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Detection of Unusual Human Activities Based on Behavior Modeling

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Abstract: A type of services that require human physical actions and intelligent decision making exists in various real fields, such as nursing in hospitals and caregiving in nursing homes. In this paper, we propose new formalism for modeling human behavior in such services. Behavior models are estimated from event-logs, and can be used for analysis of human activities. We show two analysis methods: one is to detect unusual human activities that appear in event-logs, and the other is to find staffs that behave differently from others.

Keywords: behavior modeling, N-gram models, cooperative work, event-logs

1. INTRODUCTION

A type of services that require human physical actions and intelligent decision making exists in various real fields, such as nursing in hospitals and caregiving in nursing homes. The project group including authors calls such services “physical and adaptive intelligent services (PAI-services),” and is developing an IT-based system that aims to assist cooperation and knowledge sharing among staffs, and to reduce various kinds of stresses associated with their work (Uchihira (2013)).

One of the research questions that arise in the project is how to evaluate the effectiveness of such a newly introduced system. In other words, we want to know how the system contributes to improving human activities in the services. Traditional approaches are qualitative evaluation based on questionnaires and interviews, and quantitative evaluation based on statistics on the entire activities, such as the length of traffic line and efficiency in handling tasks. However, questionnaires and interviews cannot be done so frequently, and statistics on the entire activities is not suitable for finding unusual human activities that occasionally happen. In this paper, we propose a model-based approach to analysis of human activities in PAI-services.

Theoretical contribution of this paper is to propose new formalism for modeling adaptive and cooperative behavior among concurrently acting people. The formalism is based on discrete-event systems, and has sufficient expressiveness for analyzing human activities in PAI services. Technically, the proposed formalism is a collection of N-gram models with information sharing. We call it *communicating N-gram models*. In the formalism, multiple instances of N-gram models runs concurrently, and event occurrence in each instance of N-gram models may affect other instances of N-gram models.

The obtained behavior models are used for analysis of human activities, especially for detecting unusual human activities. However, the proposed formalism does not have sufficient information for executing discrete-event simulation. Such simpleness of formalism contributes to estimating models by easy calculation on statistics of event occurrence.

The paper is organized as follows. In Section 2, relater work is described. In Section 3, mathematical definitions and notations are presented. In Section 4, definition of communicating N-gram models is given. We also show an estimation method of the models from event-logs. In Section 5, two methods for detecting unusual activities are presented. In Section 6, the proposed detection methods are applied to analysis of event-logs in field experiments. Section 7 is the conclusion.

2. RELATED WORK

As a method for building behavior models from event-logs, process mining is well-known (van der Aalst (2011)). Process mining is a technique for extracting process models from large amount of event-logs output from IT systems. The obtained process models are used for improving processes in organizations. However, the processes we consider here is more complicated and unstructured. For example, tasks may be interrupted by nurse calls.

Behavior of staffs in nursing homes tends to be nondeterministic. The next action is determined by the current situation such as patient’s response and availability of various facilities, where the patients’ choices are not controllable by the staffs. As formalism that can deal with such nondeterministic behavior, Markov models is well known. In particular, factorial hidden Markov models (Gharramani (1997)) can represent concurrent processes, and interleaved mixture of hidden Markov models (Landwehr (2008)) can handle interruption of processes, both of which often appears in the field experiments. Moreover, there are several results on learning of Markov models (Angluin (1997); Sen (2004)). However, Markov models are not necessarily suitable for modeling unstructured and adaptive behavior, because it is hard to identify global states of Markov models. For modeling adaptive and concurrent behavior, rule-based description gives more simple and flexible way for the modeling. By this reason, we propose to use formalism based on conditional probabilities.

There are various researches on modeling of medical and nursing processes. In (Avrunin (2010)), medical processes are modeled by a process description language and analyzed by formal verification techniques. By observing actual nursing processes, process models of tasks, such as blood transfusion and dripping, are identified.

Application of discrete-event simulation in health care has significantly increased. Comprehensive survey is found in (Thorwarth (2009)). In many cases on the application of discrete-event simulation, performance issues such as analysis on patient queues and waiting time is the main concern, and the results are used for nurse scheduling, resource allocation, and also for change in admission policy and hospital extension.

In (Sundramoorthi (2007)), a stochastic simulation model for nursing activities is derived from real data in a hospital. Behavior models are obtained in the form of classification and regression trees. This approach is similar to that of this paper. Comparing with this modeling technique, the proposed modeling is not designed for the discrete-event simulation of human behavior, but for analysis of human behavior including collaboration of staffs. Behavior models proposed in this paper are microscopic models for limited situation such as activities on the dining time. Moreover, the models are obtained by simple calculation on event occurrence. This enable us to deal with large amount of data.

3. PRELIMINARIES

Let Σ be a finite set of symbols and let Σ^* denote the set of all finite sequences over Σ. For a positive integer N, a sequence of length N is called *an N-gram*. Let $\Sigma^N = \{s \in \Sigma^N \mid |s| = N\}$ be the set of all N-grams over Σ, where $|s|$ denotes the length of sequence s. The i-th symbol of sequence s is denoted by $s_{[i]}$ and the subsequence from the i-th position to the j-th position of s is denoted by $s_{[i,j]}$. In addition, we write $s_{[i,*]}$ to indicate $s_{[i,|s|]}$. Let s and v be sequences over Σ, where $|s| < |v|$. Then the number of occurrences of s as a subsequence of v is denoted by $O_s(v)$.

An N-gram model is a collection of conditional probabilities $Pr(\sigma|y)$, the probability that symbol σ occurs after $(N-1)$-gram y. N-gram models were originally proposed by Shannon (Shannon (1948)). Currently, N-gram models are widely used in text processing. Given a sequence v over Σ and a positive integer N, the maximum likelihood estimation of probabilities in the N-gram model is computed by

$$Pr(\sigma|y) = \frac{O_{y\sigma}(v)}{\sum_{\sigma' \in \Sigma} O_{y\sigma'}(v)} \tag{1}$$

When the length of v is not so large, we use smoothing techniques to estimate the probability for σ with low frequency (Chen (1996)).

A probabilistic automaton is a 6-tuple $G = (X, \Sigma, \delta, P, x_0, F)$, where $X = \{x_1, \cdots, x_n\}$ is the set of states, Σ is the set of symbols, $\delta \subseteq X \times \Sigma \to X$ is the state transition function, $P : X \times \Sigma \to [0, 1]$ is the function defining probability of each state transition, where $\sum_{\sigma \in \Sigma} P(x_i, \sigma) = 1$ holds for all $x_i \in X$, $x_0 \in X$ is the initial state, and $F \subseteq X$ is the set of final states. The underlying Markov chain of G consists of the set of states X and transition probabilities $P_{ij} = P(x_i, \sigma)$ for the $\sigma \in \Sigma$ such that $\delta(x_i, \sigma) = x_j$.

Given an N-gram model, we can obtain a probabilistic automaton $M = (X, \Sigma, \delta, P, x_0, F)$, where X is the set of all $(N-1)$-grams over Σ, δ is defined by $\delta(y, \sigma) := y_{[2,*]}\sigma$, $P(y, \sigma) := Pr(\sigma|y)$, and x_0 and F are arbitrary specified. In addition, we can define the probability $q_y(v) := O_y(v)/\sum_{y' \in \Sigma^{N-1}} O_{y'}(v)$ that each $(N-1)$-gram y occurs in v, where v is the event sequence used for estimating the N-gram model. The probability $q_y(v)$ indicates significance of sequence y in v.

On the other hand, there exists an N-gram model that approximates behavior of a given probabilistic automaton in the steady state. Suppose that a probabilistic automaton G has the steady state and the stationary probability is $\pi = (\pi_1, \cdots, \pi_n)$, where π_i is the probability that the system is in state x_i, then there exists the following N-gram model that approximates the behavior of G: for each $y \in \Sigma^{N-1}$ and $\sigma \in \Sigma$,

$$Pr(\sigma|y) = \sum_{x_i \in X_y} (\pi_i / \sum_{x_j \in X_y} \pi_j) \cdot P(x_i, \sigma) \tag{2}$$

where $X_y = \{x_j \mid \exists x_i \in X : \delta(x_i, y) = x_j\}$. If the underlying Markov chain is ergodic, then estimation by (1) converges to this probability. Moreover, the value of $q_y(w)$ approaches to $\sum_{x_i \in X_y} \pi_i$.

Fig. 1 is a probabilistic automaton whose underlying Markov chain is ergodic. This automaton has the unique stationary distribution $\pi = (35/107, 30/107, 42/107)$ as the solution of equations $\pi = \pi\mathbf{P}$, $\sum_i \pi_i = 1$, where $\mathbf{P} = [P_{ij}]$ is the transition probability matrix. After an occurrence of ab, possible states are 1 or 2. Therefore, the conditional probability $Pr(b|ab)$ is obtained by

$$Pr(b|ab) = \frac{\pi_1}{\pi_1 + \pi_2} \cdot 0.4 + \frac{\pi_2}{\pi_1 + \pi_2} \cdot 0.3 = 23/65.$$

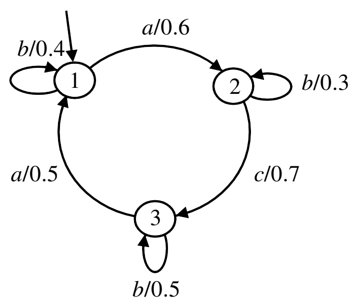

Fig. 1. A probabilistic automaton.

4. FORMALISM FOR BEHAVIOR MODELING

In this section, we describe formalism for modeling adaptive and cooperative human behavior.