A Deep Q Learning based Method for Optimized Monitoring of Activities of Daily Living using a Smart Watch and a Companion Robot

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***Abstract*—In this paper, we developed an activities of daily living (ADLs) monitoring system using a smart watch and a robot for elderly care. In order to balance the activity recognition accuracy, privacy concerns, robot resource cost and power consumption on the watch during monitoring, we proposed a Deep Q Learning model to solve a sensor selection problem. Based on the above four criteria, the robot runs the Deep Q Learning algorithm to decide whether to activate the robot sensors or the watch sensors for data collection. First, we presented the overview of the ADL monitoring system. Second, we developed the Deep Q Learning algorithm by considering the transition motions as part of the environment states. Third, we created a smart watch application for data collection and communication between the robot and the watch. Finally, the proposed model was trained and evaluated based on both offline data and real time data collected in our smart home testbed. The results showed that the proposed method could recognize ADLs with high accuracy while saving about 14.6% energy compared with the baseline periodic methods.**

Keywords— elderly care, activity monitoring, companion robot, wearable computing, reinforcement learning

I. MOTIVATION

In recent years, activities of daily living (ADLs) monitoring plays an important role in elderly care [1]. Through activity monitoring, we can understand the daily routines of older adults, which could reveal their general well-being and health condition, making it possible to take preventive actions in a timely manner. Ambient sensors such as video cameras, acoustic sensors, and passive infrared motion sensors have been employed for activity monitoring [2]. However, activity monitoring based on these ambient sensors may not work well if the resident is out of the sensing range of the sensors. In addition, some environmental sensors, especially cameras, may cause significant privacy concerns when used inappropriately [3].

Companion robots are coming to people's homes and they can be adopted for ADL monitoring [4]. These robots are typically equipped with capabilities such as chatting, playing music, medication reminder, etc. They usually collect data from the onboard cameras and microphones. However, there are issues with robot-based monitoring, such as privacy concerns caused by onboard cameras and limited sensing range of the sensors. Therefore the robot needs additional information that helps recognize the user's ADLs. Motion data offers rich information regarding human body movements and serves as a reliable indicator of the start and end of daily activities. However, this kind of information is hard to get from robot sensors. On the other hand, wearable sensors [5] can collect motion data of the wearers and their surroundings, which could provide useful information for ADL monitoring [6]. Integrating a wearable device and a robot for ADL monitoring presents an opportunity for the robot to make informed decisions utilizing data from the wearable and its own sensors.

In this paper, we aim to build a collaborative activity monitoring system (CAMS) using a smart watch and a companion robot. The system's objective is to accurately detect a broader spectrum of activities to provide caregivers with comprehensive information. Meanwhile, it must operate with reduced battery consumption on the smart watch and reduced robot resource usage to ensure uninterrupted service. It should also respect users' privacy preferences which may evolve over time and depend on the ongoing activities and locations. Therefore the system need strike a balance between activity recognition accuracy, robot resource utilization, watch power consumption, and user privacy preferences throughout the monitoring process, which is a challenging problem and has not been addressed in the literature yet.

The major contributions of this paper are as follows: First, we built a collaborative ADL monitoring system that combines a smart watch and a companion robot. We developed an Android application on the watch to collect data and send to the robot based on the robot's commands. Second, to balance activity recognition accuracy, privacy preference, robot resource utilization and power consumption on watch, we developed a Deep Q Learning model which enables the robot to learn optimal sensor selection strategies. Third, in order to train and evaluate the proposed model, we designed an offline framework to simulate the scenarios in which the users conduct daily activities and interact with the robot and watch. Additionally, we conducted a real time test in our lab environment to evaluate the system.

The rest of this paper is organized as follows: Section II introduces the related work. Section III describes the overall design of the CAMS and presents the method of collaborative activity monitoring, followed by the proposed Deep Q Learning

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based sensor selection method. Section IV presents the experimental setup and evaluation results. Section V concludes the paper and discusses the future work.

II. RELATED WORK

A significant amount of research has been conducted in the field of daily activity monitoring using various technologies such as environmental sensors, robots and wearable devices. Environmental sensors, such as cameras, microphones, and passive infrared motion (PIR) sensors, are embedded into homes to collect data related to a person's activity. For example, Hall et al. Reference [7] designed a video-based activity monitoring system in which they deployed 3 cameras in each house to collect data and recognize the individuals' daily activities. Companion robots are entering our daily lives [8]. Garrett et al. [9] proposed a mobile robot-based system for ADL monitoring. Wearable sensing and computing is also a promising way to monitor human activities in daily life [10]. Sun et al. [11] developed dietary monitoring and physical activity monitoring based on a wearable device.

Using cameras or microphones in the environment or robot cameras to monitor daily activities raises privacy concerns. Wang et al. [12] conducted a survey which shows older adults expressed greater concern about privacy and were reluctant to disclose personal information. In [13], the authors proposed a fall prediction method utilizing skeleton features from a Kinect to respect user privacy. Nevertheless, it's worth noting that due to the limited sensing range, if the targets are out of the camera's field of view, no data can be captured. On the other hand, wearable sensors can be used for ADL monitoring, but they pose a different challenge due to their limited power supply, which is crucial for wearable-based ADL monitoring [14]. To save energy, a commonly employed method for energy-efficient data collection is periodic sampling [11]. However, using a long period for periodic sampling can save energy but may result in missing short-duration activities. How to choose the optimal periodic time is a challenge. Recently, reinforcement learning (RL) has been used for energy management in wearable devices, focusing on sensor access control and transmit power control [15]. In this paper, we proposed a Deep Q Learning method that incorporates transition motion into the states to achieve a balance between energy efficiency and performance in ADL monitoring.

III. METHODOLOGY

A. *Overview of the CAMS*

The proposed CAMS design is shown in Fig. 1 while the hardware setup is shown in Fig. 2. This setup is an upgrade from our previous design [16] with a smart watch as the Wearable Monitoring Unit (WMU). There are 3 components in the CAMS: a companion robot, a smart watch and a healthcare management center. The robot is built in our lab and has an Intel Realsense RGB-D camera and four microphones on the head, which collect data in the environment for activity recognition. Moreover, the mobile base allows the robot to move around and find the user. The Rainbuvvy watch consists of an accelerometer, a microphone and two cameras and a quad-core CPU with 4GB RAM and 64GB ROM. It runs Android 9.0 and supports customized applications. As shown in Fig. 1, the robot runs an RL-based sensor selection algorithm to activate pertinent sensors for data collection and activity recognition. Depending on the selection decision, the system either activates the robot's sensors or transmits commands to trigger the watch sensors. Due to the constrained computing resources on the watch, data processing is conducted on the robot. The identified activities are recorded in the database, providing caregivers with data for additional analysis.

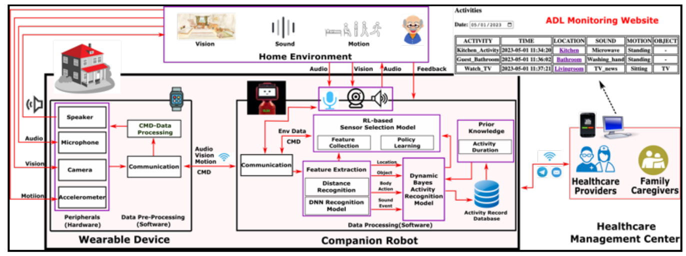

Fig. 1. The overall design of the CAMS.

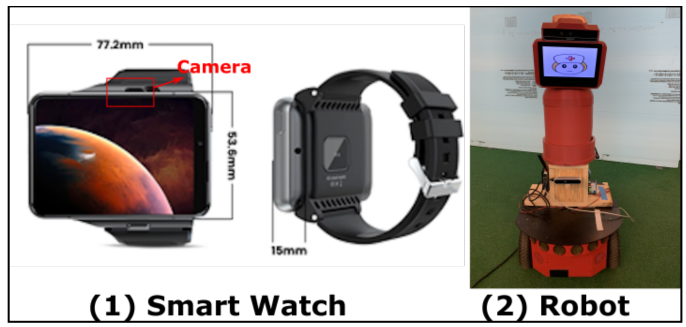

Fig. 2. The prototype of the watch and ASCC companion robot on a mobile base [17].

In human daily life, motion data is generated by individuals performing various activities such as sitting, standing and walking. By detecting these transition motions, the starting and ending of the corresponding activities can be identified, consequently these activities can be recognized using data collected from the most relevant sensors. Therefore, the motion sensor runs constantly to capture the motion information. Along with other contextual information such as current activity, robot resource cost and watch battery level, the agent can make decisions to turn on sensors using the Deep Q Learning method.

B. *Activity Recognition using Dynamic Bayesian Network*

In human's daily life, different activities occur at different locations and generate distinct sounds and body movements. As shown in Fig 3, the evidence data including location L_t, object O_t, sound event S_t and body action B_t are dependent on activity A_t, based on Bayes rule we have,

$$P(A_t \mid L_t, O_t, S_t, B_t) \propto P(L_t, O_t, S_t, B_t \mid A_t) \cdot P(A_t) \qquad (1)$$

As L_t, O_t, S_t and B_t are independent of each other, we have:

$$P(L_t, O_t, S_t, B_t \mid A_t) = P(L_t \mid A_t) \cdot P(O_t \mid A_t) \cdot P(S_t \mid A_t) \cdot P(B_t \mid A_t) \qquad (2)$$

In this study, we analyzed the dataset and counted the duration of each activity, and then combined the time label with the activity to generate the activity prior knowledge for updating the probability of A_t.

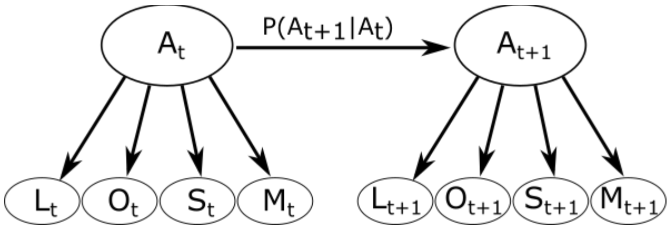

Fig. 3. The graphical representation of Dynamic Bayesian Network model for activity recognition.

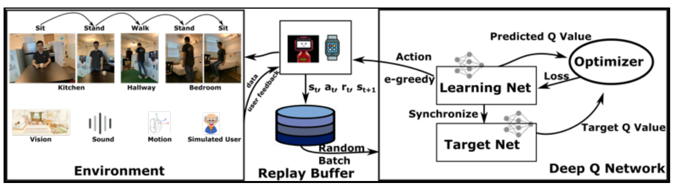

Fig. 4. The architecture of the Deep Q Learning-based sensor selection algorithm

C. *Reinforcement Learning for Sensor Selection*

As shown in Fig. 4, we considered the sensor selection problem as a Markov decision process problem, where the next state only depends on the current state which includes the transition motion, current activity, location, resources capacity level on robot and battery level on the watch. The states will be changed by taking actions such as turning on the watch sensors. The agent's goal is to develop an optimal policy that maximizes its long-term accumulated reward. We defined the state, action, reward and policy learning as follows:

1) Goal:

- Maximize the activity detection ratio
- Minimize energy consumption on the watch
- Minimize the privacy concerns
- Minimize the robot resource cost

2) State:

- Transition Motion
- Current Location
- Current Activity
- Smart Watch Battery Level
- Robot Resource Capacity Level

3) Action:

- Robot Mic Sensor: Turn on the microphone on the robot
- Robot Cam Sensor: Turn on the camera on the robot
- Robot Mic Cam Sensor: Turn on the camera and microphone on the robot
- Watch Mic Sensor: Turn on the microphone on the Smart Watch
- Watch Cam Sensor: Turn on the camera on the Smart Watch
- Watch Mic Cam Sensor: Turn on the camera and microphone on the Smart Watch
- Robot Mic watch Cam Sensor: Turn on the microphone on the Robot and the camera on the Smart Watch
- Do Nothing

For the state, firstly, we involve the transition motion information to indicate the transition between two activities. Transition motions including *Sit to Sit, Sit to Lie, Sit to Stand, Stand to Sit, Stand to Stand, Stand to Walk, Walk to Walk, Walk to Stand* are considered. Secondly, the current activities and locations can be used to alleviate privacy concerns. Finally the watch battery level and robot resource capacity level are considered to minimize the times of activating the watch sensors and robot sensors. The actions indicate how the agent activates sensors in different states.

4) Reward

A reward is the feedback from the environment. We aim to trade off the accuracy of activity recognition, energy cost on the watch, privacy concerns and robot resource cost. The activity recognition accuracy depends on activity types and the collected sensor data. The energy consumption on the watch mainly depends on the times that the sensors are activated. We also take into account the resource cost on the robot, as triggering the robot sensors increases the robot's work load. For privacy concerns, the robot needs to respect the user's privacy preferences when using the robot to capture data. To take advantage of the information provided by transition motions, we incorporated an additional factor called 'extra reward' when detecting new activities after identifying transition motions. In summary, the proposed algorithm aims to maximize rewards by detecting more activities, consuming less energy on the watch and resources on the robot, and alleviating privacy concerns. The reward formula is shown in Fig. 5.

```
# energy_cost: energy cost for data collection using the watch sensors
# resource_cost: resource cost for data collection using the Robot sensors
# activity_detected: 1: if activity is recognized, 0: otherwise
# privacy_occur: 1: if privacy violation occurs, 0: otherwise
# w_energy: the weight of energy cost
# w_accuracy: the weight of accuracy
# w_privacy: the weight of privacy concern
# w_resource_cost: the weight of robot resource cost
# extra_r: the extra reward when new activity is detected
initialization;
reward = -(energy_cost ·w_energy)
  + activity_detected ·w_accuracy − privacy_occur · w_privacy
  - resource_cost ·w_resource_cost;
if new activity detected then
   reward = reward + extra_r
end if
```

Fig. 5. Pseudo Code for Reward Formula.

5) Value-based Policy Learning

The goal of an RL agent is to learn an optimal policy $\pi(a|s)$, which represents how the agent chooses actions a by observing the states s of environment so as to achieve maximum rewards. In this paper, we adopt a value-based method, Deep Q Learning, which combines Q-learning with deep learning for policy optimization [18]. Fig. 4 shows the proposed Deep Q Learning model and Fig. 6 shows a two-layer neural network for value-function optimization. Here, $Q(s_t, a_t; w) = Q(s_t, a_t; w) + \alpha \cdot [R(s_t, a_t) + \gamma \cdot maxQ(s_{t+1}, a_{t+1}; w) - Q(s_t, a_t; w)]$, where $Q(s_t,a_t; w)$ is the neural network with the input states s_t and output actions a_t, w is the weights of the neural network, α is the learning rate, $R(s_t, a_t)$ is the reward obtained in the state transition from s_t to s_{t+1}. To train the DQN, we adopt a replay buffer to store the (s_t, a_t, r_t, s_{t+1}) experience so as to reuse the individual tuples. Further more, we use a learning network and a target network to improve the stability of the algorithm as s_t and s_{t+1} are highly correlated. The learning network can be updated frequently, while the target network is allowed to synchronize the learning network after several steps. Thus, we define the MSE loss function as $loss = 1/2 \cdot (r_t + \alpha \cdot (maxQtarget(s_{t+1}, a_{t+1}) - Qlearning(s_t, a_t))^2$. Finally, we choose the action with the maximum reward under the specific state as the optimized solution $a* = argmaxQ(s_t, a_t; w)$. Also the $\epsilon-greedy$ strategy is used to balance the exploration and exploitation for choosing actions.

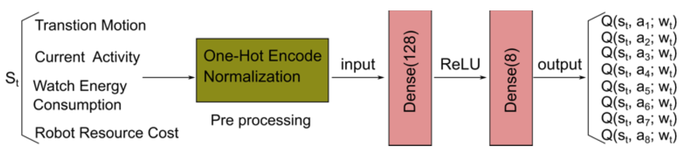

Fig. 6. Deep neural network model for value function learning.

Fig. 7. The samples of locations and activities from offline dataset:robot view (left), watch view (right).

IV. EXPERIMENTAL EVALUATION

A. *Evaluation of Location, Motion Action and Sound Event Recognition*

1) Test setup: Three CNN models for location, motion action and sound event recognition were implemented on a computer with a 16-core Intel i9 CPU, an Nvidia Geforce RTX 3070 GPU, Python 3.7 and Tensorflow 2.8.0. YOLOv3 [19] was deployed for object recognition. The dataset for training the location and motion action recognition models contains six locations including: *bathroom, bedroom, kitchen, living room, hallway and door area* and six motion actions including *sitting, jumping, standing, walking, jogging, laying*, and each sample contains 2 seconds of motion data. There are 12 sound event classes including *opening closing door, eating, keyboard, pouring water, brushing tooth, vacuum, drinking, flushing toiet, microwave, environment, watching tv, washing hands*, and each sample contains 1 second of audio data. Fig. 7 shows the location samples from robot's view and watch's view respectively.

2) Results and Analysis: The location recognition from the robot and watch images has high recognition accuracy of 96%. From the results, the 'kitchen' could be mis-recognized as a door, since the door area (inside) is similar to the kitchen area. Similarly, due to the similarity of the walls in the bedroom and hallway, the system sometimes mis-recognizes the 'Bedroom' as the hallway. The motion recognition model has an accuracy of 94%, walking, sitting, standing actions could be recognized correctly which could be used to detect transition between two activities. Finally, the sound recognition model has an accuracy of 94%. 'Door open closed' has low recognition accuracy due to the sound quality. It could be recognized as 'Keyboard' or 'Eating' sound sometimes. Fig. 8 shows the confusion matrix of the location recognition.

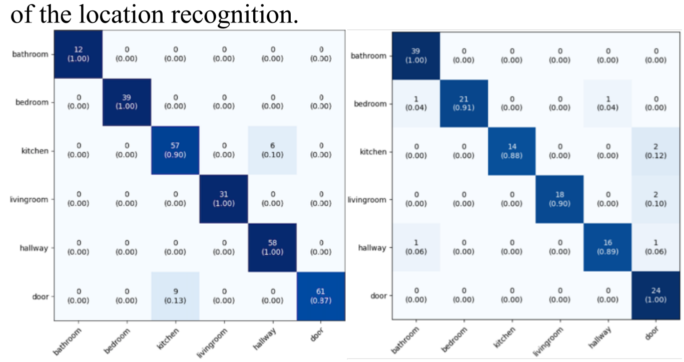

Fig. 8. The confusion matrix of location recognition. Robot view(Left), watch view(Right).

B. *Energy Consumption Measurement*

The Android OS offers the power management API, which can be used to estimate the energy consumption of the watch in different modes. We designed experiments to put the watch in four different modes for 10 minutes each: 1) Normal Mode: the watch runs the App only. 2) Idle Mode: the sensor is on, but not triggered. 3) Capture Mode: the sensor is triggered to capture data locally. 4) Capture Send Mode: the sensor is triggered to capture data locally and send data to the robot. Regarding the camera's energy cost, during the test, it captured and sent 770 images to the robot while consuming 5% of the battery capacity. This implies that each image consumes 0.0065% of the watch battery energy with a capacity of 2946 mAh, i.e. 0.19 mAh. The motion sensor incurs low computational cost, facilitating the collection of motion data from users. For the microphone energy cost, it captures 243 clips while consuming 2% of the battery capacity, each clip consumes 0.0082% of the watch battery energy.

C. *RL Model Performance Evaluation*

1) Test setup: The proposed DQN algorithm was trained and evaluated in the offline environment we simulated in our lab testbed, using a total of 14 corresponding activities including Bed to Toilet, Chores (Vacuum Cleaning), Desk Activity, Dining Rm Activity, Evening Meds, Guest Bathroom, Kitchen Activity, Leave Home, Master Bathroom, Meditate, Watch TV, Read, Morning Meds, Master Bedroom Activity. We compare two different methods for evaluation purpose.

a) Periodic: The sensors are triggered periodically with time intervals of 0.25 min, 0.5 min, 1 min, 2 mins and 3 mins.

b) RL-Based: The sensors are triggered based on the output of the RL-based algorithm.

2) Results and Analysis: We assigned weights of 0.05, 0.33, 0.47 and 0.15 to accuracy, energy cost, privacy concerns and robot resource utilization, respectively, which implies that we prioritize energy consumption and privacy issues, as the image recognition results from both watch and robot data are already satisfactory. Fig. 9 shows the accumulated rewards. We can see after 17 episodes the model converged well. As shown in Fig. 10, the robot sensor trigger time, watch sensor trigger time and privacy violation occurring time also converged. The converged trigger time of the watch sensor is less than the trigger time of the robot, which means the agent learnt the strategy to utilize the robot more than the watch to monitor activities to save energy.

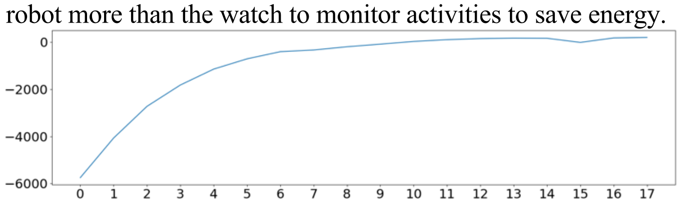

Fig. 9. Accumulated rewards(X-axis: episodes, Y-axis: rewards).

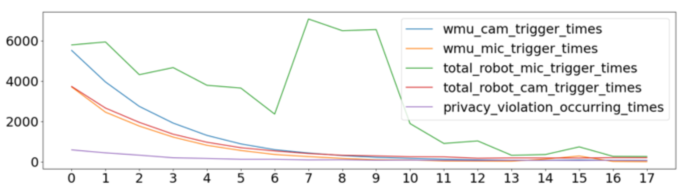

Fig. 10. Robot Sensor Trigger Times, watch Sensor Trigger Times and Privacy Violation Occurring Times(X-axis: episodes, Y-axis: trigger times).

As shown in Table. I, for the periodic method, we used the smart watch to collect data for ADL monitoring. The 0.25 minute periodic method could achieve 43/47(91%) detection ratio, but it consumed significant energy on the sensors. Meanwhile, we can increase the period to decrease the trigger time, but the detection ratio also decreases. During the real time test, with the help of the transition motion state, the algorithm turned on the camera and the microphone on the watch 96 and 14 times, respectively, and turned on the camera and the microphone on the robot 92 and 175 times, respectively. The proposed method can collaborate with the robot to achieve a detection ratio of 91% and activate the watch sensors fewer times (96) compared to a period of 0.25 minute with 2917 trigger times, which leads to saving of 14.6% of energy on the watch while maintaining the same level of detection accuracy.

From Fig. 11, we can see that the model is able to distinguish between transition motions that indicate a new activity and those that don't. Transition motions including 'stand to sit', 'sit to stand', 'stand to walk', 'walk to stand', 'walk to sit' and 'sit to walk' indicate a new activity, which could trigger the actions including 'Robot audio vision'. and 'Robot audio watch vision' to capture more data to recognize the new activities accurately. To alleviate privacy concerns, action 'Robot audio watch vision' instead of 'Robot audio vision' would be chosen in the location with privacy concerns such as 'Bathroom'. Transition motions without changes like 'walk to walk', 'sit to sit' and 'stand to stand' usually mean the user is doing the same activity and the action 2 'Do nothing' is triggered by the algorithm. It is also interesting to see that other actions like 'watch audio', 'watch vision' and 'Robot audio' are not triggered frequently, as actions 'Robot audio vision' and 'Robot audio watch vision' dominate the selections due to the energy consumption, activity recognition accuracy and privacy concerns. From Table I, compared to the periodic method using a single robot, the proposed method can reduce the privacy violation times. As turning on the robot camera causes privacy concern in the bedroom and the bathroom, the algorithm does not trigger the actions 'Robot vision' and 'Robot audio vision' frequently. This also shows that the model is able to learn the context of different activities and use it to make better predictions.

TABLE I. THE RESULTS BETWEEN THE RANDOMLY PERIODIC METHOD AND THE PROPOSED METHOD

Method	Detection Ratio	Trigger Times
0.25 Mins (Period)	91%	Watch Cam Mic: 2917; Privacy Violation Times:327
0.5 Mins (Period)	89%	Watch Cam Mic: 1530; Privacy Violation Times:163
1 Min (Period)	85%	Watch Cam Mic: 811; Privacy Violation Times:82
2 Mins (Period)	70%	Watch Cam Mic: 306; Privacy Violation Times:40
3 Mins (Period)	68%	Watch Cam Mic: 271; Privacy Violation Times:27
Proposed(Offline)	89%	Watch Cam:125, Watch Mic:64, Robot Cam:221, Robot Mic:281, Privacy Violation Times:0
Proposed(Real time)	91%	Watch Cam:96, Watch Mic:14, Robot Cam:92, Robot Mic:175, Privacy Violation Times:0

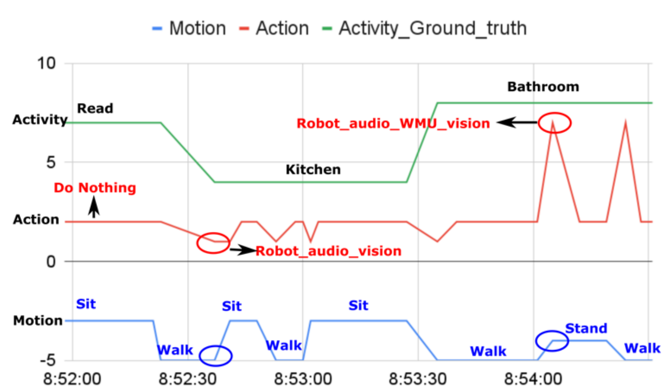

Fig. 11. The detailed distribution of activities, RL model actions, motion from 08:51:58 to 08:54:31.

In addition, the robot possesses the capacity of dynamically accommodating the user's preferences through iterative interaction and learning. As depicted in Figure 12 (Solid lines), the initial model designated the bathroom and bedroom as private areas. However, by the fourth day, the user's preference changed, disallowing the robot from taking photos in the living room. Notably, this adjustment led to an increase in privacy violation occurrences, totaling 45 instances. Nonetheless, the robot learned and refined its model over subsequent days, evident from the declining trend in privacy violations starting on day 5. Meanwhile, these adjustments impact the activation patterns of both wearable and robot sensors. Another example is shown in Fig. 12 (Dashed lines). Without learning, the robot cannot adapt to user's new preference which increases the privacy violation times.

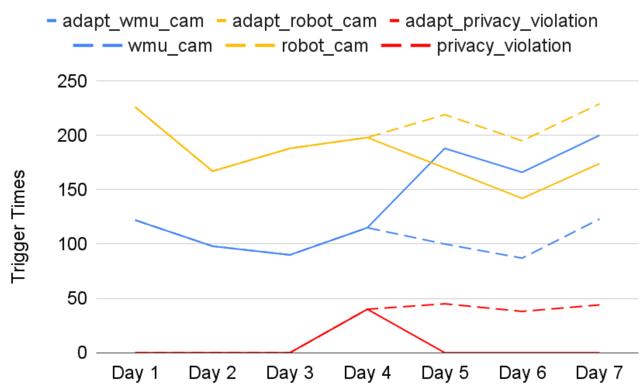

Fig. 12. The robot adapts to user's preference.

V. CONCLUSION AND FUTURE WORK

In this paper, we proposed a collaborative ADL monitoring system using a smart watch and a companion robot. To balance the recognition accuracy, privacy concerns, robot resource utilization and watch battery life, a Deep Q Learning based algorithm was developed for sensor selection. The robot makes decisions based on the Deep Q Learning model to turn on the relevant sensors on the robot and the watch. Specifically, the watch motion sensor remains on in order to capture the transition motion which is part of the states of the environment in the sensor selection model. The results show that the proposed method could achieve activity detection ratio of 89% while triggering the watch camera 125 times and the watch microphone 64 times during the offline test. The real time evaluation shows that the activity detection ratio is 91%, which saves 14.6% of energy compared with the periodic method with 0.25-minute sampling period in the offline test. For the future work, we will continue improving the system and involve more states and actions in more complicated scenarios.

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