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A new Learning Automata based approach for online tracking of event patterns

Wen Jiang [a], Cheng-Lin Zhao [b], Sheng-Hong Li [a,*], Lawson Chen [c]

[a] Department of Electronic Engineering, Shanghai Jiao Tong University, 800 Dongchuan Road, Min Hang, Shanghai 200240, PR China
[b] School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Beijing 100876, PR China
[c] Wenzhou Hongfeng Electrical Alloy Co., Ltd, Zhejiang Wenzhou 325603, PR China

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ABSTRACT

Detecting spatiotemporal pattern from noisy sequences of events plays a very important role in presence sharing, Internet of Things (IoT) and many other fields. As pointed out in existing literature, the core activities of these applications involve event notifications. However, excessive number of event notifications will lead to user's intolerability. Existing literature proposed a Spatiotemporal Pattern Learning Automata (STPLA) to solve this problem effectively in both stationary and non-stationary environments. However, one limitation of the STPLA is that it cannot be both memory balanced and bias toward any of the two actions, i.e., “suppress” or “notify”. To solve this problem, this paper proposed a new Learning Automata based approach, named as Spatiotemporal Tunable Fixed Structured Learning Automata (STP-TFSLA), for online tracking of event pattern. Furthermore, we also show that the STP-TFSLA is with small memory footprint and is able to cope with non-stationary environment.

1. Introduction

Generally speaking, events can be divided into two types, i.e., “stochastically episodic” and “stochastically non-episodic”; the former one means that the event stochastically happens with non-anticipated manner, whose examples include earthquakes and nuclear explosions. On the contrary, the “stochastically non-episodic” event occurs with a stochastically pattern [16,18,19].

In order to discover the periodicity of time patterns from event sequences, the frequent and periodic activity miner (FPAM) algorithm [15,17] tried to discover frequent sequences, periodic sequences and their periodicity. A main shortcoming of the FPAM scheme is that it works in an offline manner. Recently, Ref. [16] proposed an online approach, named as the Spatiotemporal Pattern Learning Automata (STPLA), to answer the question that “*How can one harvest the benefit of event sharing without distracting the application user with redundant notification?*”. In the literature, STPLA was compared with FPAM [15,17] and showed its ability of “suppress” when a hypothesized pattern exists and of “notify” when no pattern exists even with noisy occurring environment. They also showed that the different memory depths for “notify” and “suppress” will introduce “bias” toward the presence or absence of the spatiotemporal pattern, and proved that for the balanced-memory, which is defined as the case that the memory depths for “notify” and “suppress” are same, the notification probability that the STPLA yields will approach zero under the condition that event pattern exists and omission noise happens with probability less than 0.5, and vice versa.

From [16], it is easy to see that the STPLA cannot be both balanced-memory and “bias” toward the action of “notify” or “suppress”. That is to say, there is a strong connection between the “balanced-memory” and the “bias”, which greatly limits the applications of the learning algorithm in real world. For instance, for the IoT, a sensor is expected to send messages to a data collection center regularly. However, due to the unreliable package-switched computer network, some unexpected failures might happen. The sensor is deemed to be alive if the messages received from this sensor follow with some patterns. Server should not send out a notification if it believes that the senor is still alive. In some cases, we want to reduce the number of notifications as many as possible, which means that the bias toward suppressing is the preference. As mentioned in the literature, the unbalanced-memory STPLA can reach this goal. In this paper, our motivation is to design a new learning algorithm relaxing the relationship between balanced-memory and “bias” to overcome the above mentioned problems.

The contributions of this paper are listed as follows:

(1) This paper proposed a new Learning Automata based approach for online tracking the unknown patterns in noisy sequences of events. Compared with the STPLA [16], the proposed algorithm can be tuned with more flexibility.

* Corresponding author.
E-mail addresses: wenjiang@sjtu.edu.cn (W. Jiang), clzhao@bupt.edu.cn (C.-L. Zhao), shli@sjtu.edu.cn (S.-H. Li).

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(2) Simulations demonstrated that the proposed algorithm is able to operate in non-stationary environments.
(3) Experiments confirmed that by adjusting the corresponding tune parameter, the learning algorithm possesses different ability of suppressing notifications.

The rest of this paper is organized as follows. Section 2 reviews the related work including STPLA and Tunable Fixed Structured Learning Automata (TFSLA). Section 3 introduces the proposed learning algorithm. Experiments are demonstrated in Section 4 to verify the effectiveness of the proposed algorithm. Section 5 concludes this paper.

2. Fixed structure stochastic automaton

Ref. [16] proposed a Fixed Structure Stochastic Automaton (FSSA) based algorithm STPLA for online tracking noisy spatiotemporal event patterns. Within the context of this paper, we introduce the Spatiotemporal Pattern Tunable Fixed Structured Learning Automata which also belongs to FSSA. In order to give readers a clear understanding of our method, we shall first introduce the formal definition of FSSA.

2.1. Fixed structure stochastic automata

In general, Learning Automata [1–10,13–14] is one of the powerful tools in Artificial Intelligence, and has a myriad of applications [11,12,16]. The functionalities of LA can be summarized as follows. At instant n, the LA selects one action, $\alpha(n)$, and then sends this action to an environment which will feedback a scalar reinforcement signal, $\beta(n)$. After that, the LA receives this response and takes this response into consideration to update the LA's state. This cycle repeats until the LA selects one sole action. The FSSA, one class of LA, whose transition and output function are time invariant, can be represented by

$$\langle A, B, \Phi, T, G\rangle \tag{1}$$

where $A=\{\alpha_1,\alpha_2,\ldots,\alpha_r\}$ is the set of actions of stochastic automaton; $B=\{\beta_1,\beta_2,\ldots,\beta_m\}$ is the set of responses from stochastic environment. As mentioned before, the stochastic automaton is a Q-model automaton if $m>2$. In this paper, we consider $B=\{0,1\}$ where"1" means reward and "0" means penalty. $\Phi=\{\phi_1,\phi_2,\ldots,\phi_s\}$ is the set of internal states of stochastic automaton; $T:\Phi\times B\rightarrow\Phi$ is the transition function that maps the current state to the next state when the response from environment is received; $G:\Phi\rightarrow A$ is the output function of the automaton which maps the current state to one of the actions of the stochastic automaton.

2.2. Spatiotemporal pattern Learning Automata

In brief, the objective of the STPLA is not to find a pattern but to determine whether a given pattern can be found in a stream of events. In STPLA, each given pattern, referred to as a hypothesis, is associated with one STPLA.

As mentioned before, LA interacts with stochastic environment and accepts the response of the environment. Applying Learning Automata to solve a given problem involves modeling the actions, employing appropriate the learning algorithm (Finite Action Set Learning Automata, Continuous Action Set Learning Automata) and constructing stochastic environment (designing when to reward or penalize a given action). In the context of STPLA, the stochastic environment rewards or penalizes the STPLA based on whether the hypothesis is confirmed by the spatiotemporal event. In details, if the STPLA predicts the event as a part of a spatiotemporal pattern, the stochastic environment responses a reward.

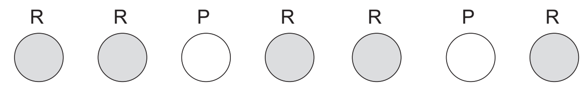

Fig. 1. Feedback sequence (R, Reward; P, Penalty) for an event hypothesis.

On the contrary, if the STPLA conjectures the event as a part of a spatiotemporal pattern while the event does not take place, the environment shall penalize the STPLA. Fig. 1 illustrates the feedback sequence for an event hypothesis [16].

As mentioned before, STPLA is actually a FSSA and hence can be formally defined as Eq. (1) where $A=\{Notify, Suppress\}$, $B=\{1,0\}$ is the set of responses from stochastic environment and "1" means reward and "0" means penalty, $\Phi=\{1,2,\ldots,N_1,N_1+1,\ldots,N_1+N_2+1\}$ is the set of internal states of stochastic automaton, T and G is specified in Fig. 2, and G is defined as

$$G(\phi_i)=\begin{cases} Notify, & \text{if } \phi_i\in\{1,2,\ldots,N_1\} \\ Suppress, & \text{if } \phi_i\in\{N_1+1,N_1+2,\ldots,N_1+N_2+1\}. \end{cases} \tag{2}$$

Ref. [16] demonstrated that the memory balanced STPLA outperforms FPAM, and is able to work in an online manner, possesses an excellent ability to cope with non-stationary environments and is with computational efficiency and small memory footprint.

This paper aims at proposing a new learning algorithm to discover and track the spatiotemporal event pattern with more flexibility than the STPLA. In the next section, we will introduce the proposed learning algorithm.

2.3. Tunable fixed structured Learning Automata

In order to explain the proposed STP-TFSLA clearly, we shall first summarize the TFSLA, in which the Markov Chain is presented in Fig. 3. Formally, TFSLA can be defined as Eq. (1), where $A=\{\alpha_1,\alpha_2\}$, $B=\{1,0\}$ is the set of responses from stochastic environment, $\Phi=\{1,2,\ldots,N,N+1,\ldots,2N\}$ is the set of internal states of stochastic automaton and N is memory depth.

At time instant n, the output function of TFSLA, G, is

$$\begin{cases} \text{if } 1\le k\le N, & \alpha(n)=\alpha_1 \\ \text{if } N+1\le k\le 2N, & \alpha(n)=\alpha_2. \end{cases} \tag{3}$$

The transition function of TFSLA, T, can be summarized as follows.

1) At state k, if TFSLA receives a reward response from the environment, Learning Automata moves to a deeper state (the deepest state of α_1 is $k=1$ while that of α_2 is $k=N+1$);
2) At state k, if TFSLA gets a penalty response, Learning Automata moves to a shallower state with probability 1-h and to a deeper state with probability h.

With the above descriptions, we shall present the proposed STP-TFSLA in the following.

3. Proposed STP-TFSLA algorithms

In this section, we propose a new FSSA based approach, the Spatiotemporal Pattern Tunable Fixed Structured Learning Automata (STP-TFSLA), which is stemming from TFSLA [6]. The motivation of the STP-TFSLA is to cope with the problem of discovering and tracking spatiotemporal pattern with more flexibility.

TFSLA which has been demonstrated with faster convergence and more precise compared with Krinsky and Krylov when the number of actions is large, and is more flexible because it can be tuned with the tuning parameter h, the modification of TFSLA to