Intent-aware Interactive Web of Things for Enhanced Collaborative Ambient Intelligence

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ABSTRACT

Internet of Things (IoT) enables the connection of a broad range of artifacts with advanced sensory technologies and produces massive amounts of data to support ambient intelligence. While the potential of IoT systems is widely recognized, there is still limited work to demonstrate such a system with the autonomy and the ability to execute in the real world. Inspired by the successful introduction of robots to specialized IoT environments, we propose an end-to-end solution for a generic, interactive ambient intelligence system, where robotic assistants can assist humans in conducting activities in IoT-enabled smart homes. We evaluate the solution based on implementations of public benchmarks on open-source platforms. We use several activities to demonstrate the effectiveness of the proposed solution in real life.

KEYWORDS

datasets neural networks, gaze detection, text tagging

1 INTRODUCTION

The Internet of Things (IoT) promises to integrate digital and physical worlds by connecting artifacts and build networks of them. Traditionally, IoT devices are designed to work on their own and may use incompatible protocols. However, inter-device communication and interactions are critical toward building a generalized connected environment, such as a smart home application. Web of Things (WoT)[1,2] is proposed by W3C to facilitate IoT applications, with standardized descriptions of actions, events, and properties of things, as an extension to existing and widely used web protocols. Enabled controls of devices with decoupled specialized APIs, broader interactions between smart things in hypermedia environments can be established comfortably. With plenty of IoT products commercially available, recent research and industry have successfully adapted connected things in our daily life.

Although WoT offers the flexibility and openness for connected things in smart systems, the connected things cannot work == autonomously but still require human intervention. For example, although a coffee machine may be able to can fill water, grind beans, brew, frother, and add milk, it faces tremendous difficulties in selecting or filling proper beans according to user preferences. The current research mostly focuses on making such recommendations yet cannot control any device to take the actions accordingly. Besides, the behaviors of things or how the connected things are used are usually predefined by the designers. However, the environments or user requirements can evolve dynamically, and there can be unexpected requirements that demand unforeseen ways of utilization or interactions. For example, a connected lamp for reading on a desktop may be moved into the kitchen for plants, and this requires the lamp to work without human attendance and to alter its light color to maximize plants' productivity instead of human comfortableness.

Inspired by Multi-Agent Systems, some efforts develop smart agents and prove them effective to support dynamic interactions with IoT systems. In a representative study, Qi et al. [22] propose a Web APIs recommendation for WoT applications based on keywords; Besides, Ciortea et al. [7] propose a smart agent that can dynamically plan new sequences of actions to better achieve its goals with available resources. A further step to address the above issues is the Internet of Robotic Things (IoRT), which introduces robots into IoT environments to leverage the combined strengths of robotics, IoT, and edge computing. The robots in IoRT are either equipped with IoT sensors or designed to fuse IoT sensory data to gain awareness of the environments. They also analyze and adapt certain actions to interact with the physical world in an extended fashion. Since invention, IoRT practices have been mostly focused on machine-machine and machine-human collaborations at workplaces (e.g., maintenance and service jobs) to circumvent hazards or reduce labor costs. Although the combination of IoT and robotics has been introduced to smart city [18], or for earlier exploration in general interactions and specialized scenarios [19]. Existing smart home studies have been focusing on particular tasks, such as social

[1]https://www.w3.org/TR/wot-thing-description/
[2]https://www.w3.org/TR/wot-architecture/

robots, which use physical sensing to assist human-machine interaction yet cannot conduct general tasks to conduct real physical interactions. There remains a significant gap to bring robotics into home applications to make the whole system work for supporting physical human-machine interactions.

Considering a more desirable scenario: Bob is preparing a bowl of cereal as breakfast, and usually, he finishes the meal with a cup of tea; the system detects a series of events in the kitchen at the time, such as movements of a cabinet door, bowl, fridge door, cereal containers and such, which leads to the recognition of Bob preparing cereal as breakfast; then based on Bob's routine, the system envisages a tea to finish the breakfast, and promotes our robot with 3D depth camera moving to the kitchen, which just identified a mug and teaspoon is on the bench, and this confirms the predicted intention; The robot then coordinates a robotic arm on the bench to make a tea for Bob while the cereal is being consumed. The above envisioning matches our goal towards ambient intelligence, thus motivating this study. Such a setup can also be found in Figure 1.

In this work, We propose a novel framework, namely Intent-aware Interactive Web of Things to enable and enhance ambient collaborative intelligence Our framework capitalizes on multi-faceted collaborations between humans, the Web of Things, and robots on top of our unified IoT-endowed platform [33].

Our framework conducts four major tasks. First, it fuses robotic and smart home sensory data to jointly infer human intention based on the subject's current and past behaviors, where the required data are gathered for supporting our ambient intelligence system and downstream tasks. Then, it combines the inferred intention with contextual information observed by the robot with sensors (e.g., a 3D camera) for semantic recognition and prompts physical interactions. This helps prompt possible interactions for the intelligent robotic assistants. Third, it further processes the interaction to actions with relations identified , which helps define the objectives for the robotic assistants in instructive steps. Lastly, a suitable physical agent conducts the actions with an awareness of the physical, sensory data or with the help of other robots. Our contributions in this work are summarized below:

(1) We propose an end-to-end solution for an interactive ambient intelligence system, with robotic assistants assist activities of the subject in IoT enabled smart homes;
(2) We engineered generic web-based descriptions for smart-home IoT device interactions, which enable the actions to be not only decided but also executed in the physical world by robotic assistants;
(3) We trained our reinforced learning-based robotic assistants to exploit rewards as well as failure experience, with the policy continuation strategy as well as Hindsight Experience Replay method, which largely fasten the learning process;
(4) We implement the simulation with the Deepbot framework in the OpenAI gym environment, which also enables us to demonstrate some selective activities in real life.

The rest of this paper is organized as follows: Section 2 reviews the related work to this study; Section 3 overviews the framework by firstly defining the objectives and introducing preliminaries, followed with detailed explanations of our framework by data-flow; Section 4 explains evaluation datasets, experiment settings, and result analysis; And section 5 concludes this work with some insights on future improvements.

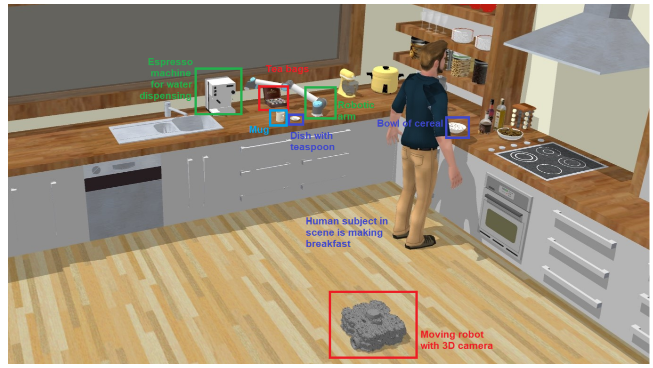

Figure 1: Basic set up and application scenario of proposed system

2 RELATED WORK

In the past decades, IoT, including smart-home-related studies, has attracted enormous attention, thanks to the availability of various networked smart devices, appliances, and improved computing capability. While due to hardware and technical limit, early studies in the field are explicitly related to specific human-oriented applications such as web management, location, tracking, activity recognition. CASAS[9] by Washington State University, for example, is one of the earliest and largest smart-home experimental platforms, where users are sensed and tracked by various pre-installed devices in the apartments. Successful studies has been produced in activity recognition[5], cognition and health assessment[10] and human behavior analyze s[23]. Ruan et al.[26, 27] identified it using wearable sensors may lead to some burdens in practice, thus proposed multiple methods that progressively achieved device-free indoor human subject localization and tracking. On the other hand, As more IoT devices available, the management of such connected devices can also be a critical step towards the ultimate goal of an ambient intelligent environment. Yao et al.[35] demonstrated that a unified management system could effectively integrate virtual and physical resources, where users can monitor, visualize, and aggregate services, they[34] later also investigate to find the most relevant things in the system according to human interactions and attend success. Shemshadi et al.[29] provide a framework for diversified and relevant search in IoT, laid the foundation for IoT search engines. Their further study[33] then reveals a real-time multi-level activity monitoring system for a personalized smart home, which fully automated continuously tracks daily activity and conducts abnormal activity detection.

These studies lay a solid foundation in the field. Although they realized ambient intelligence in some aspects or certain applications, this is yet far from the true 'smart,' intelligent environment where 'acting' can be equally important to support human activities. In fact, robots can provide even greater flexibilities in terms of 'acting' in the smart environment [8], apart from networked and smart appliances. Naturally, robots in IoT also start, or even concurrently at large are dedicated to specialized tasks. Li et al. [17]

demonstrate robotics application in fruit harvesting supported by IoT system. Kauser et al. [15] proposed a highly automated robotic system with various IoT sensors in greenhouses to relieve the labor of farmers. Kanwar et al.[14] designed an IoT-based robotics system for fire-fighting. Cheng et al. [6] come out with a robotics system with IoT toys for EFL teaching. As IoT-related robotics research becomes increasingly prominent, the concept IoRT has been proposed, where more studies are more related to integrate robots as a part of IoT networks, taking advantage of their physical existences and abilities of execution. As mentioned before, Liu et al. [18] explore robots behavior in a smart city scenario, and Mahieu et al. [19] investigate context-aware and personalized interactions on the internet of robotic things. Vermesan et al. [32] and Batth et al. [3] individually overviewed IoRT and clarified some concepts with suggested architecture and applications. And undoubtedly, those existing literature opened up our ideas and established the base of this research.

3 METHOD

As shown in Figure 2, our proposed framework is aimed to explore an enhanced ambient intelligence in the Web of Things environment. We propose to demonstrate it in smart homes with robot helpers, connected things, and sensors. And in the scope of this study, we explore to prompt the autonomous robot helpers actively collaborating with a human subject in activities of daily living in a smart-home setting with no explicit human instructions, where the ambient-intelligent system are supported by various environmental sensors in the background. Particularly, we consider the proposed framework to have three main stages, where the system infers subject intent, composites actuation for interactions, and executes the actions for the subjects in advance. The following of this section will explain the three stages in detail.

3.1 Problem setup

As mentioned before, our proposed framework starts with estimating the intents of the human subject. At this stage, it is essentially an activity prediction problem with multimodal sensor data. While different from some existing literature, here, activities are not defined instructive procedures, and each instance of activity has no clear-cut segmentation. Several activities can be done simultaneously and staggeringly. Thus we will need to first model the human activities and develop an appropriate segmentation method for recognizing complex activities, for an awareness of the concurring events and the subject intentions.

Once figuring out the intention of the subject based on the sensory data, we can narrow down the scope of activities for the subject. We propose in the second stage to finalize the conscientious moves for the robot assistants, as well as devising instructions for them towards the goal. For this, we start by motivating the moving robot on the floor, which is equipped with a 3D stereo camera, to scan the environment where the subject is conducting activities for interactable objects. For example, in our aforementioned scenario, the scanning can happen in the kitchen, and the interactable in our scope is referred to as to defined with WoT Things Description and can be interacted with APIs. With the items identified, we can infer the most likely move of our subject in the even smaller search space. Hence a more precise prediction can be produced based on the usage history as well as certain basic rules either preset or learned from the past data in the userspace. A further search with the key items can be then translated into step-by-step instructions and send to our robotic assistants to be accomplished.

However, it takes some effort to instruct robotic assistants, which cannot understand semantic procedures. Besides, in real-life home applications, the same task can alter due to environmental fluctuations and situational variations, which often are also unpredictable in the uncontrolled setting. Building factory-like streamlined automation is not viable at home. Thus a smart and adaptive robotic control system is essential here, which leads to our last stage. Luckily, recent research in deep reinforced learning and robotics provides us practical solutions for such applications. Subsequently, we adopted a similar approach, and specifically, we propose to use the aforesaid moving robot with a 3D stereo camera as the visual guide for other cooperative robot assistants for an expository collaboration with the human subject. The proposed learning process is namely powered by an adaptation of Policy Continuation with Hindsight Inverse Dynamics (PCHID), which has been proven merit for this application.

Formally, we denote the set of activities as $A \in \mathbb{R}^N$, where refers to the i-th class of activity in the set; At time t, we received sensory inputs $x_t^A \in \mathbb{R}^d$, where at the first stage we require the predicted ongoing activity correspondingly:

$$x_t^A \longrightarrow \hat{y}_t^A = a_i \tag{1}$$

Henceforth, semantic description corresponded to current input x_t^A is also fetched, and whose keywords are noted as $Q_t^A \in \mathbb{R}^q$, which is then jointly matched with a subset of corresponding semantic keywords $Q_t^O \in \mathbb{R}^p$ from object detected by the moving robot assistant R_m. Then with all the contexts and historical activity with usage information, A_H recorded in space, we can infer the most likely intended action of the subject at time $t' + 1$, $\hat{y}_{t'+1}^A = \hat{a}_j \in A$, and accordingly the action compositor $\alpha(\cdot)$ produces executable procedure with a series of interactions $\mathcal{I} \in \mathbb{R}^M$ for the target to Q^A with objects to Q^O assumed that in a short time duration $Q_{t'}^O + 1 = Q_t^O = Q^O$. That is:

$$\{Q_t^A, Q^O, A_H\} \longrightarrow \hat{a}_j \tag{2}$$

$$\mathcal{I} = \alpha(\hat{a}_j, Q^O) \tag{3}$$

Ultimately the interactions $\mathcal{I}$ will be sent to the robot, which sees each interaction ι_m as a goal and learns to reach.

3.1.1 *Things Description for Smart Home.*

Intuitively before our processes, it would be necessary to formulate a uniform operation interface for interactable devices in the smart home environment as well as descriptions, so that the system can know the functionality of a certain specific device, how can it interact, and what can be the possible outcomes of the interactions.

Connected and interactive things in our proposed smart home environment are abstracted as web resources, as recommended in WoT TD by W3C aforementioned, which enables standardization of IoT resources. With WoT TD, IoT devices and things are registered with a resource directory for dynamical discovery, and hypermedia interactions can be performed as standardized web interactions

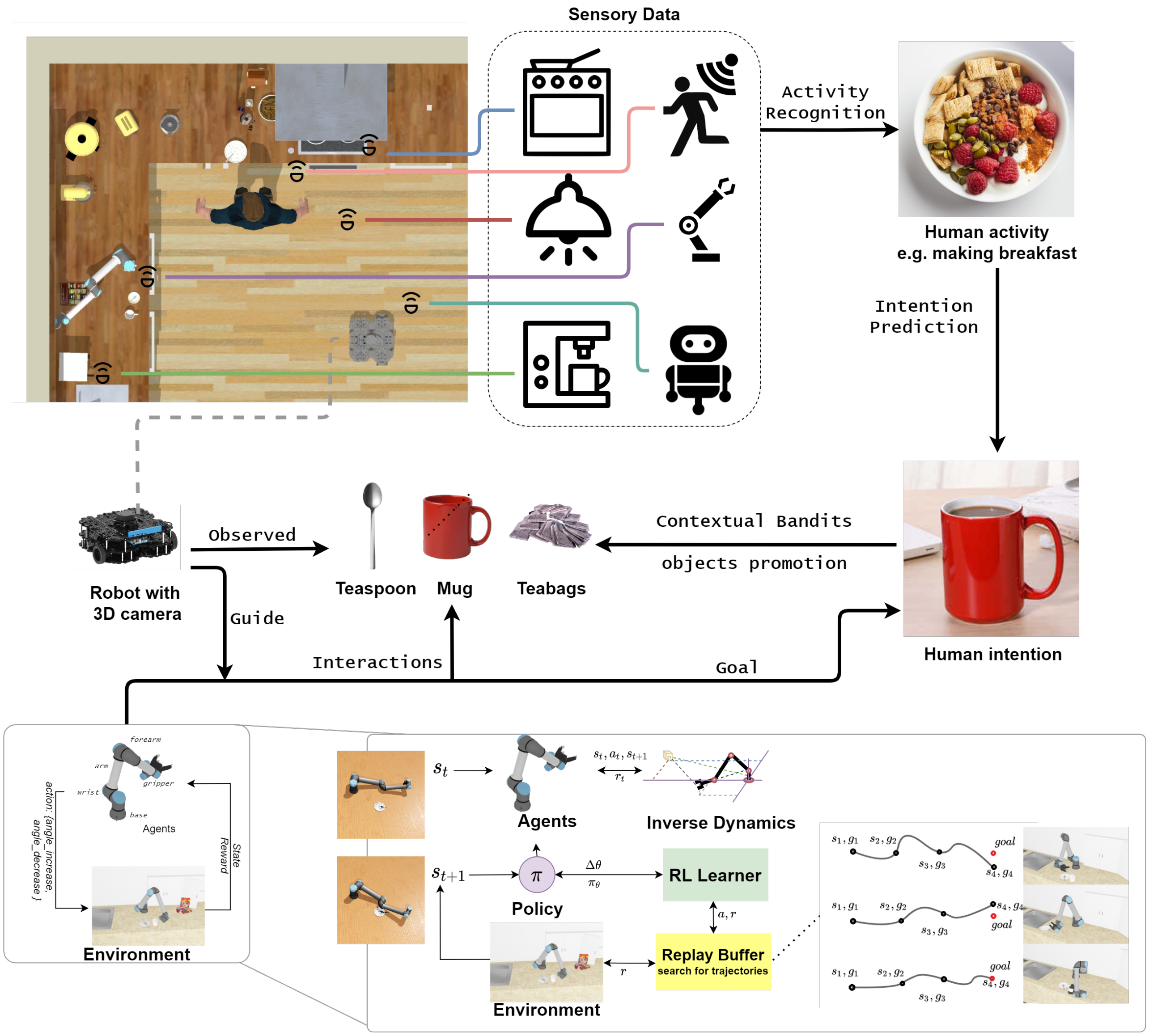

Figure 2: The workflow of this proposed system in the scenario. Generally, the robot assistant first observed human activity, which fused with the Web of things sensory data and inferred that the end-user is making cereal breakfast and want to have a cup of tea; The system then searched keywords semantics and worked out procedures of making tea; The assistant visually guided robot arm on desk executed the procedure and presented a cup of tea to the end-user.

with normal web protocols, such as HTTP; Then, the device controls and interactions are essentially advertised as web services, relying on WS-* standards. The JSON-based serialization also has advantages in implementation. Intuitively, based on the work by Ciortea et al. [7] and Ricci et al. [25], a semantic description of Web-based Artifacts are also adapted in our work, used as the first-class abstraction for a clear integration and deployment of MAS.

3.2 Intent-Awareness with Connected Things

Given the environment setups ready and devices described as required, in this very first stage, our goal is generally to predict the next human activity and generate the output in the form of semantics for the WoT API searching in the next step. And essentially, this is fundamentally an activity Relationship Modelling problem. Naturally, data collection can be the first and essential step toward this objective. Environment changes can be sensed in different sources and modalities, while particularly in a smart home, sensory data is more common under the consideration of privacy. Yet, it is worth mentioning that with the advancement of sensory technology, numerous kinds of sensors can be deployed for collecting various contextual information, even at different frequencies. This leads to studies of sensor events based on ongoing activities and new activity detection, as well as segmentation of the sensor events based on prior knowledge for better HAR analyze s and modelings. And this is extensively studied with copious state-of-the-art approaches.

As semantic features are vital in the later stages in our proposed framework, here, we adopted a workflow inspired by Triboan et al. [31], for both generalization and model efficiency. Predominantly, it is a semantic theory-based approach for sensor event segmentation, which intrinsically analyze s and compare sensor event to actions of known activities. Noted that, after learning of the activity model, a semantic activity prediction can then be adapted for the required inputs for the following stages. The following of this subsection will explain the procedure.

3.2.1 activity Modelling. First of all, the environmental context (*EC*) can be essential in our smart home settings, which can arguably consists of various entities (ET_k) such as the human subject (H_n), location (L_m), ambient characteristic (AC_o), sensor characteristics (S_p) and interactable objects (Obj_q) of classes (C_l):

$$EC = \{H_n, L_m, AC_o, S_p, Obj_q\} \tag{4}$$

As for Semantic Relations *SR* between *EC* and activities, we denote a Sensor Environment (*SR*) for the relationship (R_e) between specific sensor event and corresponding objects. That is

$$SR = a_n(R_e, EC) \rightarrow R_e \rightarrow SE \tag{5}$$

where

$$SE = instance(R_e, S_p) \rightarrow R_e \tag{6}$$

As specified by Triboan et al. [31], the actual activity performed by human subjects can vary in real-life and may not match our prior knowledge. It would be critical to consider subject preferences ($Pref_r$) as well. And it is modeled as

$$Pref_r = instance(R_e, a_n \cap Preference) \rightarrow R_e \tag{7}$$

3.2.2 Semantic Decision. Working on the above-modeled relationships, regular, generic activities can be recognized using semantic reasoning methods on the ontology. Given the streamed and observed a set of sensory events E^s, and the possible activity candidates (A'), we can construct an activity thread (AT_i). With Terminology Box (T-Box) reasoning on regular, generic activities, and Assertion Box (A-Box) reasoning for user preferred activities, it can be presented as

$$AT_i = \{\mathbf{tBox}[A', E^s], \mathbf{aBox}[Pref_r[Pref', E^s]]\} \tag{8}$$

Specifically, it is assumed the traced semantic relationship is generic, and the metadata of sensor event $e_m \in E^s$ is analyzed d for the corresponding Entity (ET_K) to deduce the candidates of relationships with activities. As the process going, the concurrent activities can be inferred using a semantic reasoner. And when the T-Box returns conflicted results, which can be identified with the mismatch of the corresponding entities and set of sensor events in our predefined knowledge base. Here, user-preferred activity is assumed for such irregular behaviors. While in this case, the current actions are learned and saved for later use, with the corresponding activity and sensor events.

3.2.3 Sensor Events Segmentation. In this subsection, sensor events segmentation is introduced for activity prediction, while it also critically impacts the overall performance as the base motivation of system actions. While in our setting, the segmentation can be challenging, and as our proposed scenario is naturally more complicated with richer contexts containing more than wearable motion sensory data as in most activity-related wors, not to mention that in our practice, very low-latency processing is preferred if not real-time. Specifically, in this work, we propose to extend literature to work with a richer context from IoT sensors in a smart home setting. Noted here, we generalize the concept of sensory events to contain also status and usage information gathered in the IoT networks.

Inspired by Mallick et. al. [20], we propose to adapt a transaction-based segmentation, as at a given activity transaction, activities may be multiplexed and accordingly we also consider that transaction segmentation may not perfectly align with individual activities. That is, given a set of sensory events $E = \{e_1, e_2, ...e_E | e_i \in E^S\}$, we can segment it in to multiple transactions denoted as $tr_i = \{e_i, e_{i+1}, ..., e_{i+j}\} \in Tr$. The transaction tr_i matches exactly with activity a_i is defined as ProperCut transaction, while OverCut denotes transactions do not contain all transactions and Undercut transactions involves multiple activities. While, as defined by Mallick et al. in their work [20], we also aimed to minimize the number of overcutting and undercut transactions here.

While differently, we argue that in our application, the transactions can have overlapped to couple with activity multiplexing. It is not critical for us to segment the sensory events into transactions with continuous timestamps. This can also simplify the segmentation and improve the latency for processing data. For example, it is totally acceptable with an activities $a_1 = \{e_1, e_3\}, a_2 = \{e_2, e_3, e_5\}$ in $E^s_k = \{e_1, e_2, e_3, e_4, e_5\}$, where we have $tr_1 = \{e_1, e_2, e_3\}$ and $tr_2 = \{e_2, e_3, e_4\ e_5\}$. Here $\{e_1, e_3\}$ is key events help us identify a_1, and similarly, a_2 is identified by $\{e_2, e_3, e_5\}$. Noted that some optional events for an activity can happen, such as it is not necessarily critical for one to use fridge when cooking. Thus, our goal is then to identify the minimal transactions of sensory events that contain complete activities for the downstream processing. Given we have contextual information of sensors and IoT devices also available in the home, such information is also embedded and clustered, where the distances are considered as weights in conjunction with the temporal sequences for the segmentation. MinMax algorithm has been proven effective and can be used for such processes.

3.2.4 activity prediction. Since the segmentation of sensory data is now available, the activity habits of the subject can be effectively learned, and thus we can infer possible next moves of the subject, which is then used for our downstream processing as input, to give commands to our execution agent, that is the robot assistant. While our focus in this paper is the verification of other parts, we adapt the state-of-the-art approach in this module. Specifically, we propose to utilize recent work propose by Altulyan et al. [1], where the approach can effectively suggest the next items to be used by the subject and learns in ambient by both the history of interactions, as well as new interactions, especially when wrong suggestions are made. Despite the proposed method are originally used as part of the reminder system for Alzheimer patients caring, its core function is essentially activity prediction and promotion. Specifically, this method involves three major stages, while we require only two of them as the removal of the reminder promotion:

(1) **Complex activity recognition.** At this initial stage, the system learns what is ongoing with the subject, and especially with sensory data, and recognized simple elementary activities such as the posture of the subject and movement of subject limbs, what complex activities, or in general, what is the subject doing. For this, we first identify the simple elementary activities, and based on our predefined ontological model; orchestrated rules are used for complex activities recognition.

(2) **Recommendation.** At this stage, we prompt activities and items to be used in the next step. Initially, this was used to remind items to the subject, while we in this study take advantage and pass the item recommendation to the ambient intelligence and ultimate our robot assistants. For this, the system firstly learns the past trajectories of activities for references as experiences, where the steps in sequences are used as states. Based on the recorded state trajectories, current contextual states can be determined and used for inferring the following ones and accordingly the activities to be performed as well as items to be used. Especially, the availability of state trajectories enabled us to build the learning process with the Q-learning RL framework.

3.3 Semantic Searching for Interactive Web of Things

As now we have learned what activity is ongoing based on the sensory observations and historical user interactions and figured out what actions next the human subject intends to perform, we can search the environment for the objects and conjecture the procedure towards the inferred intention with a semantic search, and thereafter the procedure can be passed to our execution agent, i.e., the robot arm, for completion. While to achieve this, we may need first to recognize the object on presence, and for this, we adopt Mask-RCNN mentioned above, with details explained as follows.

3.3.1 Mask R-CNN. Mask R-CNN [12] is a well-known and widely used efficient pixel-level object segmentation algorithm, which is developed from bounding box segmentation method Faster R-CNN [24] by Ren et al. Besides the Region Proposal Network (RPN) that propose RoI and the object detector from Fast R-CNN [11] extract features and refine the bounding of objects on the proposed regions, Mask R-CNN also identify if given pixels in each region are parts of certain objects, thus produces binary masks for objects. Specifically, it output 1 for pixels belonging to an object and 0 otherwise. In this work, we use the masks for (1) object detection and (2) combining with depth information to locate 3D positions of interesting objects in the scene, which are then used to coordinate both the setting of learning goals and training/running processes.

3.4 Context-aware Hypermedia Interactions

Here and now, we have contrived the procedures for an attainable activity that the human subject is likely to perform subsequently in steps, yet this can still be hard for a robotic assistant to comprehend, as it is not instructive hardware movement commands or movement coordinate for the robotic arms in our case. The steps in our generated procedure are more resemble goals. Thus we need a set of algorithms to achieve them, and specifically, we introduce Policy Continuation with Hindsight Inverse Dynamics (PCHID) as a strong and effective RL-based approach for this purpose.

3.4.1 Policy Continuation with Hindsight Inverse Dynamics. Inspired by Hindsight Experience Replay (HER) [2], Sun et al. propose PCHID [30] to expand HER to a more general self-supervised learning for Goal-conditional tasks with the ability to extrapolate the learned policy to more complex and non-linear Hindsight Inverse Dynamics(HID) applications, which can be applied both standalone and combined with other RL frameworks, such as DQN. Here they Target to learn general policy in larger policy space while meeting the restrictions of sub-policies while learning. In PCHID, they introduced the goal into inverse dynamics as Hindsight Inverse Dynamics, and specifically expand it to k-step as the goal may require multiple steps to be reached, where they ensure the goal is solvable from 0-th step, 1st step until k-th step, i.e., all the goals in each step can be reached under the optimal policy. Thus it can output the minimal k-step actions required by the goal under optimal policy. In their very study, they experiment specifically on reaching a moving target (the goal, i.e., the target is constantly changing thus requires updating in each step), while in our settings, we are considering completing a complex task in multiple steps with different sub-goals.

3.4.2 Multi-Step Goals with Policy Continuation. While Sun et al. in their PCHID [30] has proved that making the system knowing about the hindsight goal can be considerably beneficial for a faster and smoother convergence toward an extrapolated goal, it is also found more sophisticated settings are still challenging in a single goal setting. The idea is to expand the original HER model for HID to include the k-step solubility for better optimization. Similar to their bit-flipping example, we also propose to adapt such an approach.

Specifically, as in the Universal Value Function Approximators (UVFA) [28], we have possible goals $g \in \mathcal{G}$ and a corresponding reward $r_g : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$, where the $\mathcal{S}, \mathcal{A}$ is the space for states and actions, and for certain episode the goal g is fixed, and accordingly at timestamp t, we have $r_t = r_g(s_t, g_t)$ and policy $\pi : \mathcal{S} \times \mathcal{G} \to \mathcal{A}$. While expanded from the $(0, 1)$ binary problem set, the reward would then as indicated in the HER, to be

$$r(s_t, a_t, g) = \lambda |g - s_t^{object}|^p - |g - s_{t+1}^{object}|^p \tag{9}$$

Noted that, in our case, while the hyperparameters $p \in 1, 2$, the λ may not be limited to $0, 1$, which will be discussed later in the following section on evaluation and experiment.

Based on the UVFA model of HID, we follow Sun et al. to apply the k-step solvable extension, and hence the state-goal $\mathcal{S} \times \mathcal{G}$ is decomposed as $\mathcal{S}\times\mathcal{G} = (\mathcal{S}\times\mathcal{G})_0 \cup (\mathcal{S}\times\mathcal{G})_1 \cup \ldots \cup (\mathcal{S}\times\mathcal{G})_T \cup (\mathcal{S}\times\mathcal{G})_U$, see [30] for more details. Thus, our objective here is to find the optimal policy $\pi^* = \pi_0^* \cup \pi_1^* \cup \ldots \cup \pi_T^* \cup \pi_U^*$ where for each state-goal-action pair at timestamp t, we have a policy π_t^* leads toward the next sub-goal. Hence, the objective can be solved by SDG models, where

$$\theta_k = \underset{\theta_{k-1}}{\operatorname{argmin}} \sum_{s_t^i, S_{t+1}^i, a_t^i, i \in 1 \ldots k} ||f_{\theta_k}((s_t, g'_{t+1}), (s_{t+1}, g'_{t+1}) - a_t)||^2 \tag{10}$$

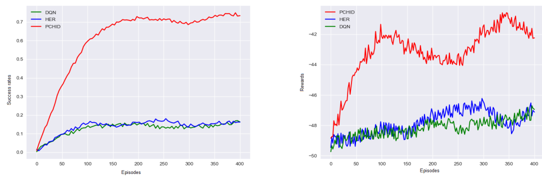

Figure 3: (a) Overall testing success rate to training episodes; (b) Overall learning rewards obtained to training episodes.

4 EVALUATION

In this study, we conduct most evaluations based on simulation, while in order to show its feasibility in real-life applications, we implemented live demonstrations of certain selective activities, whose video can be found at XXXX.

Our test mainly focuses on the task learning process of robotic assistants and is based on RLBench [13], which is opensource and contains a large number of daily activities (100 activities) for robotic related manipulation benchmark. While the RLBench uses the PyRep simulator, we implemented it with Deepbot framework [16] and OpenAI gym environment [4]. This essentially enables us to synchronize the simulation with ROS, where our real-life robots rely on, thus easier to produce the demonstration linked above.

Specifically, our setting up involves a Lynxmotion AL5D robot arm, a TurtleBot waffle Pi equipped with a 3D stereo camera, and some activity-interactive items, especially kitchen utensils.

4.1 Experiments

As mentioned, the robotic assistants actuate based on the UVFA model of HID, which is an extension to DQN [21]. It would be sensible to compare PCHID with DQN and its successor HER to demonstrate the overall effectiveness in our application with daily tasks, specifically the RLBench tasks. The reward is set 0 if the final state is within the tolerance of the subgoal for each step and -1 if the state of the robotic arm failed to be reasonably close. Figure 3 shows the overall success rates and rewards to episodes of training. It can be observed that the PCHID method is overall effective and learning significantly faster than compared HER and normal DQN method in our applications. Figure 5 presents some intermediate learning outcomes, given (a) and (b) failed to complete the task of 'Pick and lift' where (c) succeed at episode 20, 50, and 100; Figure 4 demonstrate effectiveness of PCHID in some selected tasks, namely (a) Pick and lift; (b) Place cups; (c) Remove cups; (d) Press switch.

In this study, we set the step of PCHID to 5. Larger steps may incrementally improve the results. The computational costs can be exceptionally high, not to mention in the current setting, the success rates can be argued acceptable.

5 CONCLUSION

In this work, we propose an ambient-intelligent system with collaborative robotic assistants to actively work with human subjects in smart homes. The system takes advantage of recent studies of sensory data-based human activity prediction and RL-based Robotic controlling to present an end-to-end collaborative solution in smart homes. Simulations and certain demonstrations show the effectiveness of our proposed system.

5.1 Future Work

It is worth mentioning that despite in our system, the ambient intelligent and robotic assistants can work without human invention, the environmental setup is still predefined in the system. This results in a certain amount of expertise labor work, especially the parts involving WoT Things Description on how smart objects in the environment can interact as well as the activity recognition which is based on preset ontology and rules. It would be argued the predefined items and activities are inclusive, not to mention that setups in real-life homes can be changed as time goes. Hence in the feature, we will accordingly aim to tackle the above-mentioned major shortcomings, Explicitly we will study: (1) an interactable item-discovery method to dynamically expand system knowledge about the environment and prompt robotic assistant activities, based on online observations of activities conducted by the human subject; (2) Novel robotic and ambient intelligence oriented activity modeling method, which specifically models activities for ambient and passive online learning, thus direct activity recognition in the background with the ability to learn new and unrecorded activities.

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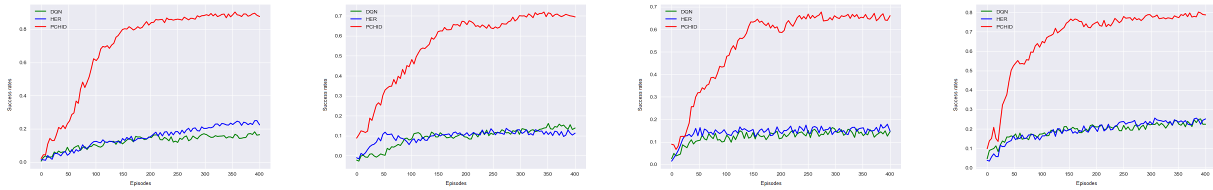

Figure 4: Testing success rates to training episodes for certain tasks: (a) Pick and lift; (b) Place cups; (c) Remove cups; (d) Press switch.

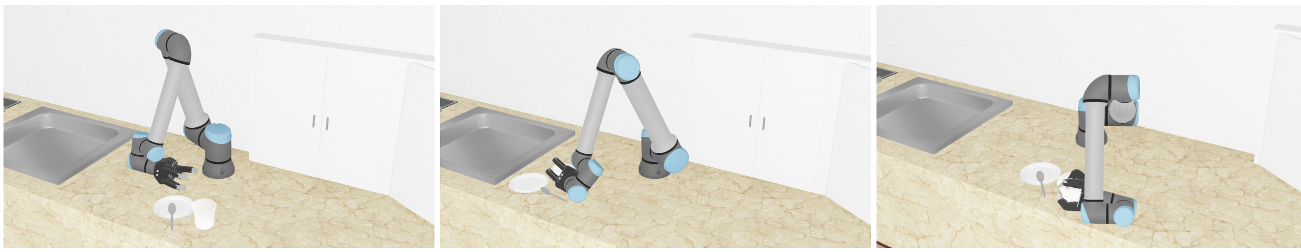

Figure 5: Learning results for task 'Remove cup' in our scene on some selected intermediate episodes, where (a) task failed with a gripper of robotic arm hit the desk; (b) the cup was gripped yet other items were knocked off; (c) the cup was gripped and removed successfully.

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