Automation in Construction 26 (2012) 69–76

Contents lists available at SciVerse ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

User behavior detection framework based on NBP for energy efficiency

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ARTICLE INFO

Article history:
Accepted 9 April 2012
Available online 29 May 2012

Keywords:
User behavior detection
Energy efficiency estimation
Contextual anomaly detection
Non-parametric belief propagation
Hybrid information fusion
Particle filters
Importance sampling

ABSTRACT

In this paper, a user behavior detection framework based on non-parametric belief propagation (NBP) is proposed to discover the anomalous events from the dataset of contextual user behaviors, as in the case of anomalous events that can make a surge of energy flow and mess the energy management schedule, such as bursty occupancy, or unusual equipment usage. Firstly, the hybrid information's fusion from multiple channels, which collects generalized information of contextual environment, is resolved by message discretization and update based on importance sampling, particle filters and non-parametric representation of multi-layer NBP. Then, the message passing process of belief propagation assists to identify the time span of anomalous events, and construct the contextual environment. Furthermore, we leverage the belief estimations of NBP inference to approximate the marginal probability of contextual anomalous events, and the Monte Carlo methods draw the samples of event states recursively to simulate the uncertainty of anomalies. Finally, the efficiency of NBP user behavior detection framework is validated by KDD2006 Calit2 Building Date Set.

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1. Introduction

Nowadays, artificial intelligence techniques and ambient intelligence techniques is deployed into building automation system (BAS) entirely, and refurbish the traditional BAS into intelligent building management system (IBMS) with the improvement of most features. Dynamic control strategy, flexible management culture, and on-demand user response represent the personality feature of modern IBMS in each building. In the ubiquitous computing environment, the system is not just driven by the sensing value, but the deriving contextual information about reasons, intentions, desires and beliefs of the users [1]. Modeling user behaviors is the attractive and popular field of building intelligence research, especially, the issues pertinent to the building energy efficiency [1–5]. From the macro view, the energy culture framework was suggested to explain the macro–micro model of energy consumption behavior through cognitive norms, material culture, and energy practices [4]. The other macro model of domestic energy use is the model based on Consumer Behavior Theories with three central factors (product, individual, and environment) which inform the energy policy decision process [2]. In the practical environment, intelligent approaches, such as HMM and Genetic Programming Algorithm, are leveraged to infer the daily routine of occupancy behavior with unsupervised learning process. The inference results are explained as semantic and context information to improve the control strategy of BAS [1,5]. Context-aware power management (CAPM) framework is a Bayesian Network model to support the prediction of user behavior patterns from a multi-modal sensor data for an effective power system [3].

In the scenario of dynamic building energy efficiency techniques, the context-awareness of user behaviors, such as occupancy in specific areas, time span of crowd stay, usage of equipments etc., is playing a critical role with the development of ubiquitous computing techniques and environmental sensor facilities. In terms of the dynamics of human behaviors and the complexity of enormous environmental data computing, we focus our topic on the detection of bursty or anomalous events, which can make a sudden surge of energy flow and disturb the schedule of energy management system. User behavior detection issue in the building, however, always involves heterogeneous observed information sources to support the unobserved state inference. Continuous, discrete and even hybrid data from environmental aware platform are converged into the user behavior detection framework to make the inference of the anomalous events, realize an approximate prediction of energy cost, and upgrade the strategy of building energy management. Thus, a generalized user behavior detection framework needs to be developed to tackle the hybrid information fusion and the potential anomaly state inference.

In this paper, we provide a user behavior detection framework based on non-parametric belief propagation (NBP) model to discover the anomalous events of immeasurable user behavior. On account of the requirement of energy efficiency, user behavior detection does not only consider the outlier classification or cluster problem, but also a specific feature, time span. Compared to general outlier detective approaches, NBP user behavior detection framework is a rational

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doi:10.1016/j.autcon.2012.04.001

solution to resolve the contextual anomaly detection issue involving non-homogeneous logic relation of anomalies. With the implementation of NBP, several improved Monte Carlo methods and a hybrid structure of belief propagation are described, and Calit2 Building People Counts Data Set [6] is taken to validate the efficiency of this framework. Under the consideration of Calit2 Building case, the pros and cons of NBP user behavior detection framework are discussed and analyzed finally.

1.1. Related works

Anomaly detection techniques are pattern matching approaches that distinguish the nonconforming pattern from raw data mass. The outliers, anomalies, discordant observations, surprises, and contaminants are what we attempt to discover. Due to the structure of anomalies, anomaly patterns can be organized into three main categories, including point anomalies, contextual anomalies, and collective anomalies [7]. As the contextual anomalies (also denoted to conditional anomalies), user behavior anomaly detection has to consider the diverse contextual effects to determine the timestamps of events that happened in the data sequence. For example, supposing a normal state data is the neighbor of high-pitched or low-pitched data collection, then this normal state data has a high probability to mark as an anomalous event. Furthermore, time span estimation of user behaviors anomalies is also a tangible question in accordance with identification of contextual data collection. Thus, the key factor of contextual anomaly detection is on how to determine the contextual environment. In some cases, the contextual environment framework is straightforward to be established by specific knowledge support. Conversely, if the contextual environments can't be identified, the anomaly detection techniques will be difficult to make much sense [7].

Compared to the point anomaly detection techniques, the contextual anomaly detection techniques are limited to the consideration of both constraints from empirical data and contextual environment. Generally, contextual anomaly detection issues are discussed along two separated directions, the first is reduction to point anomaly detective problems, and the second is to structure a predictive model of data and contextual environments [7]. Along the direction of reduction to point anomaly detection, Ma and Perkins explained the time-series contextual environments as the phase space and then used the one class SVMs to mark the anomalies embedded in the timeseries [8]. Basu and Meckesheimer segmented the contextual environment by proposing a data cleaning model, and used the outlier indicator to find the unusual values in the window with selected width [9]. Along another direction of modeling the structures, there are regression based techniques, Markov model, HMM, FSA, MCMC etc. In the earlier contextual anomaly detection research of timeseries, the main methods are regression based techniques, which model the contextual environments as ARMA or ARIMA model, and then judge the anomalies by much further deviation of data [10–13]. On the other side, the methods based on conditional inference model are alternative powerful tools that explore rare events in sequential data set. Through conditional inference model prediction of contextual environment from sequential data set, we can declare the anomalies when the empirical pattern can't match the predicted pattern. Hollmen and Tresp employed HMM structure and EM algorithm to build the hierarchical regime-switching model for cell phone fraud detection, and then the probability of a fraud taking place for a call can be predicted [14]. Salvador and Chan based on FSA to track normal behavior and detect anomalies of NASA shuttle program system by Gecko segmentation algorithm [15]. Scott proposes a Markov modulated nonhomogeneous Poisson process (MMNHPP) to monitor the transactions of a customer's account to exhibit both regular pattern and irregular bursts of activities [16].

The user behavior detection of building, however, also attempts to follow two directions to analyze the contextual anomaly detection and explore the anomalous events from sequential data set. The proposed contextual attributes of user behavior detection of building, however, can assist to position the irregular timestamp in sequential data, and to identify the time span or period of anomalous events. Thus, we prefer the techniques of modeling the conditional inference structure of sequential data, so that the unmeasurable time span or period of anomalies can be highlighted by the conditional inference of contextual environment. Ihler described a framework for detecting anomalous events in such data using an unsupervised learning approach. In Ihler's case, two large real-world time-series datasets of counts are the testbeds to validate the approach, consisting of freeway traffic data and logs of people entering and exiting a building, and both data sets can be considered as the contextual anomaly cases in specific areas. Different scales of periodicity in these cases are investigated to understand the contextual relation of data, and Markov-modulated Poisson process model inferred the timestamps and times pans of unusual bursty events from traces of normal human activity [17].

1.2. Problem statements

As contextual anomaly detection, the first challenge of user behavior detection is construction of contextual environment. In the most practical scenarios, the user behavior data sequence is non-homogeneous time series, so that the features of contextual environment are variable and need related information to perceive the diverse structure and attributes of the context. The hybrid information fusion from multiple channels is a rational pattern to support the variable contextual environment construction. Given a sequence of observed data $Y^{(l)}=\{y_1^{(l)},y_2^{(l)},\ldots,y_t^{(l)}\}$ from multiple channels $l\in\{1,2,\ldots,L\}$ and the unobserved or potential state $X_t\in\{x_1,x_2\ldots,x_s,\ldots\}$ ($t\in\{1,2,\ldots,T\}$ denotes timestamp, x_s denotes state value) of anomalous events E, the attributes of contextual environment $\theta\sim g(X_t,X_{t+1};\theta)$ and a fusion $f(X_t;Y^{(1)}\ldots Y^{(L)})=\sum_X \prod_l g(X_t,X_{t+1}\ ;\ \theta)$ $h(X_t;Y_t^{(l)})$ need to be fulfilled. The complexity of numerous hybrid data fusion, however, increases exponentially with the number L of channels. If the states X_t of anomalous events are numerous, the task of inference will become so hard to resolve by analytic approaches, even intangible in some cases. Thus, we tend to develop a generalized user behavior detection framework to perform the hybrid information fusion and related contextual environment construction.

The other challenge of user behavior detection is to identify the time span of anomalous events. Most anomaly detection techniques, especially point anomaly detection, attempt to discriminate the rare events from normal, and figure out the amount and timestamp of explicit or implicit outlier. Since time span problem of anomalous events just happens in sequential anomaly detection, point anomaly detection has not taken timespan into consideration in most cases. Nonetheless, in energy efficiency application, the time span of occupancy is an indispensable indicator to determine the energy cost. The most cluster and classification detection techniques, obviously, are not appropriate to explore the time span [8–13], whereas the inference models represent an impressive performance on time span problem [16,17]. The timestamp experience $\{E_t,\ldots,E_{t+p}\}$ of anomalous events E need to be identified from the specified time series, then the timespan $\{E_t,\ldots,E_{t+p}\}$ can be marked.

This paper is organized into 5 sections. Following this section, Section **2** explains the inference approach of non-parametric belief propagation and analyze the reason to chose the NBP models. Section **3** illustrates the implementation of NBP user behavior detection framework in Calit2 Building case, and considers possible problems and solution from a generalized view. Section 4 compares three detection approaches to validate the efficiency of our NBP detection model. Section 5 gives a conclusion and a future perspective.

2. Inference of non-parametric belief propagation

In this paper, we tend to structure a generalized user behavior detection framework based on non-parametric belief propagation model, which resolved both challenges of user behavior detection with a rational

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