Rate Modulation Strategy for Behaviors of a Mobile Robot

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Abstract: In this paper, task control architecture is proposed for a mobile robot with behaviors based on cognition theory to endow the robot intelligence. In the task control architecture, task manager is introduced especially for the management of computational resource. The management is based on classical RMS (Rate Monotonic Strategy), but with online rate modulation strategy. The rate modulation is performed using the value variances of behavior execution for the task. Because the values are based on natively uncertain sensor information, they are modeled using PDF (probability Density Function). As a rate modulation process, the range of the rate modulation is defined firstly by real-time constraints of RMS and discrete control stability of behaviors. With the allowable range, rate modulations are performed considering harmonic bases to maintain utilization bound without decrease. To evaluate the efficiency of the proposed rate modulation strategy, a simulation test is performed to compare the efficiency between the control architecture with the proposed strategy and previous one. A performance index with the formalization of propensity of resource allocation is proposed and utilized for the simulation test. To evaluate the appropriateness of the performance index, the performance index is compared with practical one through a practical simulation test.

Keywords: task control structure, behavior, rate modulation, RMS, value

1. INTRODUCTION

Recently, behavior-based control architectures are studied and implemented vigorously for autonomous mobile robot controls[1][2][3]. Behavior-based reactive systems are known to be appropriate to dynamically changed environments.

One problem of the previous studies for behavior-based controls is that most of them are based on simply reactive behaviors responding to external stimulus with predefined mapping. They are simple to implement but consequently, they are not considered as ones with intelligence. Actually, current studies from biological cognition theory show that most intelligent behaviors should be modeled as feedback systems that can consider the result of their reactions with environmental feedback or stimulus feedback[4].

Another problem of the previous studies is that most of them have just proposed or modeled abstract control architectures and haven't dealt with constraint resources which should have been studied for practical implementation. It is very critical to allocate constraint computation resource efficiently to all behaviors share it, because behavior-based systems need concurrent operating environment natively. Many studies in another field of study, QoS(Quality of service) have been performed to study this kind of constraint resource allocation[5][6].

In this paper, task control architecture is proposed for a mobile robot with behaviors based on cognition to endow the robot intelligence. Additionally, task manager is introduced especially for the management of computational resource in the task control architecture.

The management is based on classical RMS (Rate Monotonic Strategy)[7], but with online rate modulation. Rate modulation means the change in the invocation period of behavior executions and consequently means the change in the computational resource allowed.

The rate modulation is performed using the value variances of behaviors for the task. This strategy is similar to that of QoS studies. But what the distinct with the study in this paper is that the values are modeled using PDF (probability Density Function), because the values are based on natively uncertain sensor information. Most of QoS studies consider the values, qualities as being deterministic.

As a rate modulation process, the range of the rate modulation is defined firstly by two real-time constraints of RMS and by the control stability consideration[8] of behaviors. To define the control stability criteria, discrete control theory is introduced, because the behaviors based on cognition are modeled as feedback systems and current behaviors are mostly implemented into discrete systems. With the allowable range, rate modulations are performed considering harmonic bases to maintain utilization bound without decrease.

To evaluate the efficiency of the proposed rate modulation strategy, a simulation test is performed to compare the efficiency between the control architecture with the proposed strategy and previous one with pure RMS strategy. A performance index with the formalization of propensity of resource allocation is proposed and utilized for the simulation test. To evaluate the appropriateness of the performance index, the performance index is compared with practical one through a practical simulation test.

In the following chapters, the task control architecture proposed is described in chapter 2.

For the management of computational resource, rate modulation strategy based on behavior values is proposed in chapter 3.

A performance index with the formalization of propensity is proposed and a simulation test results with the performance index are shown in chapter 4. Finally, conclusions are described in chapter 5.

2. TASK CONTROL ARCHITECTURE

2.1 Overall robot control architecture

Task control architecture in this paper is based on 3-layered overall robot control architecture[9].

The highest layer is mission layer. A mission is defined as a minimum service unit to users. A mission is sequential and conditional operations of specified tasks.

The middle layer is task layer. A task is defined as a minimum work unit to the robot. A task is composed of specified behaviors running concurrently and cooperating with one other to achieve a common goal, task.

The lowest layer is behavior layer. A behavior is defined as a minimum control unit to the robot.

2.2 Task control architecture

The task control architecture proposed in this paper is composed of behaviors with feedback based on cognition theory. The feedback can be categorized into two. The one is environmental feedback and the other is stimulus feedback.

Usually, most of feedbacks are environmental feedback by sensory information. Stimulus feedback is for behaviors with special purpose. Behaviors for active sensing are a good example of the special behaviors with stimulus feedback.

Task control architecture is depicted in Fig. 1.

As shown in Fig. 1, the task control architecture is composed of multiple sensors, multiple effectors, multiple behaviors with feedback and a task manager.

A stimulus from a sensor can be shared by multiple behaviors, and a behavior also can get multiple stimuli from multiple sensors.

Analogously, an effecter can be fed with multiple responses from multiple behaviors and a response from a behavior can feed multiple effectors. Especially, when an effecter is fed with multiple responses from multiple behaviors, the responses cooperate with one other by vector summation derived from Motor schema theory[2]. What's the distinct from the vector summation with this control architecture is that the scalars of vectors are multiplied by weights configured by task manager according to the value of each behavior based on environmental variance.

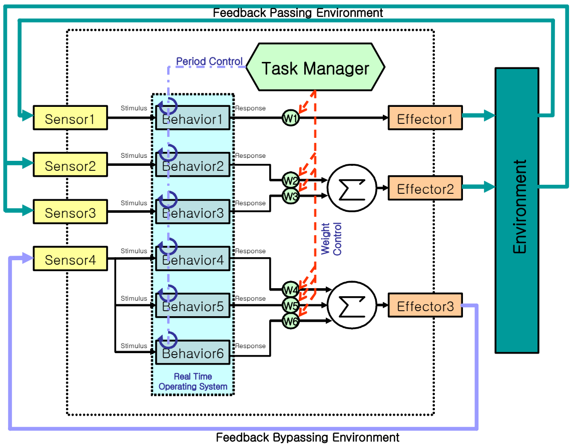


Fig. 1 Task Control Architecture

With the weight configuration of response, task manager controls execution periods, rates of all behaviors for the task according to the value of them based on environmental variance also. By this rate modulation, more valuable behaviors are allowed to use more computational resource than less valuable behaviors.

3. RATE MODULATION STRATEGY

3.1 Classical RMS

The proposed task control architecture is implemented with real-time operating system with multi-tasking feature, because multiple behaviors run concurrently and they should respond to effecter with timely manner when stimuli are given.

RMS is a representative static scheduling strategy for computational resource share of real-time operating system with multi-tasking feature. The priority of each task scheduled under RMS is defined to be inversely proportional to its rate configured offline. To run the tasks satisfying real-time constraint with RMS, two constraints have been introduced[7].

The first is utilization constraint, and the equation is shown in equation (1). The left side of the equation means utilization of the computational resource, and the right side of it means utilization bound defined by the number of task scheduled.

$$\sum_{i=1}^{n}\frac{C_i}{T_i} \le UB = n\left(2^{\frac{1}{n}}-1\right) \qquad (1)$$

Where, n : the number of tasks running
C_i : computation time of i_{th} task
T_i : rate of i_{th} task
UB : Utilization Bound

The second is real-time feasibility constraint of a task, and the equation is shown in equation (2).

$$r_i = C_i + B_i + \sum_{\forall j\in hp(i)} \left\lceil \frac{r_i}{T_j} \right\rceil C_j \le T_i \qquad (2)$$

Where, r_i : worst case response time of i_{th} task.
B_i : blocking time of i_{th} task by lower prioritized tasks.
hp(i) : task set with higher priority than i_{th} task.

3.2 Range of rate modulation strategy

Only when the equation (1) and (2) are satisfied, there is no restriction on the selection of task rates in RMS to meet real-time constraint. But if the rates are harmonically related with one other, utilization bound can be increased with maintaining real-time constraint. For an example, consider the following task sets:

Case 1: τ_1=(2,4), τ_2=(4,8)
Case 2: τ_1=(2,4), τ_2=(2.5,5)
Where, τ_i : i_{th} task with (C_i, T_i).

In both case, utilizations are same with each other. Anyway "Case 1" is schedulable, but "Case 2" is not schedulable. This is due to that in "Case 1", the period of τ_2 can be divided by it of τ_1 without remainder, but in "Case 2", the period of τ_2 cannot be divided by it of τ_1 without remainder. A task set, in which periods of all the tasks can be divided by the smallest element, is called as a harmonic chain, and the smallest element is called as a harmonic base. With less harmonic bases, larger utilization bound can be achieved with meeting real-time constraint.

In the previous study[10], equation (1) is extended to equation (3) using the harmonic base.

$$\sum_{i=1}^{n} \frac{C_i}{T_i} \le m\left(2^{\frac{1}{m}} - 1\right) \quad (3)$$

Where, m : the number of harmonic base.

In the view of scheduling, any behavior rate satisfying equation (2) and (3) can be allowed. But in the view of control theory, rate of the behaviors can affect the stability of the control. When a rate of a behavior is too slow, it can be a cause of control instability.

Because most of current behaviors are implemented into discrete systems, such sampling rate constraint[8] as equation (4) for control stability of discrete system is adopted in this paper.

$$4 \le \frac{T_r}{T_i} \le 10 \quad (4)$$

Where, T_r : system rising time of i_{th} task.

3.3 Value of Behaviors

Resource allocation strategies based on values of candidates for the resource are being studied in the field of QoS. These studies are very valuable, because when the resource is restricted, resource allocation propensity can be a criterion of goal achievement. Because most robotic systems are implemented with embedded control systems in these days, these studies in QoS can be good solutions to constraint resource managements.

What has to be considered when the QoS philosophies are adopted in the field of robot systems is that the value cannot be deterministic in case of robot system. Because the values of any such control task as behavior depend on uncertain sensory information.

In this paper, the value of a behavior is proposed to have distribution with probability density, and the probability density function (PDF) is defined by the uncertainty of sensory information[11].

When such PDF with Gaussian distribution as equation (5) is given, the distribution is same as Fig. 2.

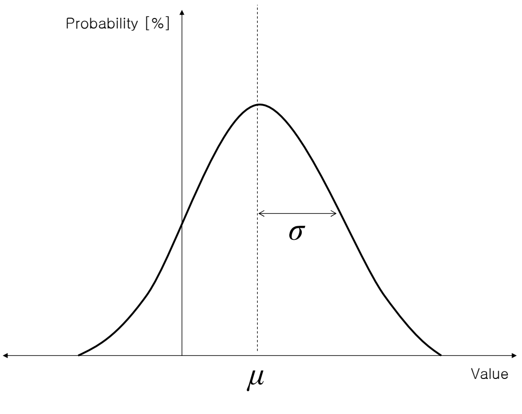


Fig. 2 PDF with Gaussian distribution

$$f(value) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(\frac{(value-\mu)^2}{2\sigma^2}\right) \quad (5)$$

With the equation (5), mean value, or expected value is determined as equation (6).

$$E(value) = \int_{-\infty}^{\infty} value \times f(value)dvalue \quad (6)$$

In this paper, equation (6) is used for value estimation of behavior executions with uncertain environmental information.

Ultrasonic sensor typically used for mobile robot is introduced here for an example.

Certainty value has been introduced for ultrasonic sensors of a mobile robot in a previous study[12]. In the study, a sensor model with Gaussian distribution, $P(r_k|o)$ is proposed by Bayesian update rule. The sensor model means the probability of getting a given range reading, when a cell in particular range is occupied by an obstacle.

The equation of the sensor model is same as equation (7).

$$p(r_k \mid o) = \begin{bmatrix} 0.99, \rho > r_k \\ 0.99\exp\left[-\frac{1}{2}\left(\frac{\theta}{\sigma_r}\right)^2\right], (\rho - r_k) < \sigma_r \\ 0.05, otherwise \end{bmatrix} \quad (7)$$

Where, r_k : measured range.
o : obstacle.
ρ : range of an obstacle.
θ : angle of the obstacle off beam center.
σ_r : scaling factor for probability of occupancy.

3.4 Rate Modulation Strategy

Rate modulation strategy proposed in this paper is performed according to variation rate of behavior values.

Firstly, rates of behaviors with decreased values are increased with the following equation (8).

$$\text{if } (T_k > 0) \quad T_k = \frac{C}{\left(\frac{C}{T_{k-1}}\right) - \left[\frac{\left(\frac{C}{T_{k-1}}\right)}{\sum_{i=1}^{n} \frac{C_i}{T_{i,k-1}}}\right] \times \alpha \left|\frac{V_{k-1} - V_k}{V_{k-1}}\right|} \quad (8)$$

$$\text{else} \quad T_k = \frac{T_r}{4}$$

Where, k : discrete time instant representing present time.
α : scaling constant for value variation

To maximize utilization of computational resource, T_k obtained through the equation (8) is quantized as a nearest element in a set represented in equation (9). Using the quantization, the number of harmonic base can be kept, and consequently utilization bound of the system can be maintained.

$$T_{k\_set} = \left\{ X \mid \min\left(\frac{T_r}{10}, r_i\right) \le x \le \frac{T_r}{4} \text{ and } x \in \text{sets of multiples of harmonic base} \right\} \tag{9}$$

After the modulation of behaviors with decreased values, utilization is calculated to get available bandwidth of computational resource to be relocated to behaviors with increased values.

Available bandwidth of the computational resource is reallocated with equation (10).

$$T_k = \frac{C}{\dfrac{C}{T_{k-1}} + \dfrac{\min\left(\dfrac{V_{k-1} - V_k}{V_{k-1}}, \beta\right)}{\displaystyle\sum_{\substack{i \in \tau_i, \\ \text{value Increased}}} \dfrac{V_{i,k-1} - V_{i,k}}{V_{i,k-1}}} \times \left(UB - \displaystyle\sum_{\substack{i \in \tau_i, \\ \text{value not Increased}}}^{n} \dfrac{C_i}{T_i}\right)} \tag{10}$$

To maximize utilization of computational resource also, T_k obtained through equation the (10) is quantized as a nearest element in a set represented in equation the (9).

Greed algorithm, called as "Winner takes all" is usually adopted in previous studies[5]. Through the greed algorithm, computational resource tends to incline. In this paper, resource reallocation is performed by proportional method to avoid the inclination.

4. SIMULATION TEST

4.1 Performance Index

For the formalization of efficiency of resource reallocation previously proposed, a performance index is proposed in this paper. The performance index is defined to represent the propensity of resource allocation in the view of consumer values.

The equation is shown in equation (11).

$$Performace\_Index(k) = \sum_{i=1}^{n} \frac{V_{i,k}}{T_{i,k}} \tag{11}$$

When resource is allocated more for valuable behaviors, performance index at discrete time instant, k is increased according to the equation (11).

The appropriateness of the performance index is evaluated with a following simulation test. In the simulation test, a mobile robot should avoid obstacles and reach a target, concurrently with sending its environmental information gathered to its remotely-located master by wireless communication. The practical performance index of the robot is the frequency of its information transmission during the movement to the goal without contacting any obstacle, and it is shown that the practical index is proportional to the performance index proposed here.

In the simulation test, obstacles are represented by certainty grids. The certainty grid is a well-known method for obstacle representation with potential field navigation[11]. According to a previous study, grid resolution is represented with sampling period and the speed of mobile robot as shown in equation (12).

$$\Delta S > TV_{\max} \tag{12}$$

Where, ΔS : grid resolution.
T : Sampling rate.
$V_{\max}$: Maximum speed.

Because the T in equation (12) is modulated by environmental variance in this paper, ΔS can be modulated according to the variance of the T.

4.2 Simulation Test

Firstly, to show the enhancement of the performance index defined in equation (11) with the rate modulation strategy proposed, a simulation test is performed with a behavior set having time properties shown in Table 1.

In the Table 1, T_{i_max} means the maximum allowable rate defined by equation (4).

Table 1 Behavior Set for Simulation Test

Behavior	C_i [mS]	T_i [mS]	$T_{i\ max}$ [mS]
1	20	200	400
2	20	200	400
3	20	300	600
4	20	400	800
5	20	800	1000
6	20	900	1000

Value variance is given for the simulation test as shown in Fig. 3.

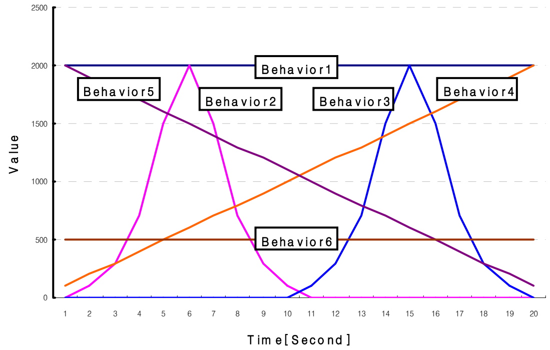


Fig. 3 Value variance for Simulation Test

With the value variance depicted in Fig. 3, each performance index is calculated for the proposed rate modulation strategy and the classical RMS strategy. The results are shown in Fig. 4. The test is performed with coefficient α=1, and β=1.

As shown in Fig. 4, performance index is increased with the proposed rate modulation strategy, especially when there are two behaviors having increasing values. In the simulation test at most two behaviors can have increasing values at the same time as shown in Fig. 3.

The results show that the rate modulation strategy is more efficient compared to classical RMS when there are more behaviors with increasing values.

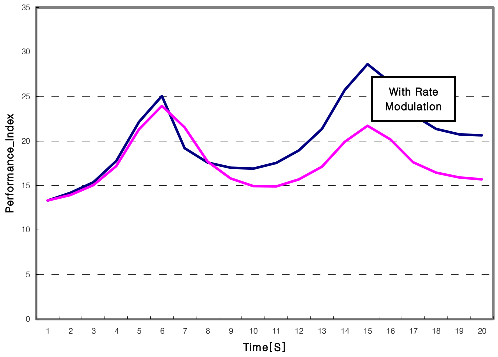
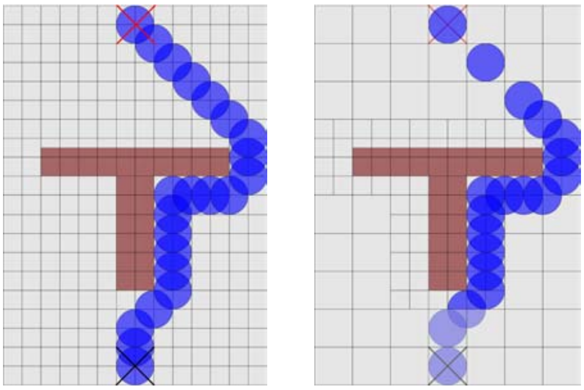


Fig. 4 Performance Index with the Simulation Test

To evaluate the above performance index, the rate modulation strategy is simulated with practical mobile robot with a task, movement to a target without contacting any obstacle and concurrently with transmission of its environmental information gathered to remotely-located master by wireless communication.

In the simulation, the task is composed of three behaviors, "Heading for the target", "Avoiding obstacle", and "Transmitting of information". During the task performance, the value of the behavior, "Heading for the target" is never changed. But the values of "Avoiding obstacle" and "Transmitting information" are changed with obstacle detections.



(a) Classical pure RMS (b) Rate modulation strategy

Fig. 5 Path Generation with Pure RMS and with Rate Modulation Strategy

With the classical RMS, the grid resolution of environment should be defined with the rate defined statically considering worst case as shown in (a) of Fig. 5. But with rate modulation strategy proposed, the grids resolution of environment can be changed with the importance of the behavior, "Avoiding obstacle" as shown in (b) of Fig. 5.

With the classical RMS, the set of available time features are same as followings:

τ_1 ("Heading for the target") = {(100,400)},
τ_2 ("Avoiding obstacle") = {(100,200)},
τ_3 ("Transmitting Information") = {(100,400)}.

With the rate monotonic strategy proposed, the set of available time features can be same as followings:

τ_1 ("Heading for the target") = {(100,400)},
τ_2 ("Avoiding obstacle") = {(100,200), (100, 400)},
τ_3 ("Transmitting Information") = {(100,400), (100, 200)}.

The selection of an element in a set is decided with obstacle detection. Value performance index measured and transmission rate of environmental information, the practical performance index with the environment of Fig. 5 is shown in Fig. 6.

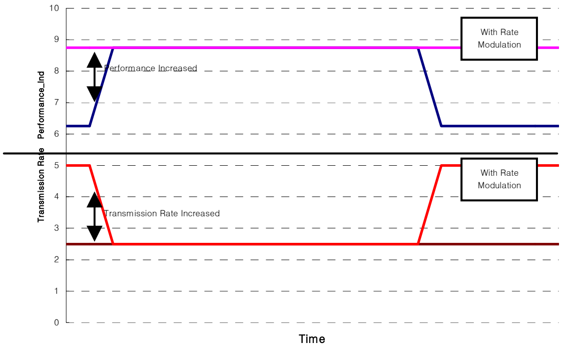


Fig. 6 Value Performance Index and Practical Performance Index

As shown in Fig. 6, with the rate modulation strategy, the practical performance index is exactly proportional to value index proposed here.

This result shows that the performance index can be considered to be the abstract performance index representing various practical performance indexes.

5. CONCLUSION

In this paper, task control architecture is proposed for a mobile robot with behaviors based on cognition theory to endow the robot intelligence. In the task control architecture, task manager is introduced especially for the management of computational resource. The management is based on classical

RMS, but with online rate modulation strategy.

The rate modulation is performed using the value variances of behavior execution for the task. Because the values are based on natively uncertain sensor information, they are modeled using PDF.

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With the allowable range, rate modulations are performed considering harmonic bases to maintain utilization bound without decrease.

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A performance index with the formalization of propensity of resource allocation is proposed and utilized for the simulation test. To evaluate the appropriateness of the performance index, the performance index is compared with practical one through a practical simulation test.

The result shows that the performance index can be considered to be the abstract performance index representing various practical performance indexes.

For further study, the study in trade-off between benefit of this kind of deliberate planning and resource consumption by the planning will be performed.

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