

A Self-Learning Autonomous and Intelligent System for the Reduction of Medication Errors in Home Treatments

Rosamaria DONNICI^a, Antonio CORONATO^a and Muddasar NAEEM^{a,1}

^aICAR-CNR Napoli, Italy

Abstract. The treatment process at home after hospitalization may become challenging for elders and people having any physical or cognitive disability. Such patients can, nowadays, be supported by Autonomous and Intelligent Monitoring Systems (AIMSs) that may get new levels of functionalities thanks to technologies like Reinforcement Learning, Deep Learning and Internet of Things.

We present an AIMS that can assist impaired patients in taking medicines in accordance with their treatment plans. The demonstration of the AIMS via mobile app shows promising results and can improve the quality of healthcare at home.

Keywords. Artificial intelligence, Reinforcement Learning, Autonomous Systems, Deep Learning, Internet of Things, Healthcare.

1. Introduction

Clinical factors and daily activities of impaired persons if left unnoticed, can cause issues and hazardous situations for the safety of the patient. AIMS based on Artificial Intelligence (AI) (e.g. Reinforcement Learning (RL) and Deep Learning (DL)) and Internet of Things (IoT) is a novel solution for continuous and autonomous monitoring.

Devices used for recording, communicating, sensing and displaying can play an important role in monitoring the routine activities and health parameters.

The interconnection of IoT devices has allowed the deployment of large-scale applications such as, for example, smart cities [27], [47], large-scale smart networks and radios [1] and smart campus systems [7], [1]. Many applications of IoT devices and sensors, improved by self-learning technologies such as RL, have been proposed in healthcare [18].

Medication errors (i.e., "any preventable event that may cause or lead to inappropriate medication use or patient harm while the medication is in the control of the health care professional, patient, or consumer" [45]) have been estimated by the United States Institute of Medicine to harm 1.5 million people and kill 7,000 patients annually in the USA alone. The situation is not very different in Europe as well [20].

The costs due to medication errors have been estimated at US \$42 billion annually or almost 1% of total global health expenditure [46]. In Europe, according to the Euro-

¹Corresponding Author: Muddasar Naeem ICAR-CNR
Email: muddasar.naeem@icar.cnr.it

pean Medicines Agency, the annual cost of medication errors is estimated between €4.5 billion and €21.8 billion [20].

Medication errors may be located either in hospital settings or in home care settings [6]. The World Health Organisation (WHO) classified different medication errors such as wrong dosage, wrong frequency, wrong medication or omission [45] and emphasised that "the elderly population may also encounter special issues related to medication errors".

This paper presents a set of Intelligent Services specifically devised to support fragile patients in their domestic healthcare treatments. The main functions are offered through a Mobile App that interacts with the patient with the aim of i) self-assessing the patient's skills in terms of audio, visual and cognitive capabilities to customize the way to communicate with the patient; ii) reminding promptly the patient to take his medication accordingly with his treatment plan; iii) checking the correctness of the medication that patient is going to take by identifying the medication box while handled by the patient.

The remaining part of the paper is structured as follows. Next section presents an overview of the related work. Section 3 introduces the fundamentals of **RL**, **DL** and **IoT**. Next, Section 4 presents our system model. Section 5 shows some results. Finally, section 6 reports conclusion and future work.

2. Related Work

Anomaly detection is being performed on health records in the project MavHome to investigate drifts and outliers in smart homes [23]. Some other projects related to smart home have been started in order to provide elderly people and patients more comfort at home with more safety. Among the most relevant projects there are those under development by Microsoft Research [10], Intel Research [12], University of Colorado [13] and the Georgia Tech [31].

Relevant Health Monitoring System (**HMS**) that exploits **IoT** and **AI** are proposed in [3] and [35].

MIT House and the Consortium and Technology processing company (TIAX, LLC) have developed the place lab [24], where they are researching techniques to validate performance of the daily life activities and biometric monitoring. The place lab is using rich sensing infrastructures to develop methods to recognize patterns of recreation, socializing, eating, sleeping, and etc. In particular, for elder people, variations in basic Activities of Daily Life (**ADL**) are considered early critical indicators of possible health issues. In addition, their work on the recognition of **ADL** using ubiquitous sensors in a domestic scenario has potentialities for monitoring the general health status of a person, but could be improved by a more widespread exploitation of **AI** technologies.

An overview of the literature on the use of **IoT** in **HMS** is presented in [2] and recent developments and trends of **HMS** in terms of security issues, wireless communications, frameworks and health parameters are discussed with advantages and limitations.

Ambient assisted living techniques may improve the quality of life of elderly with cognitive and physical disabilities, by solving assistive tasks such as medication management [19]. Social humanoid robot [9] can help to monitor indoor environmental quality [37]. A project on the "Improvement of the Elderly Quality of Life and Care through Smart Emotion Regulation" is proposed in [22] to investigate solutions for the improvement in the care and quality of life of elderly people through the use of sensors, cameras and

emotion regulation methods. A distributed fuzzy system able to infer in real-time critical situations by analysing data gathered from user's smart-phones about the environment and the individual is presented in [38].

A data analytic technique, which exploits ML and smartphone's inertial sensors to recognize human activities, is given in [11]. A method for norm compliance in the context of open and goal-directed intelligent systems working in dynamic normative environments is discussed in [39].

A screening framework for clinical care of disabled and elderly people is presented in [26]. A novel vision enhancing method for low vision impairments is presented in [30]. Monitoring is realized by a platform that verifies some clinical conditions accordingly to pre-determined thresholds.

An intelligent environment for the identification of critical situation for fragile patients has been presented in [17]. A risk management system at nuclear medical department is presented in [36].

It is worth noting that there are just few works that focus on the use self-learning technologies for the assistance of patients in their home treatment [18]. In a previous one, we have presented a preliminary version of the services for the checking of the medication via deep learning [34].

3. Background

This section presents a brief introduction to reinforcement learning, deep learning and internet of things.

3.1. Reinforcement Learning

Markov Decision Process (MDP) is the central concept of all RL problems [32]. The goal of the RL algorithms is to find the solution to an MDP. An MDP model has the following components:

- Set of states: $S = s_1, s_2, s_3, \dots, s_n$
- Set of actions: $A = a_1, a_2, a_3, \dots, a_n$
- Transition model: $T(s_t, a, s_{t+1})$
- Reward R

Reward and transition model depend upon on current state s_t , selected action a_t and resulting state s_{t+1} .

The target of RL algorithms is to interact with a given world either with some prior knowledge i.e reward and transition model (model-based RL e.g Dynamic Programing which includes value iteration and policy iteration) or without any prior knowledge (model-free RL). Examples of model free algorithms are Monte Carlo and Temporal difference (TD) learning. Q-learning and SARSA are widely used as TD algorithms [40]. After many repetitive interactions with the environment, the agent learns the characteristics of the environment. The target of RL agent is to find an optimal action out of available actions in each state. Optimal action returns best desired numerical reward to the agent. An agent choose an action in each state which results in a policy π . An optimal policy maximizes the aggregated future reward for a specific problem. The working framework of RL is shown in figure 1.

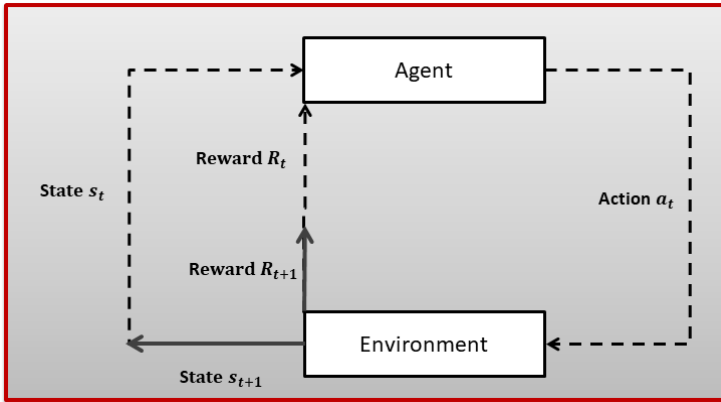


Figure 1. The Reinforcement Learning Problem.

3.2. Deep Learning

Deep Learning (DL) is a sub-field of ML concerned with methods inspired by the structure and function of the brain called Artificial Neural Networks (ANN). “Deep learning algorithms aim at learning feature hierarchies with features from higher levels of the hierarchy formed by the composition of lower level features. Automatically learning features at multiple levels of abstraction allow a system to learn complex functions mapping the input to the output directly from data, without depending completely on human-crafted features” [8].

Typical ANN challenges are: training time, overfitting and initialization of the parameters. These issues are solvable now due to various methods. We can use layer normalization [5], Batch normalization [28], weight normalization [41] and normalization propagation [4] to accelerate the training process of ANNs. Moreover, Dropouts [42] is helpful in minimizing over fitting.

DL, especially Convolutional Neural Networks (CNN), powers the major progress in computer vision and object detection e.g. face recognition [43], pedestrian and gesture detection [44], drug identification [33], [29] and self-driving cars [21].

3.3. Internet of Things

IoT is a system of interconnected smart machines and physical devices having unique identifiers [25]. IoT devices consist of sensors, electronics, radios and software. IoT devices create digital representation of the surrounding world. IoT devices collect data from the real world and then transmit the collected data to the platform for continuous monitoring.

Sensors such as thermometers, accelerometers, cameras and microphones convert a physical process into an electrical signal. A smartphone is probably a good example of interconnected device that embeds many heterogeneous sensors including magnetometers, minimum two cameras, microphone arrays and accelerometers. First generation mobile phones typically included six sensors while now a days a Galaxy S5, for example, has 26 sensors including humidity, cameras, gyro, IR, proximity, microphones, pressure, accelerometer, magnetometer etc.

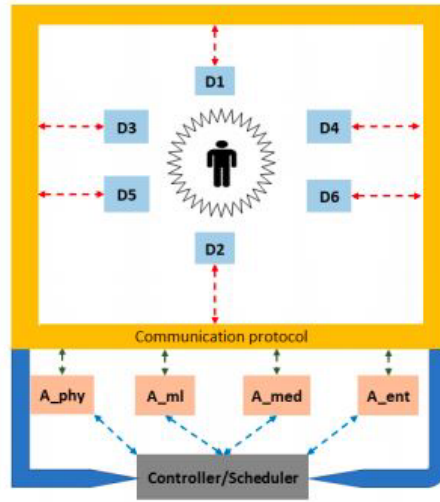


Figure 2. The proposed model.

4. System Model

This section presents the proposed system model which consists of multiple RL agents, DL agent and IoT system. Figure 2 shows the model which consist of multiple IoT devices connected to multiple RL agents, DL agent and scheduler through a communication link. Next we briefly introduce each component of the AIMS.

RL agent.1

The role of this agent is to monitor physical activities of the persons such as: sleeping, awaking, dressing, cleaning etc and will be referred as A_{phy} in the rest of the document. As an example, we have added the demonstration of one of the RL agent i.e. A_{phy} as shown in figure 3. The is dependent on three IoT devices and is being controlled by A_{main}

RL agent.2

The role of RL agent.2 is to monitor eating and drinking activities of a person e.g. preparing and eating breakfast/lunch/dinner; preparing and drinking beverage. RL agent.2 will be referred as A_{ml} afterwards.

RL agent.3

The duty of the RL agent.3 is to manage the entertainment for the person i.e. listening music, watching TV and will be referred as A_{ent} .

RL agent.4 The task of fourth agent is to take care of the treatment schedule of the person if any and to remind him/her about medication time. We will use term A_{med} for this agent onwards. We have implemented this agent on mobile app and its demonstration will be presented in result section. Some of the salient features of agent A_{med} are given next:

- **Omissions** - The A_{med} enable the AIMS to remind the patient about taking a certain pill through the mobile app;
- **Bad timing** - First the A_{med} reminds on time the medication and the then verifies that it is taken on time;

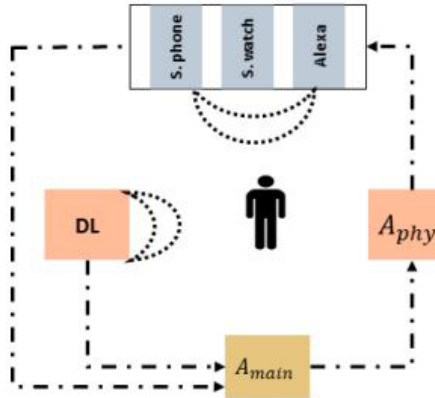


Figure 3. The work flow of A_{phy}

- **Wrong medication** - The A_{med} also verifies through a camera, that the patient is going to take the right pill;
- **Incorrect or omitted therapy annotation** - The A_{med} automatically annotates the medication that the patient has really taken.

Controller/ Scheduler

This is the central agent which control all other agents and act as controller/scheduler. It is referred as A_{main} and its goal is to schedule all agents for their respective jobs in an optimal way. A_{main} is a DL agent that is assisted with CCTV cameras to monitor the persons at different time intervals and give the status of the person to the A_{main} as input. The scheduler then activates another agent for respective task. Next we will discuss the training of DL agent.

First step to train a deep network is the selection of framework. Some of most popular frameworks deep learning models are Tensorflow, PyTorch, Theano and Caffe. We selected Tensorflow framework by considering different criteria like: 1). library management, 2). optimization on CPU, 3). open source and adoption level, 4). debugging and 5). graph visualization.

Moreover, final step before training a model is choice of network or topology. Depending on the projecting requirements including the final deployment on an edge device one should consider important factors like size, time to train, accuracy and inference speed. Some of the famous network are:

- ResNet-50
- VGG16 and VGG19
- Inception v3
- MobileNet.

However, there is no one size fits all methods for these parameters and one has to find an optimal solution by trial and error. Communication protocol Communication protocol acts as a bridge between IoT devices and multiple agents.

Most widely used IoT communication protocols are WiFi, ZigBee, Bluetooth, Z-Wave, long range wide area network and near field communication. Nowadays, WiFi and Bluetooth are frequently used but near field communication is progressing enormously. To choose which communication protocol is best for IoT devices is difficult, but the one



Figure 4. Demonstration of A_{med}

that is easily available in most of the newly manufactured IoT devices and smart phones at a reasonable price.

5. Results and Discussion

This section presents the demonstration of the AIMS, in particular, we have presented results of RL based A_{med} agent. IoT devices continuously monitor the state of the person and send the collected data to the trained DL agent which predict the state of the person. Then main agent i.e the controller activate the appropriate agent according to the predicted state/condition of the person. The AIMS is also able to predict level of risk e.g. normal, serious or emergency and in case of emergency can send automatic message to user relative or doctor.

Figure 4 presents the demonstration of the mobile app i.e A_{med} agent. Left most image in the top row of figure 4 shows the welcome interface that is displayed at the launching of the mobile App. Middle image in the top row of figure 4 indicates the treatment plan that the A_{med} agent has received from the cloud service. Medicine information may be shown by clicking on one of the drugs of the list (as an example, the figure 4c).

A reminder is sent to patient as shown in figure 4d via audio, textual or visual message (in this case reminder is being sent via the combination of scientific name of the medicine and image of the same medicine). An acoustic alert that terminates when the patient pushes the "Stop" button. Immediately after pushing the button, the App starts the camera and extracts images from the scene.

In Figure 4e the image is taken when the patient shows the pill-box. All images extracted by the camera are sent to the DL agent that verifies whether the patient is going to take the same medicine as suggested. When a medication is recognised, it is compared with the one planned for the patient. If the medication is not the one supposed to be taken by the patient, a negative feedback is returned to the App otherwise a positive feedback is

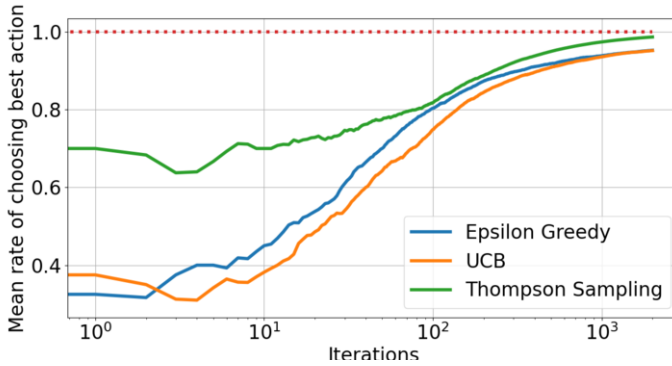


Figure 5. Learning curve of the RL agent

appeared on App as shown in figure 4f to confirm that the taken medicine was correct. We have experimented different Bayesian RL algorithms and found that Thompson sampling shows comparatively better performance. Figure 5 shows learning curves of Thompson sampling, Upper Confidence Bound (UCB) and Epsilon decreasing algorithm. We can evaluate that the Thompson sampling algorithm takes less number of trials to learn the best action.

6. Conclusion

We have presented an Autonomous and Intelligent Monitoring System consisted of RL agents, DL agents and IoT devices to assist patients and elderly at home. We have shown the feasibility of the system through mobile application. In future work, we will assess the application with respect to the risks for the patient [14] that is needed by the regulatory environment in order to approach the market. The mitigation strategies will be designed accordingly with a methodology [16] and adopting rapid prototyping tools such as [15].

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List of Acronyms

AIMS Autonomous and Intelligent Monitoring System

MDP Markov Decision Process

RL Reinforcement Learning

AI Artificial Intelligence

DL Deep Learning

IoT Internet of Things

HMS Health Monitoring System

ADL Activities of Daily Life

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