Proactive Complex Event Processing for Transportation Internet of Things

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***Abstract*—Complex Event Processing (CEP) has become the key part of Internet of Things (IoT). Proactive CEP can predict future system states and execute some actions to avoid unwanted states which brings new hope to transportation IoT. In this paper, we propose a proactive CEP architecture and method for transportation IoT. Based on basic CEP technology, this method uses structure varying Bayesian network to predict future events and system states. Different Bayesian network structures are learned and used according to different event context. A networked distributed Markov decision processes model with predicting states is proposed as sequential decision model. Q-learning method is investigated for this model to find optimal joint policy. The experimental evaluations show that this method works well when used to control congestion in transportation IoT.**

***Keywords*—Proactive Complex Event Processing; Transportation Internet of Things; Structure Varying Bayesian Network; Networked Distributed Markov Decision Processes**

I. Introduction and System Architecture

Recently Complex Event Processing (CEP) [1] has been widely used in Internet of Things (IoT). Proactive complex event processing means system has the ability to mitigate or eliminate undesired future events, or to identify and take advantage of future opportunities, by applying prediction and automated decision making technologies [2]. IoT with proactive CEP provides a new way to improve Intelligent Transportation Systems (ITS) or transportation IoT.

In this paper, we propose a proactive CEP architecture and method (Pro-CEP) for transportation IoT. Structure Varying Dynamic Bayesian Network (SVDBN) model and Networked Distributed Markov Decision Processes with future states (ND-MDP+) model are used in our method. The system architecture is shown in fig. 1. The goal of our system is to control traffic congestion using proactive CEP in transportation IoT. Probabilistic Event Processing Network (PEPN) is composed of many connected Probabilistic Event Processing Agents (PEPA). With the help of Predictive Analytic (PA) component, the decision maker selects optimal actions and the proactive agents (PRAs) execute the actions

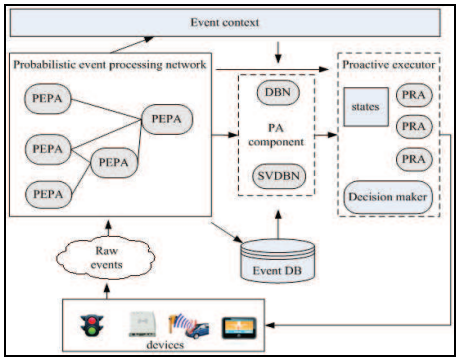

Fig. 1. System architecture

II. State Prediction with SVDBN

The basic prediction method using adaptive Bayesian network model is described in [3].

Definition 1 (SVDBN): A Structure Varying Dynamic Bayesian Network (SVDBN) is represented as $\langle G(t), \Theta(t) \rangle$, where $G(t)$ and $\Theta(t)$ are random processes whose values at time t represent the network structure and parameter of BN respectively. These random variables, regarded as structure nodes and parameter nodes, are used to construct a graph together with data nodes of BN.

Although some inference methods for SVDBN have been proposed, it is not easy to use them in our work because of calculation complexity. Based on the observation that event data with different context fit different model in transportation area, we present an approximate solution using event context. In this method, historical event data is classified into a set of classes based on event context. Then the DBN structure and parameters are learned for every class. When predicting at run time, the current event context is classified into a class and corresponding model is selected. We use a Fuzzy C-Means (FCM) method to cluster historical event data which has been described on detail in our previous paper [4].

The research work is supported by National Natural Science Foundation of China under Grant No. 61371116 and Hunan Provincial Natural Science Foundation under Grant No.13JJ3046.

978-1-4673-8590-9/15/$31.00 ©2015 IEEE

III. Sequential Decision Making

Definition 2 (ND-MDP$^+$): A Networked Distributed Markov Decision Processes with future states (ND-MDP$^+$) is defines as $\langle I, S, \bar{S}, \vec{A}, P, R\rangle$, where I is a finite set of agents. S is a finite set of states, with distinguished initial state s_0. $\bar{S}$ is a finite set of future states which can be predicted from historical states. $\vec{A} = \times_{x \in I} A_i$ is a set of joint actions, where A_i is the set of actions for agent i. $P : S \times \vec{A} \rightarrow S'$ is the state transition function, defining the distributions of states that result from starting in a given state and a joint action by agents. $R : S \times \vec{A} \rightarrow \Re$ is the reward function for the set of agents for each set of joint actions and each state.

The proactive event processing system starts from predicting future state and select a joint action to be executed by agents according to the joint policy. The execution of the joint action maximizes the total expected reward for both the future state and the current state.

We use the reinforcement learning method Q-learning to learn the joint policy. The Q-function $Q(s, \bar{s}, a)$ represents the reward of executing joint action a under state s and predicting state $\bar{s}$. The optimal joint policy π^* can be derived from $Q(s, \bar{s}, a)$ by

$$\pi^*(s) = \arg\max_{a \in A} Q^*(s, \bar{s}, a) \tag{1}$$

The extended Q-learning can be described by the following equation:

$$\begin{aligned} Q(s^t, \bar{s}^t, a^t) &= (1-\alpha)Q(s^t, \bar{s}^t, a^t) \\ &+ \alpha[(1-\beta)r_s^t + \beta r_{\bar{s}}^t \\ &+ \gamma \max_a Q(s^{t+1}, \bar{s}^{t+1}, a)] \end{aligned} \tag{2}$$

where $\alpha \in (0,1)$ is the learning rate, $\gamma \in [0,1]$ is the discount factor, r^t is the reward executing action a on state s, $Q(s^t, \bar{s}^t, a^t)$ represents the Q-value of executing action a for joint state $(s, \bar{s})$ at time t. The joint reward r^t contains two parts where r_s^t means the reward from the current state s to its next state and and $r_{\bar{s}}^t$ means the reward from predicting state $\bar{s}$ to its next predicting state. $\beta \in (0,1)$ is a weight factor.

IV. Experimental Evaluation and Conclusion

In order to evaluate our method, we created a transportation IoT simulation system based on the road traffic simulation package SUMO. In the simulation system we set a road network of 15×15 intersections and set 80 thousand vehicles. Every road has 2 lanes and every intersection has traffic lights.

We first evaluated the accuracy of our PA method with different cluster granularity and the result is shown in Fig.2. The accuracy of PA is compared with the work of Pascale et al. [3] and the result is shown in Fig.3.

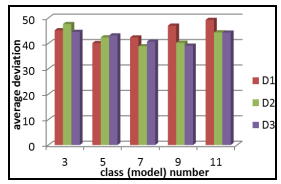

Fig. 2. PA accuracy for different class number

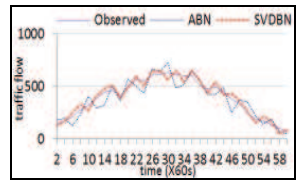

Fig. 3. PA accuracy for a typical node

Since we have not found other work which has the same function, our method is only compared with the default simulation system and the result is shown in Fig.4. We also evaluated the effect of Pro-CEP with different vehicle numbers and group partition policies which is shown in Fig.5. The performance evaluation result is shown in Fig.6 and Fig.7. From all the experiments we can see Pro-CEP works well when processing proactive congestion control in transportation IoT.

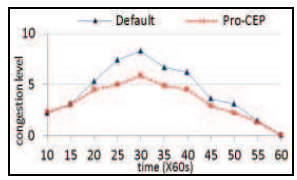

Fig. 4. average congestion level over time

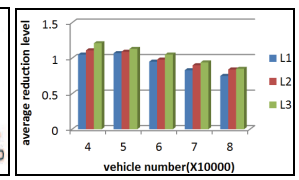

Fig. 5. effect with different vehicle numbers and group partition policies

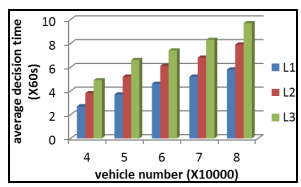

Fig. 6. performance with different vehicle numbers and group partition policies

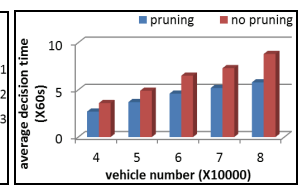

Fig. 7. performance with different vehicle numbers and pruning policies in max-sum

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