the sensor, self-driving AI recognizes it as an object and then makes some decisions Therefore, we define interaction as a scenario in which a vehicle moves into the effective range of a sensor and interacts with a self-driving AI's decision. Our simulation environment must obtain the effective range of sensors to create the aforementioned groups.

4.2 Overview of Our Approach

4.2.1 Requirement

We mentioned that our suggested mechanism requires a starting point and route information from each VM before the simulation starts. This is a precondition for interaction-based priority settings. In this paper, we do not discuss which interface is appropriate because it is simply an implementation matter and out of scope for our study. We only have to acquire starting points and route information from each VM using some type of method. To acquire the starting points and route information from each VM requires, at a minimum, more than one interface between the VMs and simulation management middleware.

4.2.2 Control Flow

The basic concept of our solution is to change the interaction information in a simulation to the priority settings on each VM. We divide this basic concept into the following four parts.

1. (**Traffic Simulation**) acquires the current location and route information from each VM, executes a traffic simulation with them, and acquires the result file, which records the position of each vehicle and the direction sorted by time. We could regard this sequence as a "pre-simulation".
2. (**Interaction Search**) searches interactions from the result file created in the previous step. Interaction search creates a time series interaction list, which consists of a set of clocks , the two vehicles' IDs, and an interaction symbol (unilateral or mutual).
3. (**Grouping**) creates priority information for each VM from the interaction information. Grouping sequence creates a group of vehicles. The group consists of "a target vehicle" and the other vehicles that interact with the target vehicle. In this sequence, we must select one vehicle as the target vehicle.
4. (**Priority Control**) sends priority settings to every virtual clock in accordance with the high-priority group information.

The above four parts are shown in Figure 6. These sequences are processed on the simulation middleware. The grouping sequence creates files that include priority information for each VM, which is the list of priority settings for every clock from the simulation start time. Priority Control sends a priority setting to every clock that corresponds to the same clock in the priority file.

In contrast to the periodic process for Priority Control, the Traffic Simulation in the simulation middleware gathers starting points and route information from each VM once before the simulation starts. If some VMs change their route, the simulation middleware must execute Interaction Search and Grouping again because the route change affects the interaction information between vehicles.

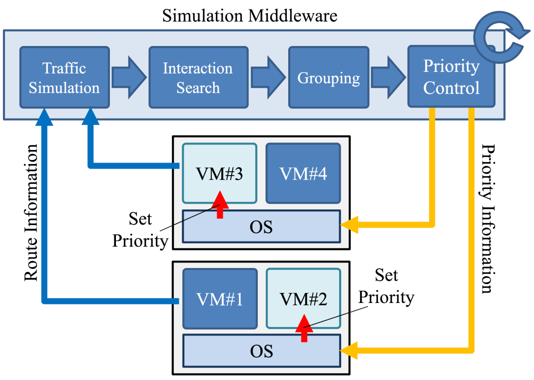


Figure 6: Priority Control flow in our simulation environment.

4.3 Interaction Search

Interaction Search searches the interactions in the simulation. As we mentioned, we must choose one vehicle as the target vehicle and then search the vehicles that interact with the target vehicle. Finally, Interaction Search generates the time series interaction list, which consists of a set of clocks, the two vehicles' IDs, and their distance between them. For an effectiveness experiment in this study, we use the SUMO (Krajzewicz et al., 2002) traffic simulator to obtain the starting points and route information instead of acquiring them from each vehicle. SUMO has a program that randomly generates any number of vehicles in a simulation, including the starting points and route information. We also use SUMO as the traffic simulation for the Traffic Simulation on the simulation middleware. We assume that the current position and route information can be acquired from each VM. Route information can also be acquired from each VM. The self-driving AI must set the destination and route information before departure; hence, this information must exist whenever we run the "pre-simulation".

4.4 Grouping

Grouping creates priority information for each VM from interaction information. Our mechanism creates a group of vehicles that consists of "a target vehicle" and other vehicles that interact with the target vehicle. As we mentioned in the definition of interaction in Figure 5, two vehicles interact somewhere on a road at $t = 0$ and then move in their own directions at $t = 1$. These two vehicles are included in one group at $t = 0$, but they are not in the same group at $t = 1$. Therefore, the number of vehicles in the group is greatest at the start time of the simulation and then decreases as time progresses.

Figure 7 shows a time sequence that describes the Grouping process. Each circle with a capital letter represents one vehicle and the horizontal axis (from $T = 0$ to $T = 5$) indicates the elapsed time. An arrow in this figure represents a vehicle moving to another place; hence, VehicleA at $T = 0$ has a different position from VehicleA at $T = 1$. A red oval represents an interaction and has two meanings : unilateral interaction and mutual interaction. For example, VehicleC and VehicleD have two interactions at $T = 1$ and $T = 5$, and VehicleA, VehicleB, and VehicleC have one interaction at $T = 3$. A short dashed line surrounds almost half of the figure, which indicates the group that we finally want to create. The figure describes the group of VehicleA. The group of VehicleA means "VehicleA as a target vehicle and the other vehicles that interact with VehicleA".

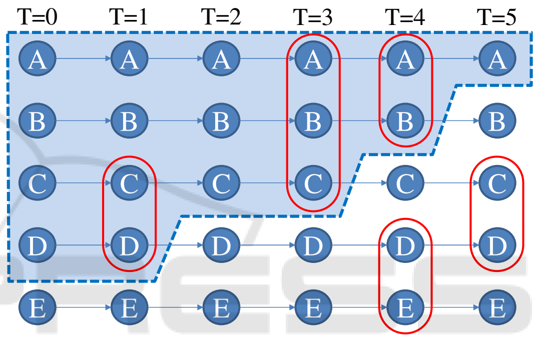


Figure 7: Grouping.

Data 1: Group Data (result of Grouping).

```
[('VehicleID', clock), ...]
[('91.0',19.0),('87.0',15.0),('99.0',12.0),
 ('15.0',12.0),('57.0',11.0),('43.0',7.0)]
```

Finally, we acquire the group data described in Data 1. A tuple consists of the vehicle ID and clock. Clock in this data means the last clock when the high-priority setting of its vehicle is canceled. In the case of vehicle ID "A" and clock "10.0," our simulation middleware assigns a high priority to vehicle A" from the starting time (normally 0.0) to "10.0" in the simulation.

5 EVALUATION

Figure 8 shows the basic sequence of the evaluation environment. The basic sequence is composed of the map and route information of every vehicle as input, simulation middleware, the VM deployment algorithm, and a cloud simulator. The simulation middleware is also composed of a traffic simulator and other parts. We prepared the SUMO traffic simulator to generate the vehicle's position and also prepared the following three components: interaction search, grouping, and priority setting . The simulation middleware created the priority setting of each vehicle and input them into the cloud simulator. We used a cloud simulator instead of an actual cloud to process the job.

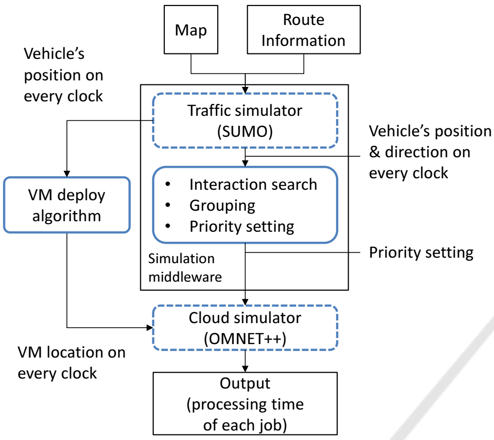


Figure 8: Basic sequence of the evaluation.

Table 1 shows the configuration that we used for the traffic simulation on the simulation middleware. The SUMO traffic simulator requires a map, a starting point and route information for each vehicle as input. We created a grid-shaped load map and the vehicle's information using scripts that are part of the SUMO simulator. Vehicles were generated in the range from 100 to a maximum of 500 vehicles at the beginning of the simulation. We prepared two methods to create a vehicle's route: one based on a random walk and another that compel the vehicles to move through a designated place. The lesser the interaction the better for reducing the number of vehicles that are assigned high priority. A random walk is an ideal method to reduce interactions. In contrast to a random walk, a traffic jam is the worst scenario at the point of reducing interactions.

Table 1: Traffic simulation parameters.

map	2km square 400 junctions
number of vehicles	100 to 500
simulation time(s)	200 to 1000
route of each vehicles	Random

We describe the details of the cloud simulator in Figure 9. The cloud simulator is based on a queuing system. A physical machine is composed of one CPU, one sink, two queues, and one selector. The number of physical machines also changes in accordance with how many physical machines are used for the simulation.

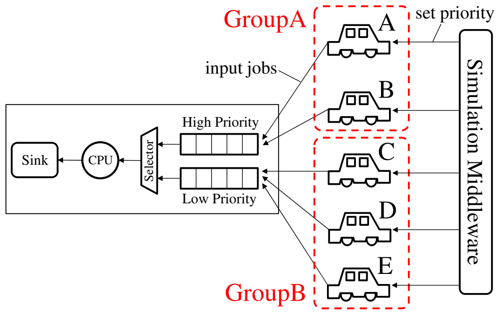


Figure 9: Cloud simulator (OMNET++).

A vehicle receives priority information and VM location. Priority information is a set of time and priority. When a vehicle receives a set of time and priority such as (4.0, high), the source changes the job's priority to high immediately and the high-priority state is finished by the 4.0 clock. A vehicle send a job to a high priority queue during high-priority state. The source also receives VM location information When a vehicle receives the new location, the vehicle sends the next job to another physical machine.

5.1 Evaluation Points

We consider the following points for the evaluation of our approach. The objective of our approach is to create a minimum group of vehicles and assign high priority to them to maintain real-time processing. The smaller number of vehicles in one group is the better. These points are the basic evaluation to observe the feature of our mechanism.

1. measure the processing time of jobs with a fixed number of vehicles and fixed duration as a fundamental evaluation, and then compare the two cases: our approach assigns high priority to the minimum group of vehicles and a normal scenario in a priority property is not assigned;
2. measure the processing time using our approach in the case in which the simulation time is increased;
3. investigate differences in the number of interactions between vehicles running with a random walk and vehicles that stay in a traffic jam

5.2 Result

5.2.1 Fundamental Evaluation

Figure 10 shows the fundamental evaluation result of our approach. We also describe the configuration of

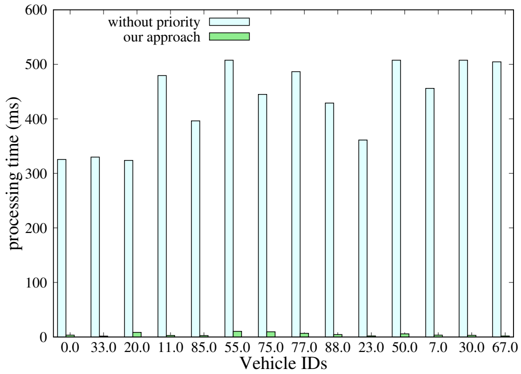


Figure 10: Fundamental evaluation of our approach.

this evaluation in Table 2.

Figure 10 shows that our approach effectively reduced the processing time compared with the processing time without our approach. The x-axis represents the individual vehicle IDs and the y-axis represents the average processing time of jobs produced by each vehicle. The best case is vehicle ID ”30.0”. The processing time with our approach was 3.03 milliseconds and the processing time without our approach was 507.53 milliseconds, which means that our approach reduced the processing time by approximately 99.3 percent. The worst case was the vehicle ID ”55.0” In this case, our approach reduced the processing time by approximately 98 percent of the processing time without our approach. The average processing time with our approach was 4.703 milliseconds and that without our approach was 432.808. Therefore, our approach reduced the processing time by 99 percent.

Table 2: Configuration of the fundamental evaluation.

Traffic simulation configuration		
	map	$2km^2$ 400 junctions
	number of vehicles	200
	simulation time(s)	200
	routes	Random
physical macine configuration		
	the number of PCs	9 nodes (4cores)

The jobs produced by vehicles took 2 milliseconds to be processed. Therefore, if they were smoothly processed without waiting on a queue, the ideal result of the above evaluation would be 2 milliseconds. The average processing time with our approach was 4.703 milliseconds. This means that some jobs were slightly stacked on a physical machine. Later, we discuss whether this delay is reasonable for the real-time processing of a self-driving simulation.

5.2.2 Increasing the Duration of a Simulation

Figure 11 shows the relationship between the duration of a simulation and the processing time. The configuration of this evaluation is the same as that of the fundamental evaluation. This result indicates that our approach could not maintain real-time processing in a simulation that had a long duration. Considering the 400-second duration in the graph, the average processing time was approximately 50 milliseconds. Generally, a delay is barely noticeable up to 50 milliseconds and is acceptable up to 100 milliseconds if no high demands with respect to realism are required. Therefore, the duration of a simulation should be less than 600 seconds for this configuration.

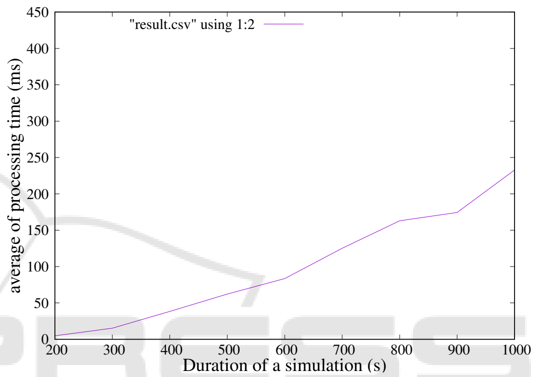


Figure 11: Influence on increasing the duration of the simulation.

5.2.3 Random Walk vs Traffic Jam

Figure 12 shows a comparison of a number of interactions between vehicles using a random walk and in a traffic jam. We prepared three cases that had different numbers of vehicles and compared the average number of interactions in the case of a random walk and traffic jam. The other configuration (duration, map, etc.) was the same as that used in the fundamental evaluation. The number of interactions in the case of a random walk was almost the same as the evaluation result described in Figure 10. By contrast, the number of interactions in the case of a traffic jam increased drastically. This result indicates that almost all vehicles interact with each other when they are involved in a traffic jam; hence, the traffic pattern should be created carefully so as not to induce a traffic jam to maintain the stability of the processing time.

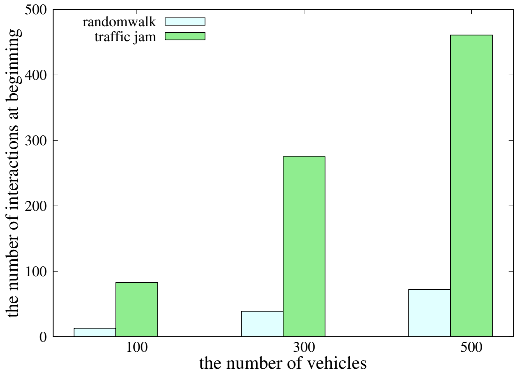


Figure 12: Difference between the number of interactions for a random walk and traffic jam.

6 CONCLUSION

We summarize several characteristics of our approach from the evaluation results as the following items:

- In the ideal circumstance for a self-driving simulation, our approach reduced the processing time to approximately 99 percent.
- The duration of a simulation should be less than 600 seconds in the configuration of Table 2.
- We should not use our algorithm in a traffic jam.

The acceptable number of vehicles in a simulation depended on the map size. We used a map size of $2km \times 2km$. If the map was larger, it would be acceptable to execute more vehicles; that is, **the number of interactions depended on the balance of the number of vehicles, duration, and map size**. Moreover, the acceptable number of interactions depended on the number of CPUs in a segment. We suggested a type of "criterion" in our evaluation when our approach was used in a self-driving simulation to enable it to work appropriately to maintain real-time processing. We will continue to test our approach with the other conditions

7 FUTURE WORK

An experiment on our actual self-driving simulation cloud is obvious as a future work. There is another major work that is to merge this priority assign approach with "our VM deploy mechanism". The load balancing in our VM deploy mechanism (Kohiga and Shinoda, 2020) is a heavy task because it utilizes VM migration. We are thinking of an algorithm that reduces the number of VM migration by replacing with this priority assign approach.

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APPENDIX

The source code of our approach.
https://github.com/akiihito/PriorityControl