Human-Robot Dialogues for Explaining Activities

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Abstract The paper focuses on issues related to dialogue modelling that allows communication between users and social robots, on topics that concern experience and knowledge of people in service industries. We discuss dialogue models based on goal-directed ontologies, as well as architectural aspects of a dialogue system that enables humans to communicate with the robot partner and engage in interactions concerning tasks and activities related to elder-care services.

1 Introduction

In present-day societies with aging populations and changes in family structures, there is a need for innovative solutions that will tackle issues dealing with the increasing medical and long-term care costs and diminishing number of carers, while supporting independent and healthy living. Large-scale plans and frameworks have been initiated to support elder care and medical care services, and active discussions concern the use of AI research and novel technologies such as robotics and cloud services, to support greater operational efficiency. Studies have focused on the adaptation and integration of technologies into various service systems, see an overview in Watanabe and Mochimaru (2017) who discuss the impact of technology-assisted service systems in the industrial and societal levels, and also how to generalise such technologies for multiple service systems. The digitalized IoT environment calls for interactive solutions, and thus applications that implement advance AI technology including dialogue models, speech and language technology, as well as cognitive science are pertinent. Projects such as the EU funded *Empathic* (http://cordis.europa.eu/project/rcn/212371_en.html), the Japanese *Robotic Devices for Nursing Care* (http://robotcare.jp/?lang=en), or *Metese* (http://www.vtt.fi/ sites/METESE) are examples of activities that aim at developing and exploring innovate new paradigms, platforms and services especially for senior citizens.

Robotic care devices have been developed to assist care-takers and elder people in daily tasks such as walking, eating, lifting, and reminding of important events and tasks, as well as providing distance monitoring or support for safe independent living. Various types of communication devices are also available, and a wide range of sociable small robots (Paro, Tapia, Sota) exists for entertainment and companionship. Much research goes into social robotics with a human-centred view as the core concept, supported by speech and dialogue technology for interactive applications which enable natural language dialogues with the user. They can provide useful information or just talk about interesting topics like WikiTalk (Wilcock and Jokinen 2014), ERIKA (Milhorat et al. 2017), and various QA systems, or aim at home assistance like commercial intelligent speakers.

Our focus is on service industries such as elder-care, nursing, and education, for which social robot applications can initiate novel services and work procedures with the help of their flexible interaction capabilities. For instance, an interactive robot can advise the care-taker of the current state of a patient or instruct a trainee health-care professional about how to perform a task, what needs to be considered for the well-being of a person, and what risks are included. Furthermore, activities that promote health and create community through hobbies such as dance and music, can also benefit from interactive robot applications which offer novel ways to learn and communicate. Our research goals are summarised as:

1. gathering and modelling of knowledge related to activities that underlie human social behaviour, especially in service scenarios,
2. interaction modelling that enables humans and social robots to interact with each other in a natural and multimodal manner,
3. exploring novel ways in which social robots can be used to improve the quality of life of citizens and the quality of services in various industries, create a community through shared tasks, and offer opportunities to learn and communicate.

Our work focuses on exploring the design and architecture for human robot dialogues that deploy ontological information about actions and activities to explicate the correct sequence of actions to the user (Jokinen et al., 2017). In practical care-work, such communicating robot agents can be of valuable help in providing useful information to the users, assisting novice care takers in their tasks or instructing them how to do a particular task, or just to provide a companion to work with. The user can thus have access to the knowledge of the relevant actions and activities for certain tasks, shared by the care workers in elder care facilities. By engaging the user in interaction, the robot can provide instructions for the correct procedure to perform a task, help the user in searching for certain information on a task, or to confirm the user’s own knowledge of how to do a task. Accessing the knowledge via a spoken dialogue system has the advantage of allowing instruction and interaction even though the user is busy acting and using his or her hands.

The challenge for such robot agents is that they need to be furnished with knowledge that enables them to communicate in a flexible and natural manner: they require rich knowledge of the tasks and activities in various kinds of care-taking and every-day situations, and of the participants and the context in which the dialogues take place. For this, it is essential to gather and analyse information on the ways people act and interact with fellow humans and with intelligent devices, and on the knowledge they possess of the facts, events, and objects in caretaking tasks. By systematizing human knowledge into ontologies and creating dialogues based on these structured knowledge bases, it is possible to reason about appropriate actions and create natural interactions to instruct and guide the user through the task. By observing human users interacting with a social robot, it is also possible to gain further information about the dialogue strategies and functionalities that affect the usefulness of such systems in practice. The ultimate goal, however, is to expand the robot's knowledge by learning: to enable an intelligent robot to learn such knowledge through its interaction with the users, manipulating objects, and grounding knowledge to the physical world (Senft 2017).

In this paper, we discuss the first step of this challenging aim, a framework for a knowledge-based dialogue model that enables interaction between users and services. The paper is structured as follows. We start with a survey of earlier research on dialogue systems and knowledge explication, continue with a presentation of our system that uses a Nao robot to explain elder-care service knowledge.

2 Knowledge and interaction concerning actions and activities

2.1 Dialogue systems

Three different types of dialogue systems can be distinguished depending on the knowledge that they can reason about. The usual distinction is between open and closed-domain systems, with the former referring to chat-type systems which can converse on any topic and the latter to limited task-based system which focus on certain task. Besides intelligent speakers that are meant to assist users at home in every-day situations, other chat-systems enable open-domain conversations with the user on a wide range of topics without any particular task to be completed (e.g. Otsuka et al. 2017; Banchs and Li 2012). WikiTalk (Wilcock and Jokinen 2014, 2015) uses Wikipedia as the knowledge source to support open-domain dialogues. It is multilingual and able to present information on any topic that is of interest to the user in English, Finnish, and Japanese. IBM Watson backs interaction with an impressive QA system and allows users to design their own domains. However, the free version restricts the number of "concepts" to 35, which does not scale up to full open-domain dialogues. A third type of dialogue system is a multidomain system which has a task-based approach but can use several knowledge-bases and talk about different topics. For instance, a rule-based, distributed architecture is described in Komatani et al. (2006), while the PyDial system explores multi-domain dialogues and how multiple domains can be included in an end-to-end statistical dialogue system (Budzianowski et al. 2017).

Knowledge-based solutions combine digital resources with advanced information search and summarization techniques to equip dialogue systems with encyclopedic knowledge that allows the systems to extend their interaction capabilities. The early dialogue systems (e.g. PLUS, TRAINS, ARTEMIS) were based on manually created ontologies and plan-based dialogue models, but modern technology, which can be used to collect, manipulate, and deploy ontologies needed for reasoning is not very commonly used in projects and systems. An exception is the current EU project KRISTINA (http://kristina-project.eu/en/) which uses extensive knowledge sources and an ontology-based dialogue model.

Besides ontologies that describe the knowledge, the system needs reasoning capabilities to infer about relations between objects and actions. An inference engine supports the dialogue manager in its task of reasoning about the human intentions, as well as planning of appropriate responses. An example of a planning framework in the context of social robots is the Human-Aware Task Planner (HATP) (Lallement 2014) which extends the traditional hierarchical planning with "social rules" that specify acceptable behavior in the domain.

2.2 Task-ontologies for elder-care

Various work situations in elder care, education, etc. include tacit knowledge of how to deal with various activities. In order to improve services, it is essential to gather and analyze knowledge that people possess when working in these kinds of workplaces and make implicit knowledge explicit. For this purpose, we have constructed task hierarchies that describe knowledge about the common tasks and actions in care-taking. Instead of hand-crafted ontologies, the knowledge-base was built with the help of the care-takers themselves, using a community-sourcing method of co-creating knowledge. The focus was on the procedural knowledge of how particular care supporting tasks are performed, and what are the risks involved. The knowledge was collected in workshops where the people who work in the area could describe the work and provide information about risks and proper ways to conduct the tasks. The explication process (Nishimura et al. 2017) was goal-oriented so that the knowledge could be structured into a hierarchy which shows how the various tasks are interrelated and dependent on each other. In this way we were able to use the knowledge within the community and capture knowledge which is often implicit in the cooperation of the workers.

The task graphs currently consist of eight of the so called *direct care support tasks* in elder care services. Each of the eight tasks can be regarded as the main goal for which the graph shows subtasks and action sequences that are needed in order to reach the goal, i.e. to perform the task successfully. All subtasks are obligatory to reach the goal, and the graph edges specify if they need to be performed in the given order or if they are commutable. Each subtask can also function as a goal and have subtasks of its own which describe the actions relevant to reaching that goal. Altogether there are 1746 tasks and subtasks, and they are stored in a json-type database. As the graph structure represents the plan for performing a certain task, there is no need for a reasoner. The ordering and subtask information is already included in the graph, and the knowledge can be stored in a more lightweight way.

Left side of Figure 1 lists the eight main tasks, i.e. the upper-most goals for the system to execute, in the order of descending number of sub-tasks included in the task, and the right side visualizes a part of the task hierarchy related to the task of transfer assistance. The hierarchy shows action sequences for changing a person's position assuming that the person is lying in the bed (there are separate action sequences if the person is sitting in a chair or wanting to stand up – these are not shown in the figure). The options for changing a person's position include a choice of moving the person horizontally or to a side-lying or seating position, to sit on a chair, or stand up, and each of them has its own subtasks. For instance, sub-tasks of the option of moving the person horizontally (not shown in the graph) include tasks such as moving the pillow, reducing friction, moving the person's upper body by supporting head and shoulders, and moving lower body by moving legs.

Some of the tasks are regarded as preconditions and post-actions for the main task. They are marked with an arrow pointing to the dependency relationship. For instance, for the task of changing a person's position there is a need to check the context and the person's situation by assessing if the person is conscious and able to move (these actions are not shown in Fig.1) as well as adjusting the height of the bed (shown to the left of the "change position" node). The post-actions are needed to finish off the task properly, and in the case of changing a person's position, these include taking care of the person by considering their psycho-physiological ability and assessing their condition (shown to the right of the "change position" node), as well as adjusting the height of the bed back to the original (not included in the figure). Fig.1 also shows that the task to consider the person's (psycho-physiological) ability requires task hierarchy also includes risks associated with the tasks, and e.g. the task of getting a person stand up brings in a risk of the person falling due to postural hypotension.

Care support	# of actions
Feeding	140
Oral care	170
Position change	197
Dressing	226
Moving	236
Transferring	247
Bathing	253
Excretion	277

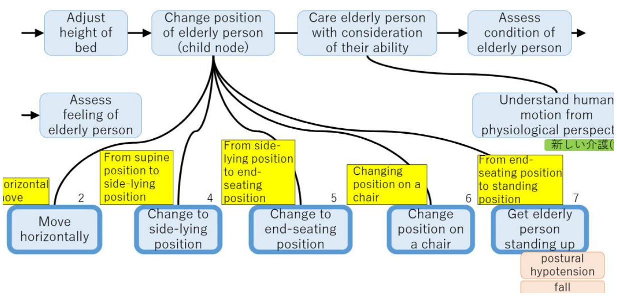

Fig. 1. On the left: a list of support tasks and the number of actions and subtasks for each type. On the right: a subtree of the task hierarchy depicting a caretaker's knowledge of how to change a position of an elderly person (translated into English). Each of the five subtasks (circled nodes) have their own subtasks (not shown in the figure), and the last one is also associated with a risk (reddish box). The yellow boxes describe the action involved.

Dialogues among the various types of communicating agents (humans, robots, and intelligent devices) require understanding of how knowledge about smart objects and relevant activities in such ambient environments affect multi-agent interactions, and what kind of consequences such dynamic IoT networks impose on the shared contexts in human interactions. Accompanying ontological data with sensor data collected in living laboratories, we can contribute not only to the development and verification of IoT sensing technology, but also to the study of different locations and workplaces as spaces that serve for understanding human activities in ubiquitous contexts. The goal is thus to explore “non-tangible thing-centric” AI technology and the changes required when moving from product-based knowledge to service-oriented and human-centred knowledge.

2.3 Knowledge and knowledge explication

Knowledge is often associated with explicitness, the agent’s conscious deliberation and ability to exert voluntary control on actions and communicate about what they know of. The ability to produce conceptual representations of the actions and events in the physical world actuates symbolic reasoning and enables agents to talk about their experiences: actions and events are referred to by concepts which can be mapped to natural language expressions. Much of the knowledge is also implicit, i.e. used without conscious effort or deliberation, and not always verbalizable. For instance, many everyday activities such as recognizing faces or using language, or learnt skills like riding a bike or playing guitar, are based on knowledge which is not possible (or even desirable) to be described in detail.

The agent’s conscious actions are aimed at changing the current state of the world into another state, the goal with certain desirable properties, and they presuppose intention and deliberate planning. However, the agent need not be conscious of all the details of the action plan or of the correct procedure to reach the intended goal. The agent may not know some pertinent facts or be able to express verbally how to perform an action, yet be able to act smoothly and accurately, or the agent may be able to verbalize an action, yet not be able to perform it in a sophisticated manner. The agent’s experience of the world is also mediated by processes that the agent may not be aware of due to sensor-level limitations in perceiving the world and cognitive inability to find suitable interpretations for the perceived events.

The agent’s knowledge and understanding of the world can thus be partitioned into different types. We distinguish different types of knowledge by drawing distinctions along two separate dimensions: the *representation* of knowledge, and the agent’s *awareness* of the knowledge. The first dimension is based upon the fact that representational issues are important for the deliberation of actions: following (Clancey 1997) we say that representations are tools for inquiry. The second dimension refers to the agent’s consciousness of its own actions, of the events and objects in the world, and self-reflexion of knowing that it knows. These two dimensions are consistent with the recent views of memory based architectures (Baxter et al. 2011) and that all knowledge is embodied (Varela et al. 1992). They facilitate talking about the different types of knowledge available when building computational systems for knowledge explication.

We use the term *explicit* to refer to the knowledge that the agent can explicate: the agent is aware of possessing the knowledge and has a representation for its verbalisation. The term *implicit* is used as a general term to refer to all non-explicit knowledge that the agent cannot explicate either because of not being aware of it or having no appropriate conceptual representation for it. Implicit knowledge can be further divided into three subtypes: *tacit*, *action-centred*, and *unknown*. *Unknown* is the exact opposite of explicit: the knowledge cannot be explicated since the agent is unaware of it and accordingly, has no representation for its verbalisation. It can be made known (explicit, tacit, or action-centred) by learning or discovery.

The term *tacit* is used to refer to the knowledge that the agent is vaguely aware of but has no appropriate representation that would allow the agent to talk about it. Tacit knowledge is implicit in the sense that it is not fully known to the agent but can be made explicit by explication, i.e. given a conceptual representation that allows the agent to talk about it. For instance, a novice care taker can be said to have tacit knowledge of the care support tasks, while a senior care taker or a robot can help the apprentice to become aware of this by explaining how to do the care taking tasks. It is worth pointing out that explication presupposes conceptual representation that enables the agents to verbalise their knowledge. The term *action-centred* refers to knowledge which the agent is aware of, but which is not directly available for the agent to be explicated. Automatic actions without conscious effort like bike riding or talking are typical examples of action-centred knowledge: they can be learnt by imitation and practice, but they avoid clear conceptualization and are beyond the effort of explication. The different knowledge types are shown in Table 1.

		Conceptual representation	
		Yes	No
Agent's awareness	Yes	Explicit knowledge	Action-centred knowledge
	No	Tacit knowledge	Unknown knowledge

Table 1 Knowledge types. All non-explicit knowledge is implicit knowledge, while unknown knowledge can be made known by learning or discovery.

Considering the knowledge graph of Fig.1, the nodes with child nodes are explainable by referring to the children, while the terminal nodes are inexplicable within the given knowledge. Consequently, the robot agent can explain a task with the help of the subtasks (including preconditions, post-actions, and risks), whereas the human agent, if not already aware of the subtasks, can be made aware of them when learning the task by verbal explanations. In our context, a proper way of lifting the person up is action-centred knowledge as it contains detection of the person's body posture and reaction to the body movements during the lifting itself, the verbal characterisation of which is difficult. In fact, it shows the limitations of verbal knowledge transfer: implicit action-centred knowledge (using the terminology above) is not possible to be explicated, since it presupposes experience of the actual execution of the action, not just conceptual representations of the action.

It should be noticed that the nodes in the knowledge graph in Fig.1 refer to complex tasks and are not basic actions in the same sense as represented in common ontologies (e.g. in OWL) in terms of Subject-Predicate-Object triplets. Rather, each node hides a large amount of human knowledge about the specific act such as lifting the person up or adjusting the height of the bed. As discussed in Section 2.2, the graphs are not action or task hierarchies, but represent goal-oriented knowledge of the community of how to perform the care support tasks, while the nodes are interpreted as steps in the procedure which explains how to reach this goal.

3 Dialogue modelling for knowledge explication

3.1 Architecture

Following the Constructive Dialogue Modelling (CDM) framework (Jokinen 2009), we assume that conversational interactions are cooperative activities through which the interlocutors build a common ground. The agents (humans and robots) pay attention to social signals that indicate the partner's awareness of the communication (contact and perception), and they are also engaged in the interaction (via understanding and reacting to the exchanged information). Figure 2 presents the CDM-based architecture, see more details in Jokinen and Wilcock (2013).

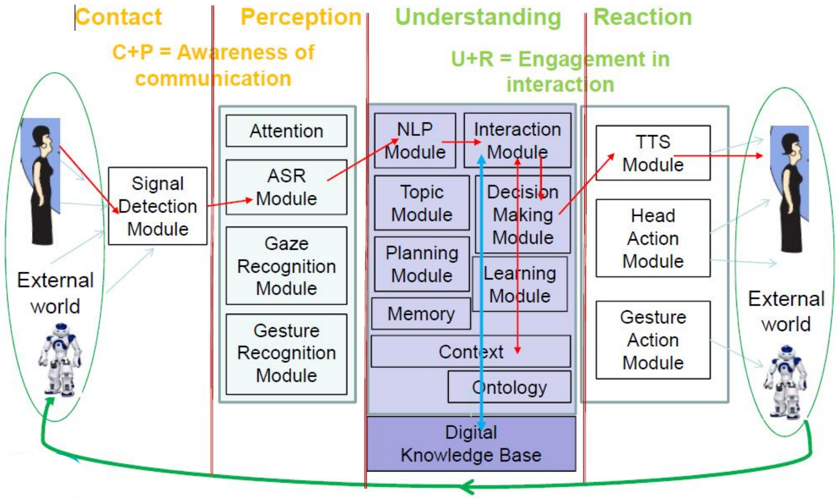

Fig. 2. System architecture in the Constructive Dialogue Model framework, following Jokinen and Wilcock (2013). The red arrows show a flow of information from the user's speech signal through some of the modules belonging to Contact, Perception, Understanding and Reaction.

3.2 An example

The system is implemented in the Nao robot platform (Softbank robotics). Speech recognition is done by the Nuance speech recognizer which comes with the robot and is based on key-word spotting. Dialogue engine uses QiChat, and each of the eight main tasks functions as a possible topic. The robot's reaction is based on the context given by the topic, the action sequence representing the subtasks for the current task, and the words expected to be found in the user utterance. The robot talks both Japanese and English. Figure 3 shows a session shot of a user interacting with the robot and an example dialogue.

U: Hello Yuki!
N: Hi Kristiina! How can I help you today?
U: Well could you tell me how to change a person's position.
N: Ok, let me instruct you how change the person's position. First, have you checked the person's current state?
U: What do you mean by the current state?
N: I mean that the person is sleeping or the person is awake and conscious. Is the person sleeping or awake?
U: Awake.
N: Ok. And is the person able to communicate with you?
U: Yes, the person can communicate with me.
N: Ok. Follow my instructions. Say next when you are ready to start.
U: Next.
N: Ok. First move the person sideways.
U: Next.
N: Then lift the person up. Check if the person sits properly and feels good.
U: Just a minute please.
N: Ok, take your time. By the way, speak slowly and carefully to the elderly person. When you are ready for the next step, say next.
U: Next
N: Then check the person's position.
U: Next
N: Finally, make sure the person feels fine. Does the person seem to be fine?
U: Yes, the person seems to be fine.
N: Ok, very good. Then we are done.

Fig.3. A session shot and an example dialogue when the robot instructs the user on changing a person's position (U = user, N = Nao robot).

3.3 On the evaluation of social robots for care services

The evaluation of the robot system proceeds in a manner common to user evaluation of dialogue systems. The robot system's functioning is successful if the goal is achieved (the instruction deals with the task that the user asked for, and the information given to the user is correct) and the goal is achieved in a reasonable time (should be shorter than what it would take by the care-taker to learn or do the task alone). However, for a social robot system to be successful, it is crucial that the care-taker feels happy for the received help and also the elderly person feels happy for having a robot assistant in the care-taking situation, i.e. neither feel useless, uncomfortable, or unsafe. Besides the common usability and user satisfaction studies that focus on the appropriate functioning of the social robot in the intended context with the help of subjective assessments, following e.g. SASSI type questionnaires (Hone and Graham 2000), it is also crucial to consider the user's previous experience and expectations of the system. For instance, the Expectations and Experience (EE) methodology (Jokinen and Hurtig, 2006; Jokinen and Wilcock, 2017) compares the users' expectations of the system with their actual experience of the system, and effectively measures the mismatch between the user's expectations and the interactive system's capabilities. It can bring forward information about the user's preferences concerning the different system functionalities, and about their attitudes towards communicative robot assistants in general.

Further development and evaluation can be carried out in a human-centred manner among the care-takers and service staff who will benefit most from a communicating robot assistant. Such assessments enable us to gather practical knowledge of the feasibility of the robot system and of the possibilities and challenges of social robot technology in care services. The care-takers' assessments are based on a real user view-point of how to best perform the task (explication and instruction of care knowledge), and in this way, they provide valuable expert feedback of the suitability, functionality, and the overall usability of the system. Such assessment sessions can also work in the opposite way and enable care-takers to become more familiar with the robot agent, thus alleviating common fears and uncomfortableness surrounding robot applications. The community-sourcing method that was used in the creation of the knowledge graphs, can thus also be used in the system evaluation, to co-create knowledge of the future direction of the development of robot assistants.

4 Discussion and conclusion

In this paper we have discussed knowledge-based dialogue management for a robot assistant which can instruct the human user on various task procedures related to elder care support services. The robot draws its knowledge from a task graph which represents the knowledge possessed by the experts and is structured into a collection of explicit actions and activities. We initiated knowledge structuring by the community-sourced method, connecting the experts' knowledge to operational procedures that support communication and sharing of the procedural information. In the future, such knowledge may be created automatically from the care-taker's hand-over protocol logs, or even by the robot learning action patterns with the help of a human teacher or by observing the situation.

Since interactions with intelligent agents are likely to increase drastically in the coming years, it is important that the agents' communicative competence increases to allow the agents to converse with humans appropriately. Our goal is to study innovative ways to enable interaction between humans and intelligent agents, based on dialogue models, knowledge graphs, and AI-technology. It can be assumed that future dialogue scenarios include robots observing human activities, e.g. care-taking activities and drawing the human partners' attention to facts which may have previously been overlooked. The robot assistant may also notice inconsistencies in the care-taking reports and inform the care-giver of the situation, thus providing helpful information which allows the human to take an appropriate action.

Future research deals with the dialogue modelling and making it more flexible concerning the robot agent's understanding of various utterances and presentation of the information to the user. This includes integration of semantic parsing and analysis of the user's focus of attention. Also, deep-learning techniques are being experimented with and their integration with the knowledge graphs explored. The work also continues on the sophistication and development of the task hierarchies.

Finally, we will focus on the research goal (3) and explore novel ways in which robots can support health and well-being in the society. Humanoid robots which can move in the 3-dimensional environment, explicate their knowledge, and show sensitivity to human partners, can embody interactions between users and technologies, and between humans, in a way that innovates new applications and services.

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