Evaluation of Network Resource Allocation Based on Monitored Traffic Condition inspired by Human Brain Cognition Process

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SUMMARY Many kinds of services have been provided through networks. Traffic from such services should be accommodated so as to satisfy the requirements which depend on services. One approach to accommodating traffic so as to satisfy the various requirements is to use the network slicing, which provides multiple network slices for the network services. Resources for each slice should be dynamically allocated so as to follow the traffic changes. Because the real-world condition has a large impact on traffic changes, real-world information is useful to predict future traffic. However, the relationship between real-world information and future traffic is difficult to model. Therefore, we have proposed a method to handle real-world information to predict future traffic and dynamically control the resources inspired by the human brain cognition process. In this paper, we apply the method to the controller of network slices for the connected vehicles. We demonstrate that the road traffic information is useful to the resource allocation in the network slice for the connected vehicles.
key words: *Network Slicing, Traffic Flow Sensing, Bayesian Attractor Model, Resource Allocation*

1. Introduction

Networks are required to allocate network resources so as to satisfy the requirements of services and accommodate the generated traffic. One approach to accommodating services with different requirements is to use network slicing technologies[1], [2]. By constructing a network slice for each service, network operators flexibly configure their network slices as to satisfy their requirements.

Resource allocation to each network slice is important for network operators. Because the amount of traffic changes in time, the resource should be dynamically allocated. Resource allocation based on prediction is one approach to handling traffic changes. By using predicted traffic, the resources are proactively allocated so as to accommodate the predicted future traffic.

Real-world information is useful for the prediction. However, it is difficult to accurately model the relationship between real-world information and future traffic demands. Therefore, we have proposed a predictive network control method using the real-world information of which the relation to future traffic cannot be clearly modeled[10]. This method applies the model of human cognition to predictive network control. In this method, we first define the options in decision making by considering future traffic and the currently monitored traffic and real-world information. Then, the method identifies the option corresponding to the current state from the observed information. Finally, the resources are allocated based on the identified option.

Our previous work demonstrated the effectiveness of the proposed method only considering the daily traffic changes, and used only the information on the number of users in each area as real-world information. On the other hand, real-world information is useful especially in the case that some events occur and the information related to the events is included in the real-world information.

In this paper, we apply the network control method based on the cognitive process of a human brain to the resource allocation of the network slices for connected vehicles. We demonstrate the effectiveness of our method using transport traffic information by simulation.

2. Bayesian Attractor Model

In this section, we introduce the Bayesian attractor model (BAM) which is used as the model to identify the current state. The BAM is a model of the cognition process of a human brain based on the Bayesian decision-making theory[9]. This model encodes the predefined i options $\phi_1, \cdots, \phi_i$ and makes decisions depending on the option corresponding to the current status. The decision state z_t is the internal state of this model, where z_t is updated by performing the Bayesian inference every time a new observation is obtained. The rest of this section explains how a human brain makes decisions in this model.

2.1 Abstraction

In this model, every time a new observation is obtained, the observation is abstracted. In this paper, we represent the abstracted observation by the vector X_t.

2.2 Generative model

This model includes the following generative model for the decision state Z_t and observation X_t,

$$Z_t - Z_{t-\Delta_t} = \Delta_t f(Z_{t-\Delta_t}) + \sqrt{\Delta_t} w_t \quad (1)$$

$$X_t = M\sigma(Z_t) + v_t, \quad (2)$$

where $f(Z)$ is the Hopfield dynamics, w_t and v_t are Gaussian noise variables whose variances are s^2 and q^2, $M = [\mu_i, \cdots, \mu_N]$ is a matrix containing the observation values, and μ_i is the observation value corresponding to the state ϕ_i, which is the ith predefined option. Further, $\sigma(x)$ is a sigmoid

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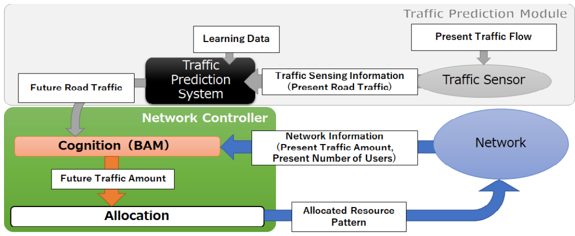

Fig. 1 Overview of the Proposed Method

function $\frac{tanh(ax/2)+1}{2}$, where a is the slope of this function.

2.3 Update of state

This model updates the decision state Z_t every time X_t is obtained by inverting the generative model using Bayesian inference. Because the generative model is nonlinear, Bitzer~et~al. used the unscented Kalman filter[12] to update the mean decision state of Z_t. In addition to the mean decision state being updated, the posterior distribution $P(Z_t|X_t)$ over the decision state is obtained.

In this paper, we used Particle Filter instead of Unscented Kalman Filter, because Unscented Kalman Filter cannot accurately estimate the state due to the strong nonlinearity of the generative model including the sigmoid function.

2.4 Decision making

The above state estimation outputs the posterior probability $P(Z_t|X_t)$. Thus, the decision is made by handling the probability. Bitzer~et~al. introduced the threshold of λ. When $P(Z_t = \phi_i) > \lambda$, the option ϕ_i is selected. When $P(Z_t = \phi_i) \leq \lambda$ for all i, no decision is made until a new observation is obtained.

3. Resource allocation method using road traffic information

3.1 Overview

Figure1 shows the overview of the proposed method.

In this method, we deploy a controller of the network slice for the connected vehicles. This controller periodically collects the information on the communication network and road traffic. The information on road traffic is used to predict future road traffic. Then, the controller estimates the required resources by using both of the predicted future road traffic and monitored information on the communication traffic.

By using the predicted future road traffic, the controller can predict the traffic increase on the slice. However, the prediction of future road traffic may include prediction error. Thus, we apply a method based on the Bayesian Attractor Model, that make decisions even if the information monitored at each time slot is uncertain, to the estimation of the required resources.

3.2 Prediction of road traffic

The future road traffic is predicted by using the collected traffic information including the number of vehicles on each lane of the monitored roads. We can apply any methods to predict future road traffic.

3.3 Estimation of required resources

The controller estimates the required resources every time new observations including the future predicted road traffic and monitored communication network traffic are obtained. We apply the method based on the BAM to estimate the required resources. In this method, we define decision options and the amount of required resources for each option. Then, the controller identifies the current option by the cognitive process based on the BAM. By doing so, we can estimate the required resources by identifying the option corresponding to the current condition.

3.3.1 Definition of the options in decision making

We define the options by using the previously obtained observations. We denote the observation at time t by O_t. O_t is a vector including the predicted road traffic and the information on the traffic on the communication network. We first scale O_t by using the predefined scale factor for each element so that each element of O_t becomes less than 1. We denote scaled O_t by X_t Then, we define the options by clustering X_t; we divide the set of the monitor into multiple clusters so that each cluster includes similar observations and define one option for each cluster.

Then we estimate the required resources for each option. In this paper, we calculate the maximum required resources from the time t to $t+p$ for each data point. Then, we define the maximum required resources for the data points included in a cluster as the required resources for the option corresponding to the cluster. By defining the required resources as the maximum value of the required resources, we avoid the lock of allocated resources.

The BAM requires the observation values for each option. In this paper, we define the mean of X_t belonging to a cluster as the observation values of the options corresponding to the cluster.

3.3.2 Estimation of required resources based on Bayesian Attractor Model

In this paper, we estimate the required resources based on BAM. We use the same process as BAM. That is, the controller has the decision state Z_t and update it Z_t by performing the Bayesian inference every time a new observation X_t is obtained. The BAM outputs the posterior probability $P(Z_t|X)$. By using $P(Z_t|X)$, the controller estimates the required resources. In this paper, the controller selects the options whose corresponding $P(Z_t|X)$ exceeds the predefined threshold λ. If $P(Z_t|X)$ for multiple options exceeds λ and multiple options are selected, the controller selects the decision state associated with the maximum resource from multiple decision states. Then, the amount of allocated resources is estimated based on the selected state.

4. Evaluation

4.1 Settings

4.1.1 Road traffic generation

In this evaluation, we focus on an area around JR Shinjuku station the size of which is about $2.4km^2$. We generate road traffic by using the Simulation of Urban MObility (SUMO)[13]. We obtain the actual road information from OpenStreetMap[14]. We generate the vehicle for the simulation-based on Open PFLOW [11], which is the open dataset for typical people mass movement. Open PFLOW includes information on only sampled people, we generate multiple vehicles for each person in a vehicle included in Open PFLOW. By randomly generating the scale factor, we generate multiple patterns. We generate the scale factor so as to follow the Gaussian distribution whose mean is 8 and variance is 1.

In addition, we also generate the case for traffic accidents. We generate the case for traffic accidents by reducing the lanes at the point accidents occur. In this evaluation, we generated the accidents at the starting point of Ome Kaido.

4.1.2 Network traffic generation

In this paper, we divide the area around JR Shinjuku station into 15 areas. We evaluate a method that allocates the resources for each area.

This paper focuses on the network slice for the connected vehicle. Therefore, we focus on the traffic generated from the connected vehicles. For simplicity, we assume that each vehicle generates a similar amount of traffic, and generates the amount of traffic by adding the number of vehicles and Gaussian noise. In this evaluation, we set the mean and variance of the Gaussian noise to 0 and 10, respectively.

4.1.3 Road traffic prediction

In this paper, the controller uses the predicted road traffic. Any method to predict road traffic can be used. In this evaluation, we use the method proposed by Lun Zhang[15]. This method is based on k Nearest Neighbors. This method stores the set of pairs of the observations and the number of vehicles on each road in the future. When a new observation is obtained, this method selects k nearest observation from the stored observations. Finally, the number of vehicles is predicted by the weighted sum of the number of vehicles corresponding the selected observations. In this paper, we use the numbers of vehicles on the primary roads as the observations for the road traffic prediction, and we set k to 82. After obtaining the predicted road traffic information, we merged them to calculate the predicted number of vehicles in each area, which is used as an input of the estimation of the required resources.

Table 1 Parameter list

Parameter	Value
Length of a time slot	1 min
p	5
s	0.3
q	0.6
λ	10^{-10}

4.2 Parameter settings

In this evaluation, we use the parameters shown in Table 1.

4.3 Compared methods

In this evaluation, we compare the following methods.

BAM with Sensing: Proposed method. This method uses both of the information on the road traffic and communication traffic and estimates the required resources by using the method based on BAM.

NN with Sensing: This method uses both of the information on the road traffic and communication traffic but estimates the required resources by selecting the nearest neighbor instead of using BAM. In this method, the controller selects the nearest neighbor of the current observation from the stored past observations. Then the controller estimates the required resources by the required resources corresponding to the selected neighbor. The comparison with this method demonstrates the effectiveness of the method using the BAM.

BAM without Sensing: This method uses the BAM but uses only the information on the communication network. The comparison with this method demonstrates that the effectiveness of the method using the information on road traffic.

4.4 Metric

In this evaluation, we calculate the amount of *surplus resources* as a metric to evaluate the method. We define the amount of the surplus resources by

$$A_{t,a} - \max_{1\leq i\leq p} T_{t+i,a}$$

where $A_{t,a}$ is the amount of allocated resources in area a at time t, and $T_{t,a}$ is the actual required resources in area a at time t.

If the resources suitable to the current condition are allocated, the amount of the surplus resources is a small positive value. If an unnecessarily large amount of resources are allocated, the surplus resources become large. On the other hand, if a lack of resources occurs, the amount of surplus resources become less than 0.

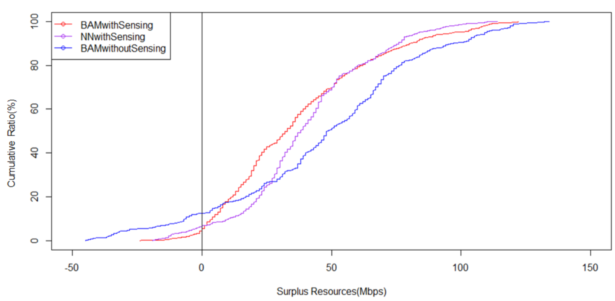

Fig. 2 Cumulative ratio of surplus resource

4.5 Result

Figure 2 shows the cumulative distribution of the amount of surplus resources. In this figure, the horizontal axis is the amount of the surplus resources, and the vertical axis is the cumulative distribution.

Figure 2 shows that the method without using the information on road traffic cannot allocate suitable resources compared with the other methods. The lack of resources occurs in 10 % of areas. Moreover, the amount of surplus resources becomes large in many areas. This is because the signs of the increase of the communication traffic are not sufficiently included in the information on the communication network. Especially, the road traffic congestion caused by an accident can be predicted by the road traffic prediction because the road traffic prediction uses the fine-grained information on the primary roads, but the information on the communication network does not include such sign of the increase of the traffic because they include coarse-grained information, the traffic amount of each area. As a result, the controller cannot identify the area and time slot that requires more resources.

Figure 2 also shows the method using the nearest neighbor requires more resources, compared with the method based on the BAM, while the ratio of the area where the lack of the resource occurs is similar. This is because the method using the nearest neighbor is sensitive to the variation of the observations. When the current observation becomes temporarily close to the past observations that require a large amount of resources, the method using the nearest neighbor allocates a large amount of resources. On the other hand, the method based on the BAM is robust to such noises and avoids allocating unnecessary resources due to the temporal noise.

5. Conclusion

In this paper, we applied the network control method based on the cognitive process of a human brain to the resource allocation of the network slices for connected vehicles. We demonstrated the effectiveness of our method using road traffic information by simulation.

The effectiveness of using road traffic may depend on the environment. For example, in the case that future road traffic is difficult to be predicted from the monitored road traffic, the future required resources of communication network are also difficult to be estimated by using the road traffic information. In this case, the effectiveness of using road traffic may be small. We plan to investigate the environment where road traffic information is useful or not.

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