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Context-Specific Intention Awareness through Web Query in Robotic Caregiving

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***Abstract*—To provide the elderly with appropriate and timely caregiving in activities of daily life (ADL), it is desired for robots to have the capability of intention awareness (IA). Different from existing context-specific intention awareness (CSIA) approaches which are based on a limited and passive knowledge database, our approach, named 'WebIA', adopts a novel web query approach to establish a vast and active knowledge database for robots to perform CSIA. In our method, robots are endowed with comprehensive commonsense knowledge towards the correlations of the surrounding environment and human intentions. WebIA enables robots to effectively infer intentions in both trained familiar and untrained new situations. By performing several experiments, we evaluated two aspects of the WebIA approach: the effectiveness of IA in familiar situations and the self-learning ability in new situations.**

I. Introduction

Context-Specific Intention Awareness (CSIA), which focuses on exploring intention-related contextual information in the surrounding environment to perform intention awareness (IA) [1][2], helps robots to implicitly understand and proactively react to the elderly's personal needs in activities of daily living (ADL) [2][3]. Compared with other IA approaches based on action/action sequences [4][5], biological/psychological signals [6][7], and plan/activity patterns [8][9], the consideration of the environmental context could decrease the dependence on user involvements in IA [1][3]. With minimal user requirements, CSIA could naturally infer the implicit intentions of the elderly who often suffer from motion/psychological impairments [3][10].

Currently, CSIA has been broadly applied in various ADL. By integrating the surrounding context information such as relative distance to obstacles/human and location, a smart indoor navigational robot autonomously adjusted its route and destination [11][12]. By considering time, the surrounding people, and activities a human wishes to perform, a context-aware reminder intelligently reminded a human of different issues [13]. Combining the location, time and user-attended destination, a smart monitoring robot assessed the physical and psychological statuses of the elderly [10][15]. Integrating context information like time, location and the surrounding objects while also taking into account current human activities, an assistive kitchen robot inferred human intentions and then timely cooperated with the human [16][17][18].

Although CSIA plays a crucial role in providing natural assistance for ADL, challenges still exist in current CSIA. First, knowledge stored in a local database is limited for robots to perform IA in various situations. This limitation constrains the completeness and comprehensiveness of robot cognition towards the surrounding world [2]. This limitation in knowledge (or 'gap') also influences the accuracy and robustness in trained familiar situations [2][16]. Moreover, the database of CSIA is passive, lacking the active adaptation to various situations. Robots couldn't proactively check and compensate their knowledge shortage to tackle untrained new situations. Actively updated knowledge is needed to obtain a good understanding of the intention-related situations [3].

In this paper, the research objective is to actively acquire broad commonsense knowledge through web query to perform CSIA in robot-assisted ADL. Our research investigates the task 'recognizing the intentions (e.g. cup-related intentions 'drink/wash') by using the environmental context (e.g. 'room temperature'). WikiHow (www.wikihow.com), which contains numerous detailed descriptions of 'how to do' and their correlated life scenarios, is used to largely increase the knowledge source that a robot can learn such that the robot gains a good understanding of the real world. Commonsense knowledge includes object affordances (a relation of an action/activity/intention and a specific object used to predict the next action/activity [19]). For example, the cup-correlated affordance is drink/wash and the intention-context correlation is drink-hot day. The potential intentions are generated from the affordances; and their probabilities are calculated based on the correlation strengths. We also create principles for the robot to learn new knowledge when dealing with new situations. In the information processing process of web query, the natural language processing (NLP) tools such as Stanford Parser (nlp.stanford.edu:8080/parser), ConceptNet5 (conceptnet5.media.mit.edu) and WordNet (wordnetweb.princeton.edu) are adopted to obtain a comprehensive understanding of the natural language descriptions on webpages.

The approach proposed in our paper is named 'WebIA' (shown in Fig. 1), which actively addresses open challenges caused by the knowledge gap in CSIA by using the Web query approach. WebIA is designed with a self-learning framework [20][21], which could acquire the knowledge from the Web and actively update the existing knowledge throughout the whole application stage. The architecture of WebIA is shown in Fig. 1. We first identify the human-attended objects by using CamFind (www.camfindapp.com, a web-based commercially viable object recognition server). Then the object is compared with existing knowledge in a local database to judge whether it is a new object. If the identified object is new, then the robot queries WikiHow to get the object-related affordance knowledge which is used to generate the potential intentions (an intention usually consists of several actions). Based on the potential intentions and the object, the robot queries the Web to get the relevant intention-context correlations with specific correlation strengths. Probabilities of each intention is

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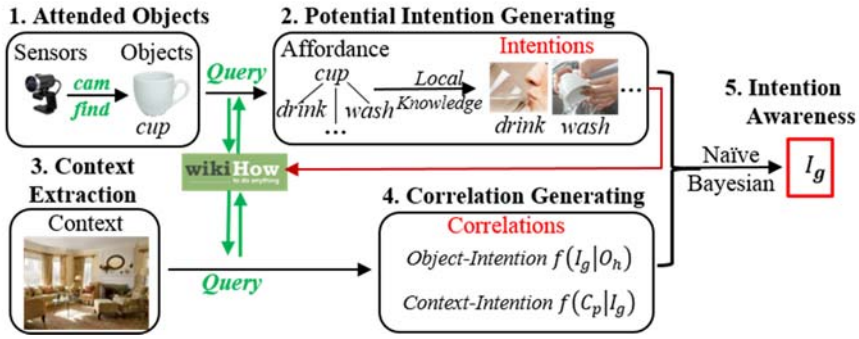


Figure. 1. Intention Awareness Architecture using WebIA Approach

calculated by a Naïve Bayesian Network (NBN) algorithm and the intention with the highest probability is considered to be the most likely human intention. The robot then provides the corresponding assistance for the user.

In this paper, we mainly evaluate two crucial characteristics of the WebIA approach. First, we verify that WebIA is able to effectively explore the commonsense knowledge through web query and confirm that, based on the explored commonsense it can accurately predict human intentions. Second, we also verify that when a robot encounters with untrained new situations, WebIA provides the robot the self-learning ability, which proactively explores WikiHow to fill the knowledge gap, in order to deal with these new situations. In the self-learning process, some existing knowledge in the local database will be refined. This self-learning process would be conducted throughout the whole application process. Our main contributions in this paper are:

- Through web query, the commonsense knowledge of object affordances and intention-context correlations has been increased greatly.
- By proactively filling the knowledge gap, a robot is endowed with the self-learning ability that allows it to acquire new knowledge in untrained new situations. Therefore, the local database would be refined, allowing it to be more adaptable to the actual application environment.

II. Related Work

Information from the Web has been extracted to create various knowledge databases. Instructive websites such as cooking.com, ehow.com and wikihow.com were used to collect procedural knowledge, such as step-by-step executable instructions, for robots' task execution [22][23]. The general webpages on the World Wide Web were processed to generate tailored biographical knowledge such as the biographies of artists to establish personalized database [24][25]. Semantic network websites such as ConceptNet5 and OpenCyc (http://sw.opencyc.org/) were used to collect the general conceptions, events, and their semantic graphs in the real world to get better understanding of textual language written by human [26][27]. Entity description websites such as Google Image (http://www.google.com/imghp), 3Dwarehouse (sketchup.google.com/3dwarehouse) and Amazon (www.amazon.com) were used to collect valuable object-related information such as appearance, configuration, function and price [23][28][29]. Encyclopedia websites that contain descriptions towards various life scenarios such as www.wikipedia.org [2] were used to explore human activity-related environmental information (this information is generally defined as 'context') such as spatial relations between objects, the meaning of text in the pictures and object status-action relations, etc. Encyclopedia websites were also used to collect facts about various entities and perform named-entity disambiguation by which the entity attribute information was linked to the targeted entities [32].

Currently, intention awareness through web query is still a relative new area. A large amount of valuable context-intention correlation information hiding in the Web is waiting for us to explore.

III. WebIA

Our novel web-based IA approach, WebIA, improves robots' cognitive ability by endowing them with vast commonsense knowledge to effectively infer human intentions. WebIA could also endow robots with a self-learning ability to refine knowledge through the whole application process to accurately infer intentions in both familiar and unfamiliar situations.

A. Commonsense Knowledge in WebIA

Commonsense knowledge describes the general correlations among objects, environmental context, and human intentions. By using their life experience, humans make reasonable inference in various situations. For example, when someone places a cup in a sink she/he may want to wash it. In our research, we focus on endowing robots with commonsense to infer intentions in a human-like way. We combine the probability values with entity/event/intention correlations to create specific commonsense for a robot in order to let it know the likelihood for the happening of involved entities. For example, when the cup is placed in a sink, how likely it would be washed. By gaining this type of commonsense knowledge through web query, robots' limited local database would be expanded and refined to perform better IA; then appropriate and natural assistance would be provided by robots.

Human-attended objects are closely connected with human immediate intentions. For example, when a person is frequently looking at a cup and a water machine, she/he may feel thirsty. Given object affordances describe the object-action correlations and an intention normally consists of several actions, we use affordances AF to generate information of potential intentions I_g(the g − th intention, g = 1,2, … , G) . Assume the attended objects are O_h(the h − th object, h = 1,2, … , H) ; through web query, the likely actions are A_v (the v-th action, v=1,2,…,V) and the

affordances AF are generated as O_h- A_v. Based on affordances O_h- A_v and the Web, we get potential intentions I_g and the object-intention correlations are $f(I_g|O_h)$ (the probability of the intention I_g when objects O_h is involved).

Environmental context usually strongly indicates human intentions. For instance, 'the day is hot' often makes a human 'thirsty and desire to drink'. Through web query, we get the context-intention correlations $f(C_p|I_g)$ (the probability of the p-th context feature C_p if the g-th intention occurs).To avoid the irrelevant context information, a threshold ∂_O for object-intention correlations $f(I_g|O_h)$ and ∂_C for context-intention correlations $f(C_p|I_g)$ are set to perform feature selection. Correlation strengths less than ∂_O or ∂_C are filtered out. The overall knowledge representation for the commonsense knowledge is shown in Fig. 2.

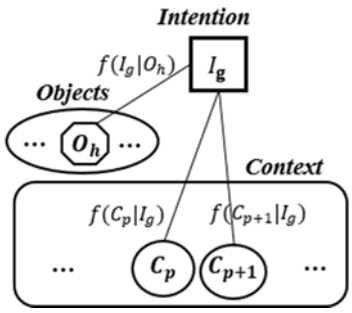


Figure. 2. Commonsense Knowledge Structure

B. CSIA Methodology

To effectively infer human intentions, a Naïve Bayesian Network (NBN) algorithm is adopted in the CSIA model due to its high classification efficiency with a 'bag-of-word' way to handle numerous involved features. In a specific situation with attended objects O_h, environmental context C_p, and commonsense knowledge, the most likely intention is calculated by equation (1). In IA process, using attended objects O_h through web query, the potential intentions I_g and the intention-object correlations $f(I_g|O_h)$ are generated. Then through the web query again, the environmental context C_p set and context-intention correlations $f(C_p|I_g)$ are generated. Probabilities $f_{NBN}(I)$ for intentions I_g are calculated and the intention I_{max} with the biggest probability value would be considered to be the true human intention. The calculation process is shown in Fig. 3.

$$f_{NBN}(I_{max}) = max_{\,g=1,2,\ldots G} \prod_{h=1}^{H} f(I_g|O_h) \prod_{p=1}^{P} f(C_p|I_g) \quad (1)$$

C. Web Query for Commonsense Knowledge

In the commonsense knowledge learning process, we establish the commonsense knowledge database by querying WikiHow. WikiHow currently contains more than 180,000 articles describing numerous daily scenarios correlated with human intentions. For example, in the description of 'How to Drink on WikiHow', it describes an object 'cup' is connected with the action or intention 'drink'. When intention 'drink' takes place, it is usually accompanied with the environmental context such as 'table is clean' or 'water intake is low'.

1) Natural Language Processing (NLP)

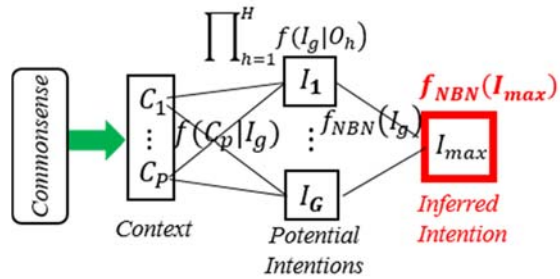


Figure. 3. Intention Awareness Methodology

Through web query, tailored knowledge embedded in semantic texts of numerous webpages is acquired by a natural language processing (NLP) method. To analyze sentence structures and dependence relations between semantic words, we apply the Stanford Parser to assign various words with various tags to distinguish their syntactic categories and phrases. First, the Stanford Parser labels the words with part-of-speech tags (PoS) like VP (Verb Phrase), NP (Noun Phrase), PRPS (Possessive pronoun), WRB (Wh-adverb), TO (to) and S (Sentence). Second, the hierarchy binary dependent relationships between words would be detected like S: VP-NP (Sentence: Verb-Noun.), PRP-NN (Personal Pronoun-Norm), etc. For instance 'On a hot day, drink with ice' would be analyzed as {On/IN a/DT hot/JJ day/NN ,/, drink/VB with/IN ice/NN}. The dependence relations are analyzed as {prep(drink, On); det(day, a); amod(day, hot); pobj(On, day); root(ROOT, drink); prep(drink, with); pobj(with, ice)}. We detect objects/actions based on words' tags norm/verb. For affordance generation, besides the fact that the object and action should appear in the same sentence, we also require that they should have dependence correlations. For example, only if drink is dependent on a cup would the cup-drink affordance be established. Through dependence relations prep(drink, on), pobj(on, day), and amod(day, hot), we establish the environmental context-intention correlation 'hot day-drink'.

2) Information Retrieval

For the AF extraction, we query WikiHow with attended objects $\{O_h\}$ to get related actions A_v which are used to get the potential intentions $\{I_g\}$ based on existing knowledge (e.g. cup-drink/wash/…). For the context extraction, we query WikiHow with keywords $\{I_g\}$ to get related environmental context $\{C_p\}$ (e.g. drink-water intake is low; wash-after dinner).

For correlation strength calculation, we use a statistical method to process knowledge extracted from web. The stronger the context-intention correlation C_p-I_g is, the more frequently the context C_p would appear together with the intention I_g. We assume that with sufficient intention-related scenarios, the frequency of the appearance of object/ environmental context would be approximately equal to the probability that the object/environmental context appear in the real world. For the object-intention correlation strengths $f(I_g|O_h)$, querying WikiHow with the keywords intention-object pairs $\{I_g, O_h\}$ gets the number an object would be used $n_{I_g-O_h}$ in the related situations (e.g., drink-cup: $n_{I_g-O_h}$.); For the context-intention correlation strengths $f(C_p|I_g)$, querying WikiHow with the keywords context-intention pairs $\{C_p, I_g\}$

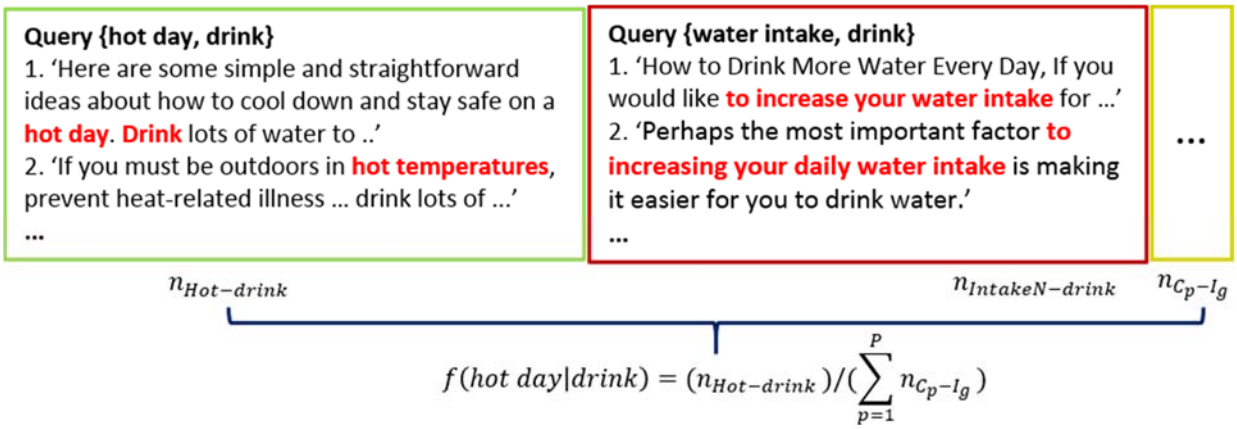


Figure. 4. Web Query Process

gets the number $n_{C_p-I_g}$ in the related situations (e.g., hot day-drink: $n_{C_p-I_g}$). Final calculation processes for correlation strengths are shown in equations (2) and (3). An example of the web query process is shown in Fig. 4.

$$f(I_g|O_h)=n_{I_g-O_h} / \sum_{g=1}^{G} n_{I_g-O_h} \quad (h=1, 2, \ldots, H) \tag{2}$$

$$f(C_p|I_g) = n_{C_p-I_g} / \sum_{p=1}^{P} n_{C_p-I_g} \quad (g=1, 2, \ldots, G) \tag{3}$$

3) Self-Learning of Commonsense Knowledge

In general trained situations (defined as 'Old' situations), the pre-defined commonsense knowledge is used for IA; however untrained new situations may take place when a robot assists humans in the real world. A robot should have the self-learning ability to proactively update its knowledge to adapt to these untrained new situations.

Self-learning includes new situation detecting and self-tailored knowledge refining. To be treated as a 'New' situation, the object name should not be included in the existing database and meanwhile isn't a synonym of an existing entities. Each time an object is encountered, the detected object name would be compared with objects in the local database. For instance, 'glass/mug' is the synonym of 'cup'. If any of them appears, it would be considered as an old situation. 'Cup of coffee', which consists of the objects 'cup' and 'coffee', would be considered as a new situation because a cup with coffee hasn't been trained before and the existing knowledge is about a cup in general uncombined with other objects. Merely based on the general cup-related commonsense, the IA performance would be influenced.

When new situations are found, web query would be performed to update the corresponding intention-object/context and their correlations. The query key words would be (new object 1, new object 2, …). For example, for the new situation: cup of coffee, the query words would be (cup, coffee). The information retrieval process is the same with that in previous section. After retrieval, the corresponding knowledge would be updated.

IV. Evaluation

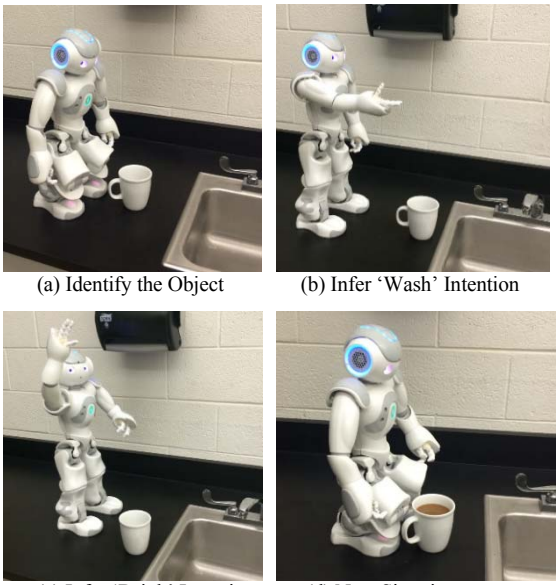
Two main characteristics of the WebIA approach were evaluated by using a humanoid NAO robot to infer cup-related human intentions in simulated ADL situations. First, the effectiveness was evaluated by using the web-generated commonsense knowledge to infer human intentions. We first compared the knowledge generated through the WebIA approach with the knowledge collected from volunteers' questionnaires. Then based on the web-generated knowledge, IA was performed in volunteer-designed situations and IA results were assessed. Second, the self-learning ability was evaluated by generating the new knowledge through web query to perform IA in new situations. A new situation was intentionally created for the NAO robot. For this new situation, it proactively queried WikiHow to collect the corresponding knowledge. IA was conducted in this new situation with improved performances.

A. Evaluation for WebIA's Effectiveness

In this section, the scenarios were designed as 'the human-attended object, cup, was identified. The robot needed to infer his/her intentions based on its commonsense and the current surrounding environment' shown in Fig. 5 (a), (b) and (c).

To generate the commonsense knowledge correlated with the object cup, 1470 WikiHow webpages were queried. In these 1470 webpages, 180 webpages were queried to get object-related intentions and environmental context features. 570 webpages were queried to get object-intention correlations. 720 webpages were queried to get context-intention correlations. We also surveyed 120 volunteers with different ages and genders. They were split into two groups: a training group and a verification group. In the training group, 100 volunteers were required to establish the correlations between an environmental context set and cup-related intentions. Questions were designed as 'Water Intake Enough □Wash □Drink □None; Not Enough: □Wash □Drink □None.' In the verification group, 20 volunteers were required to design 40 different cup-related scenarios in which the specific intentions would happen. Scenarios were set as {drink: low water intake, hot day, …}. In these 40 scenarios, 20 were designed for the 'wash' intention and 20 were designed for the 'drink' intention. These volunteer-designed scenarios were applied on NAO to perform IA.

The cup-related intentions were categorized as {Wash, Drink, Others}. The environmental context selected for our experiment were {Close to meal time (MealC); Cup location is close to sink (SinkC); the day is hot (Hot); Water intake isn't



(a) Identify the Object (b) Infer 'Wash' Intention

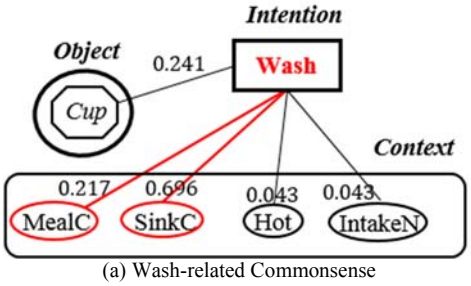
(c) Infer 'Drink' Intention (d) New Situation

Figure. 5. NAO Robot performs IA. (a) The object cup has been identified by NAO. IA was performed based on the commonsense knowledge generated from WikiHow. (b) NAO points forward to the sink when the inferred intention is 'wash'. (c) NAO waves its right hand to notify the caregiver when the inferred intention is 'drink'. (d) The new situation 'cup of coffee' is detected; then NAO gains new knowledge by querying WikiHow to perform IA in this specific situation.

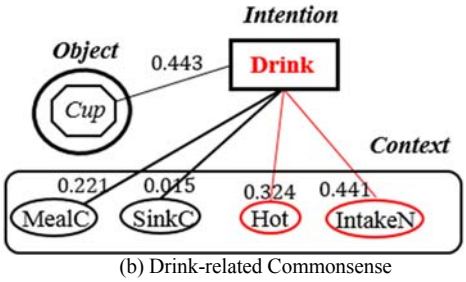
enough (IntakeN)}. Ambiguous context would be processed and classified by ConceptNet5.

Commonsense knowledge results are shown in Fig. 6 and Fig. 7. WashW and DrinkW were results generated through web query. WashS and DrinkS were results generated from survey. In the results, correlation distributions generated by both approaches were consistent. This consistency shows that web-generated knowledge is reliable. Moreover, comparing correlation values among these different context features, the correlation values of {MealC-Wash, SinkC-Wash, Hot-Drink, IntakeN-Drink} were significantly greater than others which is highly consistent with common human life experience. The intention-object correlations are show in Fig. 8(the old situation). The probability of drink (0.443) was relatively higher than wash (0.241), which indicated that in our daily living, drink happens more frequently than wash.

In volunteer-designed 40 scenarios, intention probabilities were calculated, shown in Fig. 9. When the IA result was consistent with volunteers' designated intention, IA was considered as a success. In 20 'wash' intention situations, 17 were successfully inferred. In 20 'drink' situations, all 20 were successfully inferred. The high accuracy showed that the WebIA approach is effective for intention inference.

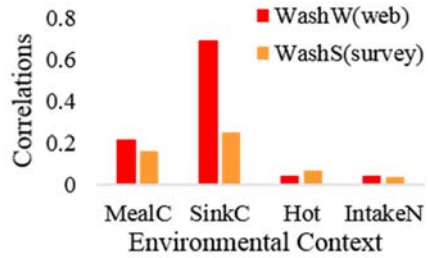


(a) Wash-related Commonsense

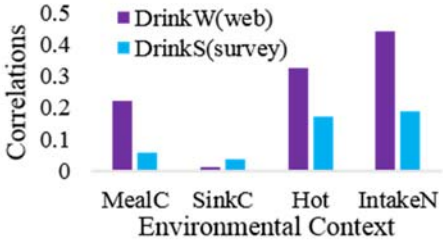


(b) Drink-related Commonsense

Figure. 6. Cup-related Commonsense Knowledge Representation



(a) Wash-related Correlations



(b) Drink-related Correlations

Figure. 7. Comparison of Correlations Got by Web(W)/Survey(S)

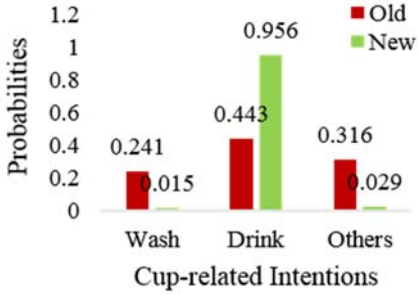


Figure. 8. Intention Probability Adjustment from Old to New Situations

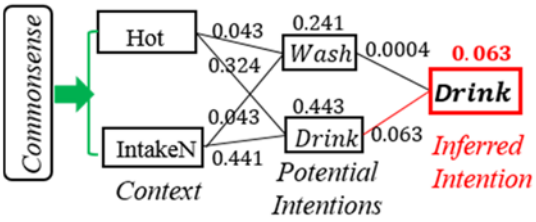


Figure. 9. Detailed IA process in One Situation

B. Evaluation for Self-Learning Ability

In this section, we intentionally created a new situation 'cup of coffee' (shown in Fig. 5(d)) which was an untrained new situation for the NAO robot in order to test its learning ability endowed by WebIA. When the new situation was detected, the self-learning process was triggered to collect new knowledge by querying WikiHow. After querying 570 webpages, potential intentions were still {wash, drink, others}.

Therefore, the intention-related context remained unchanged. New intention-object knowledge was though updated as shown in Fig. 8 (the new situation), where the intention probabilities were adjusted greatly. The previous 40 scenarios were then applied to NAO again for IA.

Among the 40 volunteer-designed scenarios which were inferred as 23 drink and 17 wash using the old knowledge, all the 40 scenarios were inferred to be drink using the new knowledge. That is, when the attended object was a 'cup of coffee', the drink intention was significantly higher than the other intentions. In previous web query process, knowledge only for general cup-related situations were gained while the coffee & cup-related situations were ignored. If we just used the general cup-related knowledge to perform IA in new scenarios, the IA performance would be reduced. This performance improvement shows the importance of the new knowledge learning ability.

V. CONCLUSION

In this paper, we presented a novel approach, named WebIA, which infers human intentions through web query. We demonstrated that by using WebIA, a robot could generate vast and valuable commonsense knowledge about the correlations among object, environmental context, and human intentions. This commonsense knowledge could help robots to improve their understanding towards the real world. Moreover, we also have verified that WebIA could endow robots with the self-learning ability to proactively refine existing knowledge and perform IA in untrained situations. In future, we will explore more websites like Wikipedia to extract information and further evaluate the WebIA in real world. The method for evaluating the query effectiveness will be considered.

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