# Efficient navigation of mobile robot based on the robot's experience in human co-existing environment

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**Abstract**: In this paper, it is shown how a mobile robot can navigate with high speed in dynamic real environment. In order to achieve high speed and safe navigation, a robot collects environmental information. A robot empirically memorizes locations of high risk due to the abrupt appearance of dynamic obstacles. After collecting sufficient data, a robot navigates in high speed in safe regions. This fact implies that the robot accumulates location dependent environmental information and the robot exploits its experiences in order to improve its navigation performance. This paper proposes a computational scheme how a robot can distinguish regions of high risk. Then, we focus on velocity control in order to achieve high speed navigation. The proposed scheme is experimentally tested in real office building. The experimental results clearly show that the proposed scheme is useful for improving a performance of autonomous navigation. Although the scope of this paper is limited to the velocity control in order to deal with unexpected obstacles, this paper points out a new direction towards the intelligent behavior control of autonomous robots based on the robot's experience.

**Keywords:** autonomous navigation, obstacle avoidance, velocity control, intelligent behavior

## 1. INTRODUCTION

Recently, "dependability" receives much attention in the field of autonomous service robotic applications. From the viewpoint of autonomous navigation, safe navigation in human-coexisting environment is an essential problem to be solved. On the other hand, high speed navigation is preferable in order to achieve service efficiencies. There are fundamental difficulties when we want to increase the speed of a mobile robot. Such problems can be classified into three categories as follows:

1) Dynamic and mechanical limitations.
2) Control and computational limitations.
3) Unexpected dynamic changes of environment.

The first problem implies that there might take place wheel slippage or rollover of the robot when excessive speed is applied when the robot makes a sharp cornering or an emergency stop. This problem can be solved by appropriate modeling of a mobile robot dynamics. In practical applications, the first problem is rarely considered, because other problems provide more strict limitation on the maximum speed of the mobile robot.

The second problem can be interpreted as a real-time obstacle avoidance problem. A speed of navigation can be limited by sensor capabilities to detect obstacles, sensing speed, computational cost of the obstacle avoidance algorithms and motion control response. There have been a lot of research activities for the dynamic obstacle avoidance problem. A mobile robot can navigate real environment without collision by adopting some useful developed technologies. Owing to the fast computational speed of recent CPU's, a robot's motion can be controlled with acceptably high update rate.

Our major scope in this paper is to solve the third problem addressed above. In order to deal with unexpected dynamic changes of the environment, a robot should utilize its own experiences. Humans fully exploit their experiences in real environment in many cases. Suppose that a person is walking in corridor. He might walk fast when there is no obstacle. He might reduce the walking speed when he expects that another person possibly burst into the corridor through the door from a room. Alternatively, a person might reduce the speed when he already knows that a part of the floor is slippery. This fact implies that a person possibly changes walking speed even though there are no visible obstacles. In the presented case, a person should have a location dependant, preliminary knowledge of the environment for control of a walking speed.

So far, we have proposed the behavior selection criteria using Generalized Stochastic Petri Nets in [1], a range sensor based integrated navigation strategy in [2], and practical navigation experiences of the museum guide robot in [3]. From our experiences on autonomous navigation, we recognized that it is extremely significant environment. A lot of advantages can be obtained by empirical navigation. This paper focuses on high speed navigation without collision with unexpected dynamic obstacles in corridor environment.

The human co-existing environment has the two types of dynamic obstacles to cope with. The first is the expected dynamic obstacle which can be detected by sensors. The second is unexpected dynamic obstacles that abruptly emerge to the robots. Although current state-of-the-art solutions solved the problem of the safe and fast navigation against the expected dynamic obstacle, it is still the difficult to be solved for the case of the unexpected dynamic obstacle. The objective is to achieve safe and fast navigation for the both cases of dynamic obstacle.

Because the dynamic obstacle avoidance is one of the main issues for the robot researcher, there are many previous research activities about controlling robot behavior avoiding the obstacles. The approaches can be classified into three categories, one is a model based path planning. Another is a sensor-based reactive motion control. The other is a hybrid approach which combines two schemes.

A model based path planning uses models of the world and robot to compute a path for the robot to reach its goal. One of the widely used path planning schemes is to use the potential field in [4]. Although the motion of the robot can be obtained in a quite simple way, it is difficult to use the original potential field due to a local minima problem. Konolige proposed a gradient method in [5]. The gradient method provides a global optimal solution for the path planning problem. However,it is still difficult to be applied to dynamic obstacle avoidance problem, because those computational schemes assume a static or quasi-static environment. Furthermore, complete environmental model should be given for the model based path planner. In order to over come such limitations, sensor based reactive control strategy can be adopted.

In the sensor-based robot control, the motion of robot is reactively controlled based on sensory information such that obstacles are avoided while the robot continues to move towards the goal. Vector field histogram approach [6], in the obstacle-free direction is chosen based on the sensor data. The dynamic window approaches [7] suggested that the optimal velocity of robot is computed using the admissible velocity space. The search space is the set of tuples $(v,\omega)$ of translational velocities $v$ and rotational velocities $\omega$ of the robot. The admissible velocity space is the collection of proper velocities which satisfy the kinematic and dynamic constraints of robot. However, it is not guaranteed that the robot reaches its desired goal when only a sensor based reactive control is applied.

A hybrid approach is a combination of the model based planning and a sensor based reactive control It is possible to achieve advantages of both method, for example, a goal oriented dynamic obstacle avoidance problem can be solved. The elastic band [8] regards the planned path as deformable one. With the virtual bubble on sensory data, it bent the original path toward obstacle-free path. The other kind of hybrid approaches adapts path planning based on the sensor-based robot control. The global dynamic window [9] solved the problem of local minima in the dynamic window approaches. With the real-time global path planning algorithm, the approaches ensure that the robot is guided to goal position by the local admissible velocities.

Despite much progress in the obstacle avoidance researches, the most of researches assumed only the expected dynamic obstacle. We focus on the both the expected and unexpected dynamic obstacle. To detect the location-dependent unexpected dynamic obstacle, we adapt the human cognitive-motivational model [10] that recognizes the afraid of external environment. Based on the conceptual model, we specified the quantitative measure of uncertainty and risk as a cognitive-motivational term, ‘afraid’. During the autonomous navigation, the robot gathers the data of risky. Thereafter, the robot learns the information of dangerous area from the gathered data. Because the process is the supervised learning, the solution of computational learning theory [11] [12] is congruent with this problem. In the Empirical Risk Minimization approach, we use square-loss function and Gaussian kernel for achieving afraid-expect function. Finally, we control the robot with the experienced information for the location, kinematics constraints of robot and dynamic information of environment. The experimental result showed that the safe and fast navigation is successfully conducted.

## 2. COLLISION-FREE HIGH SPEED NAVIGATION

### 2.1 Problem statement

This research is a part of intelligent behavior control using experience based location information. As a specific subject, we selected autonomous navigation of service robot that navigates along the corridor in the building. We conducted following procedure in this research.

i) The robot repeatedly navigates the corridor with slow speed navigation for gathering environmental information including obstacle.
ii) The robot gathers location-dependent information. The special locations, in which high speed navigation is impeded by abruptly appeared obstacle, are accumulated.
iii) Based on the acquired information, the robot could conduct high speed navigation in the safe area.

In this environment, robot uses a couple of laser range finders. Abrupt appeared obstacles were people who burst into corridor from the door. For reducing the complexity of control logic, we made the robot navigate along the center of corridor and behavior control was confined to the problem of velocity control. Because slippage was occurred during repeated navigation task, we use the probabilistic map-matching scheme based on Monte Carlo localizer [13] [14] and a grid map for environmental representation.

### 2.2 The collision condition and collision area

As the car stopping model, the robot has a stopping model that is composed of delay distance and breaking distance. The delay distance is the distance that the robot moves during the time between the emergence of obstacle and the detection of obstacle. Breaking distance is the distance that robot move from the breaking action to totally stop. The stopping distance is the sum of two distances.

Based on the dynamic and kinematics constraints, the stopping distance is defined as the Eqs. (1)-(3).

$$dist_{stop}(t) = dist_{delay}(t) + dist_{break}(t) \tag{1}$$

$$dist_{delay}(t) = time_{delay} \cdot vel_f(t) \tag{2}$$

$$dist_{break}(t) = \frac{1}{2} \cdot \alpha \cdot vel_f^{\,2}(t) \tag{3}$$

Where $dist_{stop}(t)$, $dist_{sense}(t)$ and $dist_{break}(t)$ respectively indicate a stopping distance, a sensing distance and a breaking distance at time $t$. The $vel_f(t)$ is forward velocity of time $t$. The $time_{sens}$ is the constant maximum delay of detecting dynamic obstacle. The α is the maximum acceleration constant.

Based on the the Eqs. (1)-(3), we can state the collision condition in high speed navigation.

$$\left| x_{robot}(t) - x_{obstacle}(t) \right| < dist_{stop}(t) \tag{4}$$

Where $x_{robot}(t)$ and $x_{obstacle}(t)$ is the location of robot and the location of obstacle along the corridor.

The collision area is gray area within a dotted line, as shown in Fig. 1. Based on the constraints in Eq. (4), the high speed robot cannot avoid the obstacles in case the obstacle is located in the collision area.

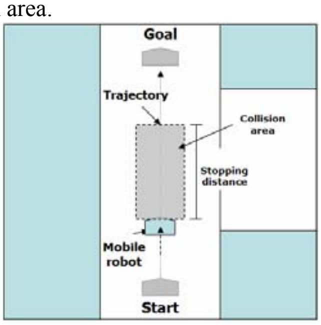


Fig. 1 Collision area of high speed navigation

Thereafter, it is clear that the collision area increase in proportion to accelerated speed.

### 2.3 Dynamic obstacle detection

Despite collision area, the robot avoid expected dynamic obstacle. Because the distance of a laser range finder is 8 *m*, which is longer than the stopping distance, the robot avoid the detected dynamic obstacle by executing stopping behavior at the static trajectory. We can detect the expected dynamic obstacle using the Fig. 2, Eqs. (5)-(6).

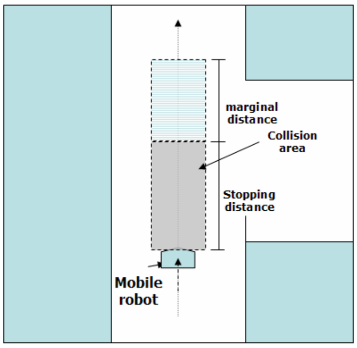


Fig. 2 Stopping distance and marginal distance

$$obs_{cur}(t) = \begin{cases} 1 & dist_{obs}(t) \geq dist_{stop}(t) + \beta \quad \forall obs \in Obs \\ 0 & dist_{obs}(t) < dist_{stop}(t) + \beta \quad \exists obs \in Obs \end{cases} \quad (5)$$

where the $Obs$ is the set of detected obstacles and $obs$ is an element of $Obs$. The $dist_{obs}(t)$ is the distance from the robot to a specific obstacle, $obs$. The $obs_{cur}(t)$ is an indicating factor which is changed to 1 from 0 when any dynamic obstacle appears within the collision area. The $\beta$ is marginal distance that can be detected from sensor data.

$$obs_{predict}(t) = \prod_{i=1}^{foot_{step}} obs_{cur}(t-i) \quad (6)$$

Where the $obs_{predict}(t)$ is an indicating factor which is changed from 1 to 0 when the appearance of dynamic obstacle is expected based on the previous $foot_{step}$ steps of observation, $obs_{cur}(\cdot)$.

Through this logic, we can computationally expect the appearance of dynamic obstacle based on previous observations. The remaining problem is to detect the abruptly appeared obstacle.

### 2.4 Abruptly appeared obstacle detection based on afraid model

In the cognitive researches [10], it was shown that the human behavior directly depends on the afraid level, Fig. 3. The afraid level is high when the real input of sensory organ is not congruent with the expected input. With the high level of afraid, human especially pay attention to current environment for overcoming the dangerous factors. The high level induces cautious behavior such as slow movement and even stops. The conceptual description can be written as a Eq (7). However, the cognitive based model is ambiguous, because there is no quantitative measure to specify the levels of afraid.

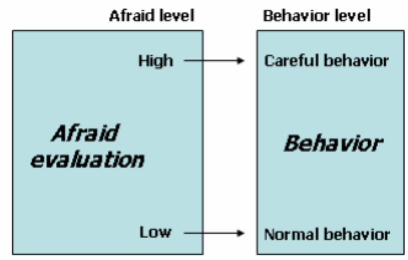


Fig. 3 Cognitive-motivational afraid model

$$Afr = |E - A| \quad (7)$$

Where $Afr$ is the level of afraid; $E$ is expected environment condition; and $A$ is actual environment condition.

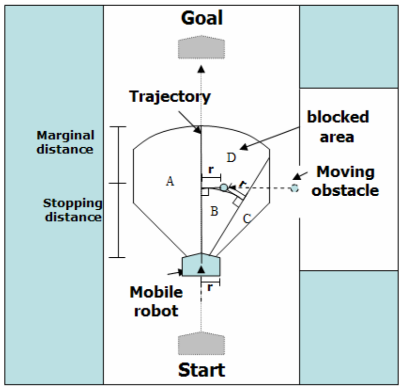


Fig. 4 Calculating environmental condition

We model the afraid level with a quantitative measure of uncertainty and risk. We define the collision possible area as a quantitative measure of environmental condition. In the area, collision area and marginal area are included. The moving obstacle within stopping distance divides the collision area into two distinct area; blocked area and non-blocked area. In the Fig. 4, 'D' is a blocked area and 'A', 'B' and 'C' are non-blocked area. We adapt the non-blocked area as a quantitative measure of environmental condition. The non-blocked area is good indication factor for the current environmental condition. The abruptly appeared obstacles, which impede high speed navigation, induce abrupt change of the measure. Thus, the area is an appropriate measure for afraid model. We calculated the actual environment condition using laser range sensor data, Eqs (8)-(9) and Fig. 5. Concurrently, we calculate the expected environment condition using map data and current position. In the calculation, expected laser range sensor is used instead of actual sensor data. Thereafter, binary afraid level is decided from the difference of the two measures, Eqs (10)-(11). When the robot confronts with the abruptly appeared obstacle, the $Afr(t)$ become 1.

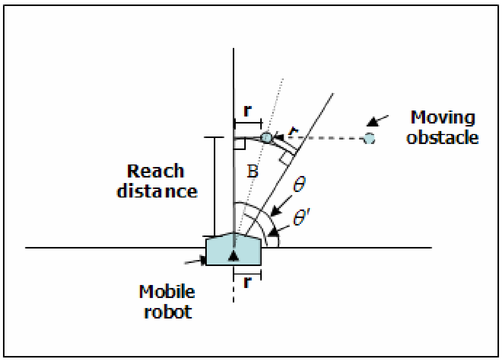


Fig. 5 Calculating reach distance

$$dist_{reach}(t,\theta) = \min_{obs \in Obs} \begin{Bmatrix} dist_{obs}(t)\cdot\sin(|\Delta\theta|) & \sin(|\Delta\theta|)\cdot dist_{obs}(t) \le r \\ dist_{stop}(t) & \sin(|\Delta\theta|)\cdot dist_{obs}(t) > r \end{Bmatrix} \quad (8)$$

$$\text{when} \quad \Delta\theta = \theta - \theta'$$

$$A_{area}(t) \cong \sum_{\theta=0}^{\pi} dist_{reach}(t,\theta) \quad (9)$$

where $A_{area}(t)$ indicate the non-blocked area

$$diff(t) = |E_{area}(t) - A_{area}(t)| \quad (10)$$

where $E_{area}(t)$ indicate the expected non-blocked area

$$Afr(t) = \begin{Bmatrix} obs_{cur}(t) & diff(t) > diff_{threshold} \\ 0 & diff(t) \le diff_{threshold} \end{Bmatrix} \quad (11)$$

where $Afr(t)$ is binary afraid level and $diff_{threshold}$ is the constant for deciding afraid based on the measure.

### 2.5 Information accumulation and generalization

Under the favor of binary indication of afraid, we accumulate the location dependent information at each cell, Eq (12)

$$Afr_{cell}(x,y,t) = Afr_{cell}(x,y,t-1) + Afr(t) \quad \forall (x,y) \in Obs \quad (12)$$

where the $Obs$ is the set of detected obstacles and $Afr_{cell}(x,y,t)$ is the accumulated afraid information in the cell $(x,y)$ at time $t$.

Because of the incompleteness of the accumulated information, we conducted generalization procedure. That is, we adopt the smoothing technique. However, we focus on the procedure in the perspective of supervised learning. It is because we should estimate the emergence of unexpected dynamic obstacle from the experiences of emergences in specific locations. That is, the key is learning from examples. At the computational learning theory [8], conventional method is using Empirical Risk Minimization (EMR). In this perspective, our research subject is learnable. It is because that we can hypothesize Reproducing Kernel Hilbert Space (RKHS). We used Gaussian kernel, because location information is relevant to close location. As a loss function, we chose the square lose due to effective and simple property.

### 2.6 Velocity control

Upon the sensor based behavior control, we adapt accumulated location information. When the robot navigates in the safe area, the robot is controlled by the normal behavior control. The velocity of robot is controlled by not only the ordinary behavior control but also the afraid indicator in the unsafe area, Eqs (13)-(14) .

$$Vel_{afraid}(t) = \begin{Bmatrix} Vel_{\max} & Afr_{cell}(x,y,t) < 1 \\ Vel_{safe} & Afr_{cell}(x,y,t) > 1 \end{Bmatrix} \quad (13)$$

where $Vel_{afraid}(t)$ is the velocity that is regulated by the afraid indicator. $Vel_{max}$ and $Vel_{safe}$ is respectively the constant of maximum velocity and safe velocity. $x,y$ is the current position of robot and $t$ is time.

$$Vel_{result}(t) = \min(Vel_f(t), Vel_{afraid}(t)) \quad (14)$$

where $Vel_f(t)$ is the output forward velocity of the sensor based behavior control. $Vel_{result}(t)$ is regulated result velocity.

## 3. EXPRERIMENTS AND RESULTS

### 3.1 Physical environment

Fig. 6 Infotainment robot platform

The proposed approach has been implemented and tested on the Infotainment Robot Platform ver. 1 mobile base by Dasa Technologies, Inc. shown in Fig. 6. This base moves at translational velocities of up to 1.0 $m/s$ and accelerations of up to 1.0 $m/s^2$ with two-wheel differential drive. It is equipped with two SICK laser range finders with a field of view 180º and an accuracy of up to 1 $cm$. Using the on-board 2.2 $GHz$ CPU and 1 $GB$ memory PC, servo rates of 5 $Hz$ are achieved for behavior control. At the platform, Linux and RTAI support realtime task capability. We use the shared-memory architecture for exchange the date between realtime sensor reading module and any other internal modules. The rate of sensor reading, 5 $Hz$, is bounded by RS232C communication bandwidth. Moreover, we use the probabilistic map-matching scheme based on Monte Carlo localizer [12]. Due to the computational cost, the update rate of localizer is confined in 0.5 $Hz$.

### 3.2 Corridor navigation

Fig. 7 Corridor environment and a grid map

Because the major scope of this research is to obtain the adaptive behavior of robot, we can simplify the navigation task without the loss of generality. Thus, we consider corridor environment and its 30 *m* × 10 *m* size grid map, Fig 7., in which the robot navigates through the center. The robot repeatedly conducted autonomous navigation for gathering location dependent information at the environment.

We model normal pedestrians- expected dynamic obstacle- who navigate along the corridor at 1.6 *m/s* and up to 2.0 *m/s*. We suppose the chance comers who emerge from the door at 0.8 *m/s*. We also assume that no dynamic obstacle intentionally collide with the robot. Thus, proper velocity control prevent the robot from collide with any dynamic obstacle. Along the 1-dimensional axis, the robot slowly navigates at 0.2 *m/s* for gathering location information. When the robot encounters any dynamic obstacles, the robot easily stops. After the location learning, the robot quickly moves at 0.8 *m/s* in the safe area.

### 3.3 Robot constraints

We experimentally measure the stopping distances and stopping times at 0.2 *m/s*, 0.5 *m/s* and 0.8 *m/s*, Table 1.

Table 1 The maximum stopping distances and stopping times per velocities.

| | Stopping distance | Stopping time |
|---|---|---|
| 0.8m/s | 1.01m | 1.7 sec |
| 0.5m/s | 0.58m | 1.4 sec |
| 0.2m/s | 0.20m | 1.1 sec |

The infotainment robot has two types of constraints that have an import influence to safe and fast navigation. The first one is dynamic constraints. We build a sensor based control algorithm on the platform. Despite the realtime capability with Linux and RTAI, the robot has some mount of time delay in detecting dynamic obstacle. Because we operated loosely coupled component model in asynchronous communication, the data processing can be delayed by the waiting time of each module. In this robot, device driver commands the laser range finder at 5 Hz, due to the communication bandwidth of RS232C. Moreover, the realtime resource manager read the data from the device driver and set down to the global shared memory at 5 *Hz*. Finally, the sensor based behavior control algorithm operated at 5 *Hz*. Despite hard-realtime constraints, the delay time, which is measured from the emergence of obstacle to the recognition of obstacle, takes 0.9 *sec* at most. However, the time delay does not impede our environment modeling. Because it cannot be eliminated, the modeling is required in any robot system.

The second one is kinematics constraints. The servo motor can make the robot move at translational velocities of up to 0.8 *m/s* and acceleration of up to 1.0 $m/s^2$ with two-wheel differential drive. Due to the acceleration limit, it takes some times to stop robot based on the current translational velocities.

### 3.4 Information plotting and generalization

We counted the number of danger obstacles per 10 cm unit cell. From the origin point (0m) to 20m, 200 units' information are accumulated, Fig. 8.

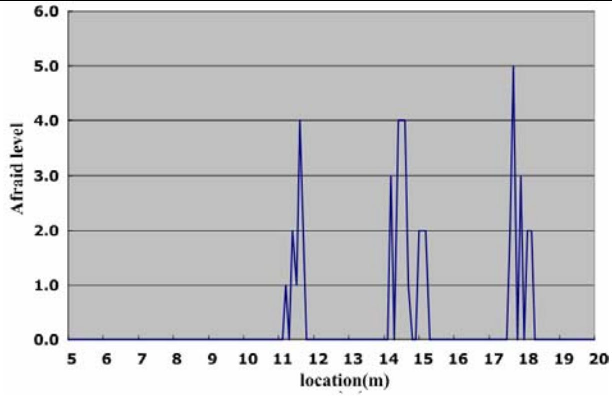


Fig. 8 The number of danger obstacle per location

The data is generalized by Gaussian kernel, the dotted line in Fig. 9.

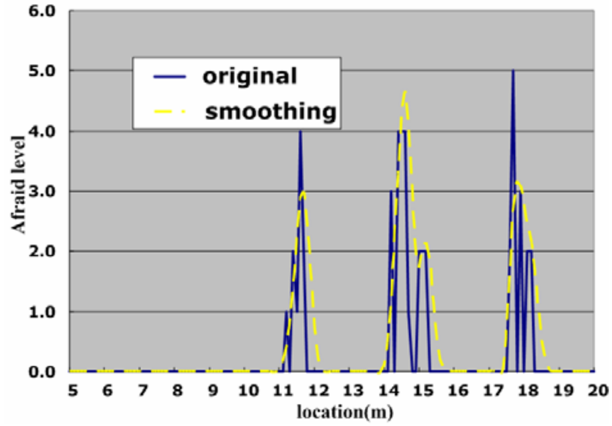


Fig. 9 Generalized number of danger obstacle per location

This result is congruent with the actual corridor environment. That is, the generalized afraid level is high at the front of door and low at the other places. In the real corridor environment there are three regions of high risk, between 11.21m and 12.02m, between 13.68m and 15.10m, and between 17.53m and 18.95m. Those locations correspond to the door locations.

### 3.5 The result of high speed navigation

We obtained experimental results in the corridor environment. The velocities of robot in each navigation are monitored at the periodical interval, Fig. 10. From the upper layer, each layer respectively represents the configurations of physical doors, the gathered experience data, the trajectory of inexperienced robot, and the trajectory of experienced robot. In the dangerous area, the velocity of robot is regulated by safe speed, 0.2 m/sec on both cases. However, in the experienced knowledge the robot can speed up to 0.8 m/sec in the safe area. For navigating 10 *m* section that is composed of unsafe and safe area, the robot only took 24.3 sec after completing risk accumulation, while the robot took 51.3 *sec* without experience. That is, the average velocity was respectively 0.41 *m/sec* and 0.20 *m/sec.*

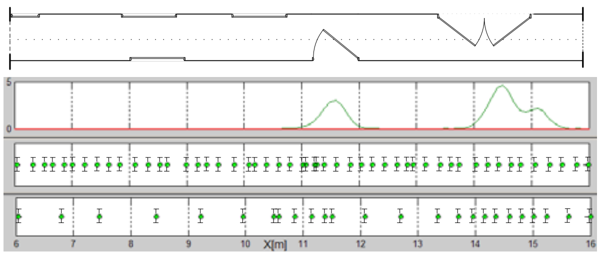

Fig. 10 The location of robot at the periodical interval.

## 4. CONCLUSION

In this research, we proposed intelligent navigation for indoor service robot. The new approach is composed of following procedures

- The stopping distance is experimentally measured. Based on the distance and robot constraints, collision area is modeled. Thus, we can computationally calculate the collision area with range sensor data.
- To investigate the environmental condition, the sensor based navigation task is prepared. With low speed navigation, the robot gathers location-dependent information with afraid model that is evaluated by non-blocked collision area. When afraid signal is appeared, the robot plots the locations.
- With the Gaussian kernel of computational learning theory, the accumulated location-dependent information is generalized. Using the generalized information, high speed navigation is achieved. The robot can navigate with high speed in the safe area, while the robot navigation with low speed in the dangerous area.

Experimental results showed that this approach is proven for the safe and fast navigation of mobile robot. We have convinced that this intelligent behavior control that is based on the experience of real environment is appropriate for indoor service robot.

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