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Patient History-driven Framework for Healthcare Analytics

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Abstract*: Wireless body are network (WBAN) is evolving more rapidly due to the development of internet of things (IoT). Decision making is the main concern in medical field which leads to optimization. Medical evidences in patient care improve optimization in patient care. Partially observable markov decision process (POMDP) helps in making accurate decisions with the help of observations and past actions in medical field. Hence dynamic decision making makes it possible. In POMDP, the incremental method is designed to incorporate any immediate change and immediately send updates. In this paper, process mining is applied in finding the history of patients who are travelling from one country to another for in search of job or for doing a major clinical operation. Event data is very much important for handling patient's history. Event data stores the date and time at which the patient gets consultation. Electronic medical records (EMR) are nothing but storage of all the event data of patients visiting the hospital. Event data gives the evidence of patients when they had a consultation with a doctor. Event data is present anywhere. Partially Observable Markov Decision Process for Patient-history and Careflow mining Algorithm for Heuristic Comparison are presented in this paper. Process mining gives a direct relationship by step by step evaluation and improvement of the process. It also exhibits patient care by identifying the execution errors, understanding the process heterogeneity. The online process mining tool, PROM helps finding the history of patient.

***Keywords:* Decision making, IoT, POMDP, PROM, WBAN**

I. INTRODUCTION

A POMDP consist of a set of states, S, a set of actions, A, and a set of observations, O. If action 'a' is executed in the state, s's ', then the state changes to s' according to the probability distribution P(s' |s, a) and a reward R(s, a) is received. Rather than observation state, s' directly, the agent receives an observation o according to the probability, P (o| a, s'). JuliaPOMDP consists of POMDP Toolbox such as simulators, state estimators and policies. An approximate POMDP planning task will give the required no. of beliefs that must be added as constraints.

This paper proposes POMDP. for automatic retrieval of patient-history, focusing on the health of the patient. It allows to find a contingent optimal policy when some information is not observable. By this a decision is made considering the immediate goals and also long-term goals. Our assumption is that the patient-history is known and their health is given as distribution with uncertainty.

A. Process model for history-driven healthcare analytics

Evidence based medicine was implemented in [1], it explores through the history of patients which uses PROM tool through process discovery methods and event logs. The event logs are inspected through pattern inspector, dotted chart and event-log filtering. The key aspects in healthcare mining was specified in [2]. Process mining is a 4-stage process and depicted in Fig. 1.

- Data Collection & Preparation: Data collected from hospital information system is analysed for any incomplete cases, fine-grained activities are aggregated and patient cases are grouped according to triage categories.
- Process Discovery: For the discovery of process, Inductive miner is used in PROM. Overall emergency department triage and process categories are extracted.
- Process Monitoring: For monitoring the process, key performance indicators are defined and measured. Finally deviations from the target values are accessed.
- Process Analysis: Conformance checking is used to detect some process deviations with inductive miner, petrinets as process model notations and by using alignments.
- Predictive Analysis: Predictive analysis through history-driven healthcare approach can be made through the available event logs compared using the process comparator model.

II. LITERATURE SURVEY

POMDP computes optimal policies to select particular actions for achieving a specific goal. POMDP plans to take actions according to the computed optimal policy. POMDPs sets framework optimally for imperfect models with uncertainty. The procedure is as follows. At every time instant, there will be an unobservable state. When S_t is known partially, belief states i.e. the probability of b to be in state S_t are formed. With the current belief state b(s), it receives rewards according to the actions it performs. Hence an optimal policy is found based on states, observations and actions. Imperfect observability and action outcome uncertainty can be perfectly modelled by POMDPs model. This optimization can be formulated dynamically with value function in combination with multiple costs or rewards.

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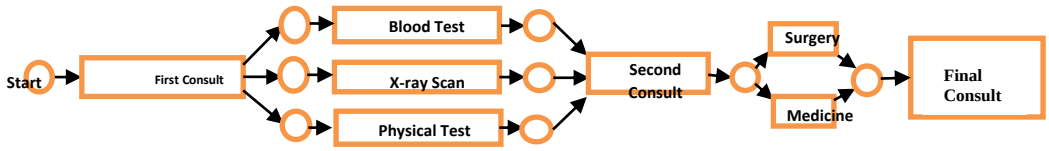


Fig. 1.Process model for obtaining patient history

Event log extraction is done after the initialization of events. Process mining for software systems is in parallel with the systems registration.Learning analytics on coursera event data is also attempted with analytic workflows. Process mining in domain knowledge is compared with clustering and decomposed process mining [4]. Several health models are examined and optimal policies are computed for the assumed model and true healthcare model. The impact of these models are explored through healthcare examination by doctors and simulations.

The effectiveness of the policies are compared by selecting actions randomly and maximizing the gain. POMDP helps in reducing the cost and increasing the reward [5]. Since POMDP planning finds a policy minimizing the expected costs and maximizing rewards, the cost model specifies the doctor's objective as well as incentives for every action. For example, health objective would be the patient's health condition reaching the state's' that finds the disease quickly. The actions for finding state's' zero cost and actions for finding disease immediately are encoded [6]. The structure of cost is given by model r(s,a) [7]; A real-valued cost function is given for every state s and action a. Belief state b which gives the distribution in accordance with the past actions and the past observations. POMDP gives a computing framework for optimizing the objective [8], [9]. There can be multiple goals in objective function but can be challenging to achieve. So simple objective like health state of the patient is considered. Here the information regarding health is made automatic.

POMDP policies are computed for analysing the health of patients. These help in achieving the in short time rewards and as well as long-time rewards [10]. Given a POMDP, the policy is computed according to the action at each time setup. For each POMDP, a optimal policy is computed for each time step, which maps the prior actions and observations which minimizes the discounted future costs that is very difficult to compute because of prior history..

III. PROPOSED POMDP FRAMEWORK FOR PATIENT HISTORY RETRIEVAL

POMDP of tuple $\langle S, A, Z, p(s'|s,a), p(z|s,a), r(s,a), \gamma \rangle$, where S - set of state's', A - set of actions a, Z - set of observations z, is taken for analysis. The current state,'s' gives a transition to the next state s' modeled through the transition model $P(s'|s,a)$. The final portion of POMDP is the cost model which has to be adapted to the healthcare model. POMDPs are analysed with Kruskal–Wallis tests to find the differences of expected time based on the healthcare policy.

A. Mathematical Model for POMDP based Patient History Retrieval

The treatment decision in state is given by S_t: a $(S_t) \in A$ (S_t). Optimality equations for all states is given by S_t, t =1… T-1. The health status is represented by $S_t \in S = \{1, 2, 3….L, L+1\}$. Modeling health related patient history in the framework of POMDP requires a space *S* and a transition model $p(s'|a,s)$ for checking how the patient's health condition. All healthcare models make different assumptions about how the health of the patient is encoded. Alternatively, the states represent the illness of the patient or medications for particular illness. A particular representation is required to compute the policy since POMDP framework requires a different possible representations for determining effects. Next, the observation model maps to the health of patient which gives some information about the patient's health. Given that an automated healthcare model updates the belief states about the patient's health condition. The belief state is updated using the healthcare model and the transition model of patients' health conditions.

The POMDP is used for collection of patient history details and are analysed with present complaint, investigations are made with past illness, surgery, complications and trauma is shown in Fig.2.

B. Careflow mining algorithm for Heuristic Comparison

Careflows are mined from process data, then clinical data are added to the mined careflows using enrichment given in [3]. Process data is obtained from different wards in hospital, i.e. inpatient and outpatient admissions. Clinical data is extracted using the most frequent clinical path on the basis of some threshold parameters. The XES log of process models 1 & 2 of all the events are shown in the Fig. 3 (a) & 3 (b) below. In both the process models, there are different cases and events.

The event logs also contains the department classifier which gives a clear detail about the events taken place since the patient's admission. The start events whether they all got ended can also be easily figured out using These XES event logs provides acknowledged format for the interchange of event log between tools and the application domains

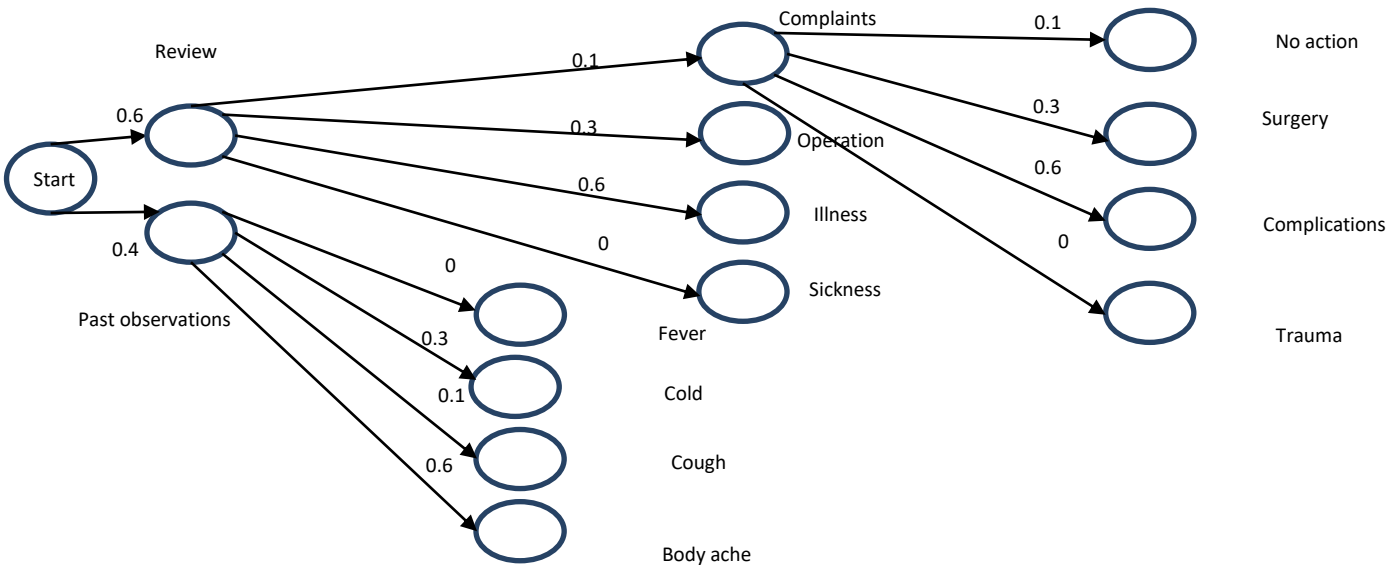
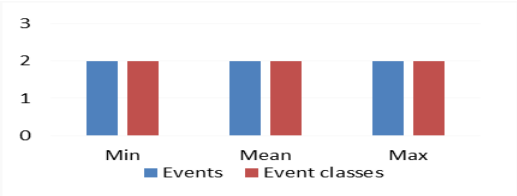
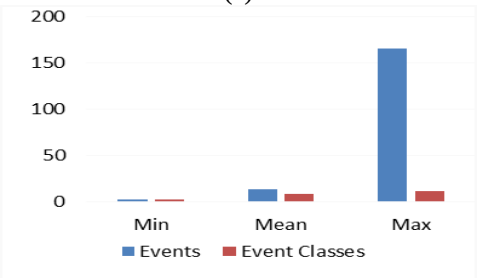


Fig. 2 POMDP decision tree model for patient's history data collection



(a)



(b)

Fig. 3 (a) XES event log of process model 1
(b) XES event log of process model 2

. Careflows helps in monitoring and analyzing the vital signs of patient and provides the scores.

IV. RESULTS AND DISCUSSION

This section explains the Performance analysis, Petrinet in XES event log and Conformance checking for process mining in healthcare under emergency situations. Petrinets describe state changes with directed arcs. In this section, the health of patient is modeled in POMDP framework of the patient-history process. The automated healthcare will analyze the patient according to the probabilities of past history. For example, the automated healthcare will check the patient for review, illness and past-history. The patient health state at step t is unobserved and will be at state, s_t of the POMDP at time t. The state can be considered as a healthcare state, corresponding to the health of the patient. However, the state could include information such as medications he took on his recent illness.

A. Performance Analysis

The performance of each process model using data, waiting time vs work time, paths and sojourn times is figured in dotted chart as in Fig. 4. Each colour represents each patient details got recorded during specific duration of time. POMDP as MDP has states, actions, transition states and rewards. The observations added to POMDP helps in finding the states. Though the current state is not accessed directly, the decisions are arrived through history. The probability distribution is updated when action and observations occur. POMDP makes decision making sequentially with uncertainty. The metrics like dynamics, observation, beliefs, goals, value function and policy are defined for POMDP. POMDP goal is to select actions appropriately. POMDP was implemented in building a tutor system, where agent takes decisions based on belief states that are uncertain. It addresses exponential state space and complexity. POMDP was used for finding best teaching methods and it focus on history. POMDPs.jl helps in solving POMDP problems with extensive functions such as simplicity, expressiveness, extensibility and usability. Tutoring problem with POMDP is solved and includes hidden uncertainty. The beliefs are updated using Bayesian inferences. Formulation of POMDP problem was made with teaching algorithms having initial belief exploration. The expected utility depends on beliefs. POMDP solve according to human planning. POMDP was utilized for monitoring and maintenance in real time where the agent is aware of transitions but starts with uncertain conditions and learns via observations. The agent behaviour changes according to prior probability.

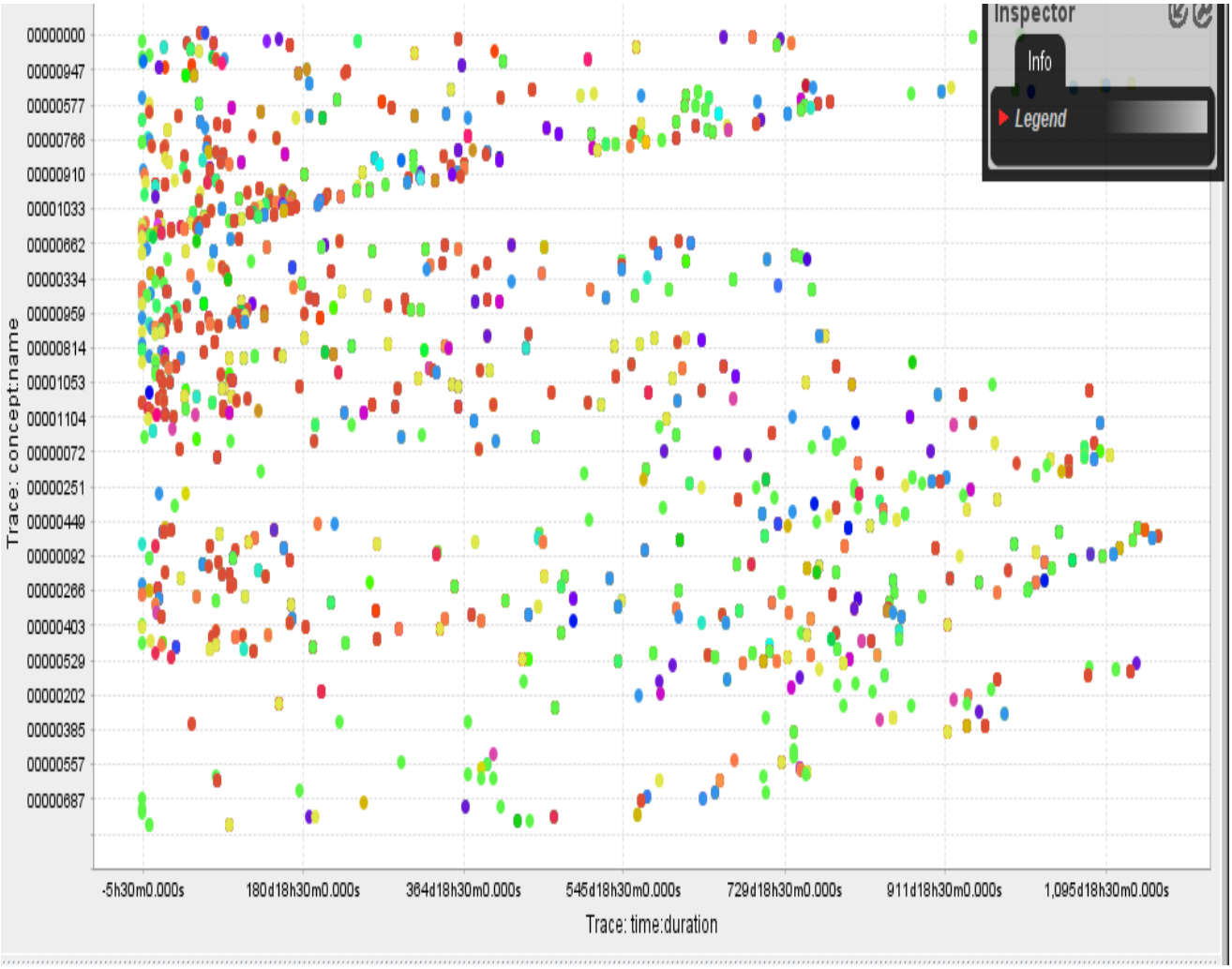


Fig. 4 Dotted Chart showing the start and end events

B. Petrinet in XES event log

The history of each patient can be found out by choosing petrinet of XES event log. Through the petrinet process, the start and end process of each patient can be found with the help of classifiers, pre-mining filters. There is also a process comparator model which compares the two event logs as shown in Fig. 5. [11], [12] explores process mining as a research agenda. The handover of network analyse is analysed by the social network. This clearly gives the in-turn connections of how each event is inter-related through doctors. Data are checked if procedure execution conforms to process model as shown in Table- I. Sepsis is a life threatening condition caused by infection [13], [14]. These cases shows path and time from admission of the patient till the discharge of the patient from the hospital.

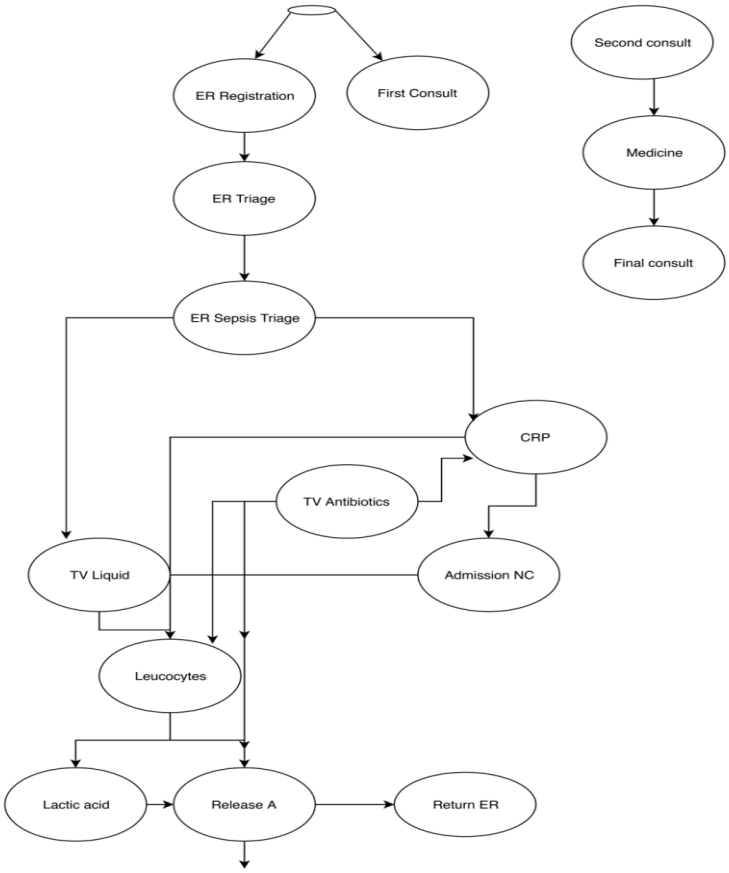


Fig. 5. Process comparator analyzing two events for sepsis

Table- I: Result displaying Sepsis log

	Admission IC	Admission NC	CRP	ER Sepsis Triage	IV Antibiotics	IV Liquid	Lactic Acid	Leucocytes	Release A	Return ER
Admission NC	3288	24.56	1212	122.56	185.3	458.12	825.41	1425	8976.13	10784.52
CRP	2514		1452			154.23	11.2	11.4	8475.12	
ER Registration	1541	12.56	1789	6.5	20.56	115.2	15.8	1478	10987.1	10457.69
ER Sepsis Triage	3547	14.32	1598	2451.68	18.69	147.8	85.2	12.9	8569.87	10231.96
ER Triage	1459	11.68	1478	111.2	19.56	159.2	58.7	85.2	10853.2	10147.12
IV Antibiotics	2144	78.90	1112	14.5	14.21	123.2	111.2	1465	10578.4	10132.74
IV Liquid	1542	23.23	2456	250.6	15.85	114.2	48.7	87.6	8479.23	10478.65
Lactic Acid	2589	12.89	3578	75.6			21.6	2415	10789.8	10328.36
Leucocytes	3210	10.32	1489	50.3	115.6	142.1	88.8	3698	10987.1	10741.52
Release A	1235	18.12	1897	15.2		102.5	114.2	1478	10524.3	10148.12
Release E										10854.32

V. CONCLUSION

Decision making helps patient in the critical situations and finds easiest way for the patient through evidences. It finds applications in point of care situations where remote health monitoring is in practice. E-health, e-prescription, are the buzz words of today's IoT era. PROM, the process mining tool helps in finding the history of patient along with the different approaches and algorithms. POMDP analysis helps in finding the history of patient who are travelling from one country to another for in search of job or for doing a major operation. In future, the edge computing will be further analysed w.r.t patient care.

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Latha R has completed Bachelor of Engineering from the Anna University (GKM College of Engineering and Technology), Perungulathur, Chennai and Master of Engineering in Communication Systems from Anna University (Rajalakshmi engineering college), Chennai. She has 3 years of teaching experience in Rajalakshmi engineering college (Affiliated to Anna University). Currently she is a full time research scholar in School of Electronics Engineering, Vellore Institute of Technology, Chennai. She has authored book chapter, and proceeding in lecture notes by springer publisher and many Scopus indexed journal papers and conference papers. Her research interests are Wireless Body Area Networks, Medical Body Area Networks, Bayesian Networks and IoT.

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