Paper:

Autonomous Knowledge Acquisition and Revision by Intelligent Data Carriers in a Dynamic Environment

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In this paper, we built a device and algorithm for implementation in autonomous robots that can enhance efficiency through autonomous knowledge acquisition and sharing. We also propose an algorithm to adapt our robotic system to dynamic environments. In this robotic system, the "Intelligent Data Carrier" provides navigational knowledge for autonomous mobile robots. An IDC summarizes fragmyents of knowledge from individual robots and tells the best direction toward a destination at which a robot wants to arrive. We make models of dynamic environments, and investigate the behaviors of autonomous robots that navigate using an intelligent data carrier system. We also create an algorithm that estimates the validity of knowledge in an IDC and allows the IDC to renew the knowledge autonomously. We verify effectiveness of the proposed algorithm by means of simulations.

Keywords: Autonomous knowledge acquisition and sharing, Intelligent data carrier, Dynamic enviroment

1. Introduction

Currently, researchers are trying to create a robotic system that can function in any general environment. Realization of autonomous task execution would be especially advantageous in hazardous environments. Most robotic systems require a model environment in order to execute tasks effectively. Autonomous robotic systems should create models of the environment by themselves. However, such tasks are not easy for current autonomous robots because they have only limited ability to sense and thus survey the environment. In such cases, the method of knowledge acquisition and sharing becomes very important. Some researchers have proposed "intelligent environments" in which motion detectors and information providers are located.[1-8] It is very advantageous that autonomous robots can build and maintain such intelligent environment by themselves.

Some researchers have proposed local communication methods for enhancing communication between robots.[9-12] In previous related studies, robots kept knowledge individually. Let us consider what takes place on the ground, ants forage effectively by pheromone trails, and dogs claim territory by smell. Social creatures improve the efficiency of their actions by storing information regarding the environment. Simulation results by Drogonal and Feber[13] have suggested that the pheromone trails are very effective for the completion of iterative transportation tasks to be performed by autonomous agents. This kind of data storage and communication system can be applied by creating model environments for robotic systems for the sharing of knowledge and for cooperation.

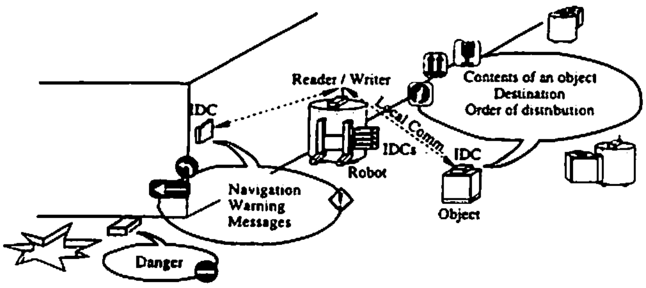


Fig. 1. An overview of local communication by the IDC.

We have proposed a device that enables local communication; we refer to this device as an "Intelligent Data Carrier (IDC)[14,15]" (**Fig.1**). We have not only developed such a device but also propose in this study an algorithm to enhance the efficiency of task execution performed by autonomous robots via knowledge sharing and acquisition through the intelligent data carrier system in particular environments.

In this paper, we create a model of a dynamic environment in which the destinations are frequently changed. We investigate the behaviors of autonomous mobile robots that navigate in dynamic environments by means of the intelligent data carrier system, and propose an algorithm that allows each IDC to revise its own knowledge.

This paper is organized as follows: In section 2, we introduce the intelligent data carrier and solution of the problem. We describe an algorithm by which robots can acquire and share information regarding an environment via an intelligent data carrier system. In section 4, we make models of a dynamic environment, and in section 5 propose an algorithm to adapt the IDC system to the

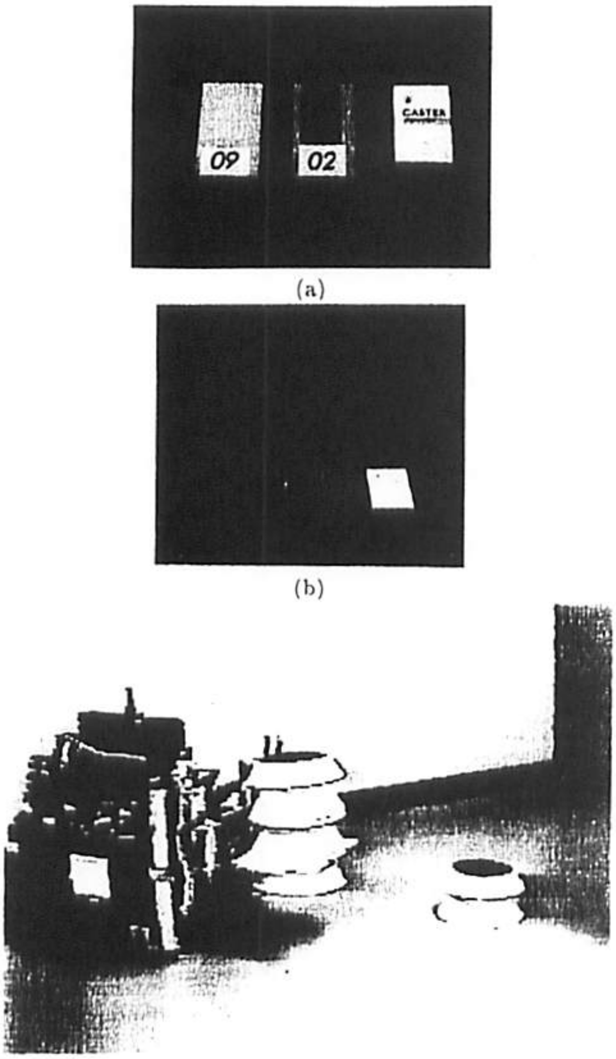


Fig. 2. The prototype of the IDC system: (a) Tags, (b) A reader/writer device, (c) Handling system for autonomous robots.

dynamic environment. Section 6 provides a summary of the paper.

2. Problem Settlement

2.1. Intelligent Data Carrier System

We have developed an Intelligent Data Carrier (IDC)[14,15] in order to reduce the traffic of global communication by providing local communication links and local information management functions. By reading information from and writing it into the IDCs, robots can use them as media for inter-robotic communication.

The IDC system consists of portable information storage (tags) and read-write devices carried by the robots (**Fig.2**). Tags are usually referred to as an "IDC". A tag has its own CPU, memory, and battery. A user can download and execute original programs into the tags. The specifications of the IDC are shown in **Table 1**. By placing the IDCs in specific locations in a particular environment, robots can allocate functions to act as agents for information storage and management (**Fig.2(c)**). The

Table 1. Specifications of the IDC

Media	Electromagnetic wave
Frequency	290, 310 MHz
Memory	32 Bytes
Modulation	ON/OFF keying
Data rate	1200 bps
Power source	a Li-ON battery (3.6V)
Size	tag: 110x65x25 mm reader/writer: 195x130x 50 mm

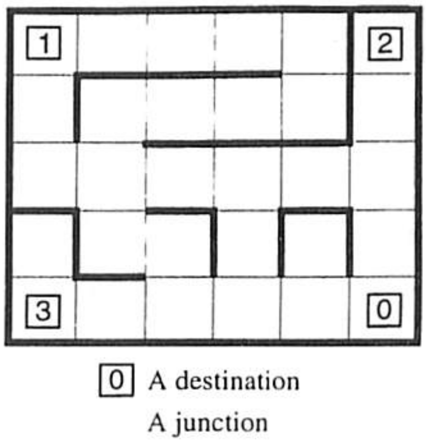


Fig. 3. An example of a work area: 4 destinations are located in a maze-like environment.

communication range is up to 3m.

2.2. Problem Settlement

In this paper, we consider iterative transportation tasks (e.g.[16]). A robot has to carry objects to given destinations. We posit an environment in which several destinations are located. When a robot arrives at a desired destination, it receives instructions regarding the next destinations and then continues with the task at hand.

We assume that robots do not have maps, because fixed maps, made by humans, may decrease the flexibility of autonomous robotic systems. We consider adaptability to unknown environments as crucial. We assume that a robot consists of the following characteristics.

- A robot does not have a map and does not estimate its global position.
- A robot can sense walls and distinguish paths, junctions, and destinations. It can also distinguish branches at junctions.
- A robot can remember the last visited destination and count, in steps, the duration of running time.

A robot cannot understand its global position, but it can understand its position in elation to its immediate context.

In this example, we assume that the transportation task is as follows:

- A robot is given only the ID number of a destination. When a robot arrives at a destination, it receives another destination ID at random.
- The work area is a maze-like environment which

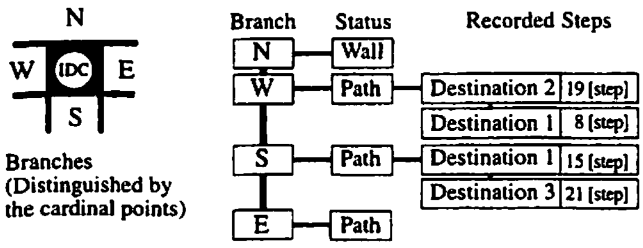


Fig. 4. Data structure in an IDC.

consists of square cells and walls (**Fig.3**).

- A robot can move to neighboring cells, but only at one step at a time.
- We do not consider cases of collisions among robots.

3. Knowledge Acquisition and Sharing

3.1. Algorithm to Acquire and Share Knowledge

In this section, we propose an algorithm to build knowledge for navigation autonomously. Upon reaching a junction, a robot should select the most feasible branch, which allows the shortest path to its current destination, since effective transportation is the robot's goal. We set IDCs at junctions to facilitate autonomous robots' decisions. Robots can store and share their fragments of experience by means of the IDCs. A robot does not need to estimate its global position if a robot can obtain sufficient knowledge from an IDC.

As we assured, a robot does not know its global position. Thus we propose an algorithm to locate where branches connect at junctions leading to expected destinations. This proceeds according to the last visited destination and entered branch. For example, when we see that a robot, which has started from destination 1, enters a junction through a southern branch, we can expect the southern branch may lead us to destination 1.

We describe the data structure of an IDC in **Fig.4**. At the initial state, no valid data is recorded. When a robot enters a communication area of an IDC at a junction, it reports to the IDC the branch of entry, the ID number of the most recently visited destination, and the running step measured from the destination.

When the IDC has already received data about the same destination in the same branch, it compares the current running step with a former one. If the new one is shorter than the former, the record is renewed.

When a robot wants to go to destination 1, it should choose a branch involving the fewest number of steps from the destination. In the example of Fig.4, the robot should choose the W(western) branch. We implemented a algorithm that selects the most probable path. The steps of this algorithm are as follows.

(1) When a robot can not communicate with an IDC at a junction, it chooses a branch at random.

(2) A robot whose destination is j comes to a junction, which has m branches. We describe the recorded steps from destination j in branch $i \in m$ as t_{ij}. We can find 4 data, $t_{W1} = 8$, $t_{W2} = 19$, $t_{S1} = 15$, $t_{S3} = 21$ in the example shown in **Fig.4**.

(3) When the IDC has no record regarding destination j, the robot chooses a branch at random.

(4) When the IDC has one or more branches which contain records regarding destination j, it finds a branch i which indicates minimum t_{ij}. It chooses to proceed via branch i. Note that a robot has the ability to choose a branch at random. We set P_{min} which denotes a fixed probability that a robot chooses a branch random.

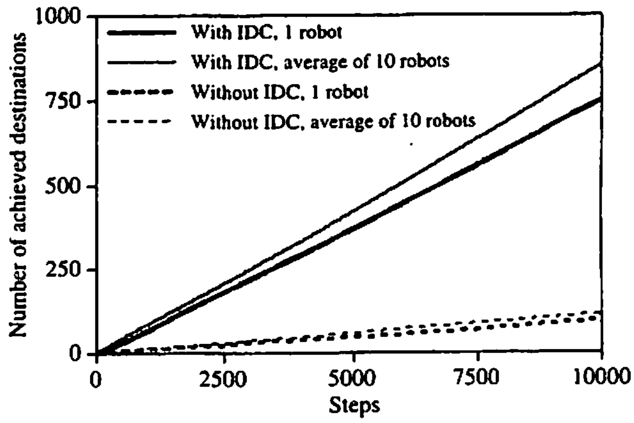


Fig. 5. Comparison of task execution.

3.2. Simulation Results

We verified the effectiveness of the proposed algorithm by performing simulations. We evaluated the number of achieved destinations by counting a constant number of steps. We assure an environment like the one given in **Fig.3** and performed simulations with or without IDCs at the junctions. Each robot worked for 1000 steps. We set $P_{min} = 0.01$. We set IDCs in all junctions when applying the IDC and the proposed algorithm.

Figure 5 shows a comparison of results achieved by a single robot and by ten robots. We can see that the proposed algorithm using IDCs achieved about 600% more destinations than did the algorithm without IDCs. We did not provide the robot any knowledge about the environment in advance of performing simulations. Additionally, other robots can share the knowledge stored in IDCs by just the same algorithm. In the case of ten robots, the average number of achieved destinations increases about 10% more than that of a single robot. Without the use of the IDCs, the number of results achieved by a single robot and the average of the results achieved by ten robots was approximately the same.

These results suggest that the proposed algorithm and IDC system realized implicit cooperation among autonomous robots without explicit communication and without a priori knowledge.

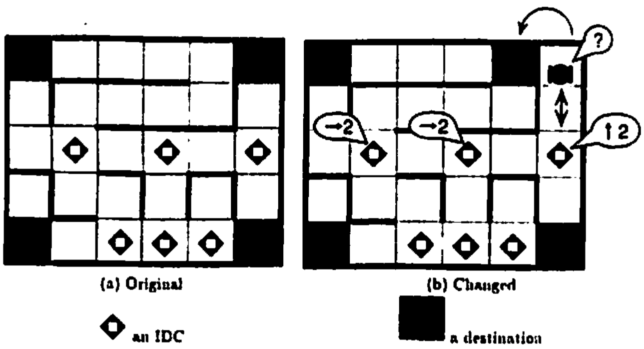
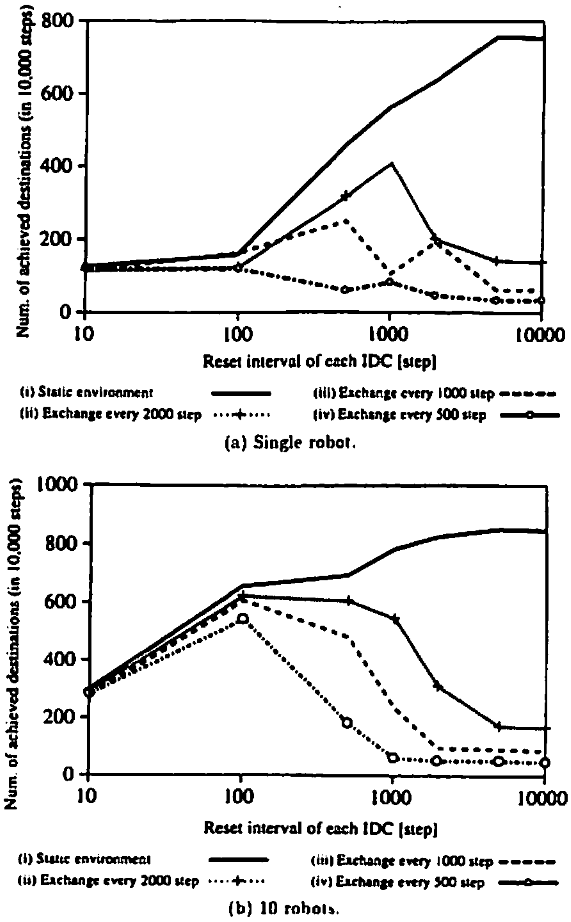


Fig. 6. An example of incompatible information.



(a) Single robot.

(b) 10 robots.

Fig. 7. Achieved destinations in dynamic environments.

4. Behaviors in Dynamic Environments

4.1. Model of Dynamic Environment

We consider changing destinations in an environment. **Figure 6** shows destination 2 having moved to a new place. In this case, IDCs, which has previous knowledge will lead robots in incorrect directions, thus lowering the effectiveness of transportation. In some case, robots that do not make use of knowledge in an IDC perform better than robots misled by IDCs. We have to realize an algorithm that allows each IDC to evaluate and renew its knowledge by itself.

4.2. Behaviors in Dynamic Environment

Before building a new algorithm, let us investigate the behavior of the distributed navigation system in a dynamic environment. Much like the consciousness of a pheromone, an IDC is provided a very simple algorithm in which the IDC's knowledge is erased at particular constant intervals. We performed simulations in which the intervals are 10, 100, 500, 1000, 2000, 5000, and 10000. Note that IDCs are not synchronized. To create the dynamic environment, we exchange locations of destinations as 1 → 2, 2→ 3, ... every constant step. We create 4 cases in which the constant step is 500, 1000, 2000 and ∞(static environment). **Figure 7** shows the number of achieved destination in simulations for 1000 steps. **Figure 7(a)** and **(b)** denote the simulation results of a single robot and ten robots. In static environments, the longer the interval, the more effectively the robotic system works. Curves have peaks in dynamic environments (constant steps = 1000 or 2000). The environment may demand special reset interval value to ensure the greatest effectiveness, which depends on both the condition of the environment and the number of robots. However, each IDC cannot know the most effective interval because it works individually. Thus, we need an algorithm in order to estimate timing to reset knowledge in an IDC. When the destination locations are changed every 500 steps, the performance level of the robotic system becomes quite low. This may suggest that such an environment is too dynamic to allow autonomous robots to construct the knowledge necessary for navigation.

5. Algorithm Adaptation to Dynamic Environments

5.1. Autonomous Data Renewal by ICD

Because an IDC works individually in an environment, it has to evaluate the validity of its knowledge by itself. An IDC can obtain only reports of steps from autonomous robots. It cannot contain global knowledge regarding an environment. Thus, an IDC calculates probability in order to erase its current knowledge according to the number of steps reported by robots which denotes steps from the arrival of a robot at a previous destination. An IDC decides whether delete its knowledge or not based on probability.

(1) A robot r started from previous destination i and proceeds to new destination j. After t_r steps from destination i, it meets IDC k and reports the steps. When the IDC k has knowledge about both i and j, we call them d_j. When the IDC k does not have both, skip 2.

(2) We can expect that the robot r can reach IDC k by d_i steps, and it will arrive at j after d_j steps when there are no changes in the environment. So we compare t_r with d_i to calculate probability p_{del} to erase the IDC's knowledge. We apply logistic function to calculate (Eq.1).

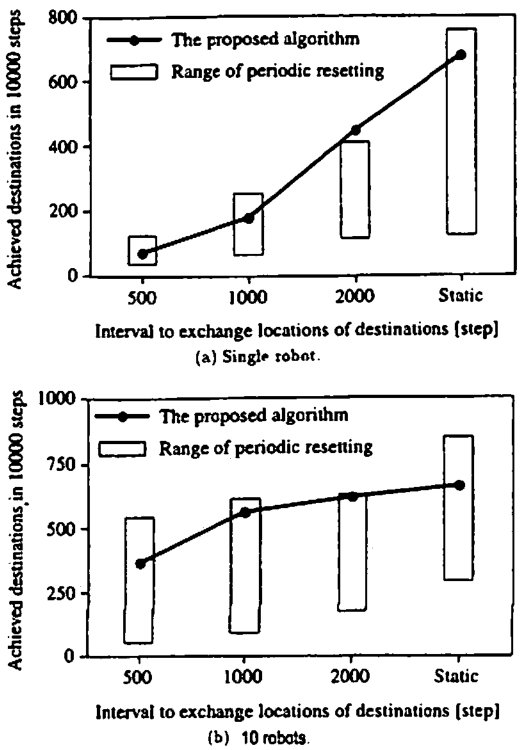


Fig. 8. Comparison of the number of achieved destinations.

$$p_d = K \frac{e^{m(t_r-(d_i+d_j+d_j^2))}}{1+e^{m(t_r-d_i+d_j+d_j^2)}} \quad \cdots\cdots\cdots\cdots \quad (1)$$

The range of this function is (0 K). The function derives $K/2$ when $t_r = d_i + d_j + d_j^2$. K and m are constants. We set $K = 0.5$. Equation 2 determines m, which results in $p_{del} = 0.01$ when $t_r = d_i + d_j$.

$$m = \frac{\log 99}{d_j^2} \quad \cdots\cdots\cdots\cdots\cdots\cdots \quad (2)$$

In the above functions, the greater t_r a robot reports, the higher p_{del} an IDC calculates. Additionally, the smaller d_j knowledge is contained, the higher p_{del} because the center of the function is set at $d_i + d_j + d_j^2$. This means that the nearer the destination j is, the more often knowledge is deleted.

(3) When the IDC does not erase its knowledge, it obtains data from and suggests a direction to the robot as a former algorithm.

5.2. Simulation Results

We use simulations to verify the effectiveness of the proposed algorithm. In the simulations, we set $K = 0.5$ and $p_{min} = 0.01$. As the dynamic environment, we exchange locations of destinations as $1 \rightarrow 2$, $2 \rightarrow 3$,. ... every constant step, as in section 4.2. We create 4 cases in which the constant steps are 500, 1000, 2000, and ∞(static environment). **Figure 8** shows the number of achieved destinations in simulations involving 10000 steps. We compare the results of the proposed algorithm with those of simple "metabolism" shown in section 4.2. We used both single robot and ten robots in the simulations.

In the case of a single robot in a static environment, the proposed algorithm achieved about 90% of its destinations as compared with the best value of the constant reset interval (described section 4.2). The proposed algorithm lost about 10% of its destinations as the overhead. In the case of ten robots, the proposed algorithm achieved about 80% of its destinations as compared with the best value of the constant reset interval. The proposed algorithm lost about 20% of its destinations as the overhead.

In the case of a single robot in a dynamic environment (constant steps = 1000, 2000), the proposed algorithm achieved 69% and 108% of its destinations, as compared with the best results of the simple periodic resetting method. In the case of ten robots, the proposed algorithm achieved 91% and 98% of its destinations, as compared with the best results of the simple metabolism method. These results show that the proposed algorithm realizes autonomous adaptation to both dynamic environments and the number of robots, even though individual IDCs cannot know the global state of an environment.

When the locations of destinations are changed every 500 steps, the performance by a single robot system becomes quite low even if we apply the proposed algorithm. This may suggest that the environment is too dynamic to construct knowledge to allow the navigation of single autonomous robots. However, in the case of ten robots, the proposed algorithm achieved about 512% of its destinations as compared with the single robot system. This result demonstrates that the knowledge sharing IDC system works quite effectively to accelerate cooperation among individual robots.

6. Conclusion

In this paper, we proposed a device and an algorithm intended to enhance the efficiency of autonomous robots by means of autonomous knowledge sharing and acquisition. In conclusion, we accomplished the following:

- We developed a device that enables local communication, and we refer to this device as an "Intelligent Data Carrier (IDC)"
- We implemented a system of autonomous navigation knowledge acquisition and sharing, applied to autonomous mobile robots.
- We investigated the behaviors of autonomous robots that navigate by using the intelligent data carrier system in dynamic environments, and proposed an algorithm to adapt the IDC system to a dynamic environment.

When robots break down, we need only to replace them with new ones. The new robots can perform as effectively as the original robots. This is because the knowledge is derived from the environment, and this knowledge can be easily shared among the robots. We conclude that the proposed system successfully realized a robust autonomous robotic system.

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