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Modeling Affordances and Functioning for Personalized Robotic Assistance

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Abstract

A key aspect of robotic assistants is their ability to contextualize their behavior according to different needs of assistive scenarios. This work presents an ontology-based knowledge representation and reasoning approach supporting the synthesis of personalized behavior of robotic assistants. It introduces an ontological model of health state and *functioning* of persons based on the *International Classification of Functioning, Disability and Health*. Moreover, it borrows the concepts of *affordance* and *function* from the literature of robotics and manufacturing and adapts them to robotic (physical and cognitive) assistance domain. Knowledge reasoning mechanisms are developed on top of the resulting ontological model to reason about stimulation capabilities of a robot and health state of a person in order to identify action opportunities and achieve personalized assistance. Experimental tests assess the performance of the proposed approach and its capability of dealing with different profiles and stimuli.

1 Introduction

Socially Assistive Robotics (SAR) aims at designing robots capable of continuously assisting users through social interaction, supporting their daily living activities (Feil-Seifer and Matarić 2005; Tapus, Mataric, and Scassellati 2007). A challenge for SAR is to ensure continuous assistance, facing a large variety of situations and contextualized interactions ranging from, e.g., reminding dietary restrictions and medical appointments to monitoring physiological parameters (Mataric, Tapus, and Feil-Seifer 2007). *Personalization* and *adaptability* are key features to effectively address specific user needs and achieve good acceptance levels (Moro, Nejat, and Mihailidis 2018; Rossi, Ferland, and Tapus 2017).

In our view, *personalization* is crucial to tailor general assistive capabilities of a robot to the specific needs of a person. Different users may require different types of assistance according to specific health conditions. For example, a user may need a cognitive stimulation or a constant monitoring of different physiological parameters, etc. *Adaptability* is crucial to *keep track* of the evolving state and behaviors of users. Indeed, health conditions of a patient may change over time and therefore, it is necessary to change (i.e. adapt) online the types and characteristics of robot assistance. Namely, adaptability allows robots to take into account *user feedbacks* in order to dynamically update the user profile (or the robot abilities) and dynamically change the way assistance is carried out, potentially improving its efficacy. Additionally, *explainability*, i.e., the general ability of an artificial agent to explain the rationale behind its choices (Arrieta et al. 2020; Miller 2019), is also crucial for robots interacting with people. The realization of such SAR systems poses technological and research design challenges.

Our research objective is to realize (autonomous) assistive robots endowed with abstract thinking features in order to internally represent *health needs* of an assisted person and contextualize their behaviors by reasoning about their *assistive capabilities*. To achieve personalization and adaptation of assistive behaviors we borrow some relevant concepts from the literature on robotics and manufacturing and adapt them to SAR. We consider the concept of *affordance*, widely used in robotics, to enhance flexibility and adaptability of robot behaviors (see e.g., (Bozcuoğlu et al. 2019; Awaad, Kraetzschmar, and Hertzberg 2015; Yamanobe et al. 2017; Beßler, D. and Porzel, R. and Pomarlan M. and Beetz, M. and Malaka, R. and Bateman, J. 2020)). This concept is generally used to contextualize robot's capabilities with respect to the properties and features of elements (e.g., objects) composing an environment and dynamically identifying *opportunities of actions*. In SAR, affordances may allow (autonomous) assistive robots to adapt or take advantage of action possibilities that can facilitate assistance. In this work we propose an interpretation of affordances as situations characterizing *opportunities of assistance* that *link* health needs of a patient to the capabilities of a robot. To support such reasoning features, the capabilities of a robot are here described with respect to general health needs of a person. And we consider also the concept of *Function* introduced by (Borgo et al. 2014; Borgo et al. 2009) to define a *taxonomy* characterizing the capabilities of agents in manufacturing domains. *Functions* are classified according to their *effects* on the *qualities* of domain entities (e.g., the color of physical objects). This *interpretation* supports flexible reasoning and pursues a clear separation between the capabilities of an "acting entity" and the concrete implementation (instance) of such an entity. We thus refine this concept to define the capabilities of an assistive robot and characterize them in terms of the *effects* they have on the *health state* of an assisted person.

The above concepts are deployed within a cognitive control framework (Umbrico et al. 2020a) whose objective is to integrate knowledge abstraction, goal triggering and acting to achieve flexible and continuous assistance in a variety of scenarios. The present work advances the above framework extending its ontological model enhancing its knowledge representation and reasoning functionalities. The main contribution consists in the design of an ontology-based control approach allowing assistive robots to represent and reason about cognitive health needs of a person (*impairments*) and identify a number of suited assistive actions accordingly. Specifically, the paper introduces an ontological representation of health features based on the *International Classification of Functioning, Disability and Health* (ICF) proposed by WHO[1]. From this model, the paper describes the ontological concepts defined to represent impairments and stimulation capabilities and then the developed knowledge processing mechanisms to *extract* suited *assistive actions*. Finally, the paper presents an experimental assessment of the approach together with some preliminary considerations about explainability, showing how the approach lays the foundations for supporting explainable assistive behaviors.

2 Cognitive Stimulation: an Inspiring Scenario

The authors are currently involved in a research project called SI-Robotics (*SocIal ROBOTics for active and healthy ageing*) whose aim is to design and develop novel solutions for SAR in order to support humans in health-care scenarios. A more specific objective is to propose novel AI-based robotic solutions realizing a variety of complex assistive services in different scenarios ranging from daily-home living to hospitals.

Daily self-management of own health, declined in activities such as, e.g., following a correct diet, practicing constant physical/cognitive exercise and taking drugs adequately, often represents an important challenge for older adults, usually characterized by fragility, declining health and cognitive status and poor technological literacy. Personal robotic assistants, able to promote healthy lifestyles, characterized by an empathic communication and reliability over time, can help solve this problem by adopting some strategies that also aim to motivate the assisted persons. A particularly relevant service is *coaching*, which entails to: (i) identify user's needs, abilities, desires and objectives; (ii) prescribe personalized training plans; (iii) provide support by monitoring users progress; (iv) dynamically modify (if needed) training plans. Referring to cognitive sphere, it can be implemented by an assistive robot supporting stimulation through a constant administration to a patient of suited exercises while sharing her domestic environment (see Fig. 1).

Coaching can also be used to support physical group rehabilitation and exercise in shared environments. For example, during an exercise, a robot can monitor the parameters of the participants, signalling any difficulties or user fatigue to a therapist, allowing her to intervene on individuals. A robot can also provide support and motivation during exercises.

[1]https://www.who.int/classifications/icf/en/

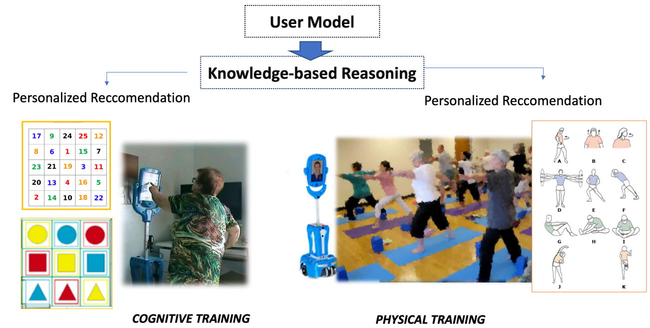

Figure 1: Examples of robotics assistance scenarios in domestic environments and group physical training

For sake of simplicity, in this paragraph we will focus on cognitive stimulation domain, but the approach is generalizable to different cases. The first step for an assistive robot is to *know* the cognitive *impairments* of a person and *contextualize* its behaviors accordingly in order to carry out stimulation actions tailored to the specific needs of the assisted person. We propose a general ontology-based knowledge representation and reasoning approach to autonomously identify the actions a robot can perform to address the specific needs of an assistive scenario (e.g., health needs of a patient) and adapt its behaviors accordingly. To this aim an assistive robot will first *profile* a patient to internally represent her health status. A correct acquisition of health information is crucial for the synthesis of correct and effective *stimulation plans*. We propose to use knowledge reasoning mechanisms to analyze the profile of a patient to *infer* her physical and cognitive *impairments* and *identify* accordingly a specific set of (either physical or cognitive) stimuli. This set of stimuli will be part of the *stimulation plans* synthesized to support the assistive scenario. Additionally, an assistive robot has to *know* the capabilities of available stimuli and *infer* accordingly its *stimulation capabilities*. Namely, it should be endowed with a domain knowledge characterizing a *portfolio* of stimuli determining the set of stimulation actions from which it can choose to support a patient. We propose knowledge reasoning mechanisms to contextualize stimulation capabilities of a robot (i.e., portfolio) with respect to the specific health needs of a patient (i.e., user profile) and extract a subset of stimuli for personalized stimulation plans.

In this context, the novel proposed contribution specifically concerns the development of the technologies needed to *reason* about cognitive and physical capabilities of patients, *reason* about robot stimulation capabilities and *decide* the set of stimuli that better fit the particular needs of an assistive scenario. This paper shows how these technologies support personalization by contextualizing *known* robot capabilities with respect to the health needs of a person (i.e., her impairments). Concerning adaptability, these technologies and the continuous alternation of a profiling and stimulation steps would allow a robot to keep its internal knowledge updated and adapt the synthesized and executed stimulation plans to the evolving health state of a person.

Before entering into the details of the developed knowledge representation and reasoning services, the next subsection generally describes the pursued cognitive approach.

2.1 A Cognitive Architecture for Adaptive Assistance

We developed our solution as an extension of KOaLa (*Knowledge-based cOntinuous Loop*) which is a recently designed cognitive architecture for flexible and dynamic robot control. The capabilities of KOaLa have been evaluated in both assistive scenarios (Umbrico et al. 2020a; Cesta et al. 2018) and reconfigurable manufacturing settings (Borgo et al. 2019; Borgo et al. 2016). KOaLa takes inspiration from the literature in cognitive architectures (Kotseruba and Tsotsos 2020; Lieto et al. 2018; Laird, Newell, and Rosenbloom 1987; Anderson, Matessa, and Lebiere 1997) and considers the capabilities elicited by (Langley, Laird, and Rogers 2009) as a reference for the integration of the developed Artificial Intelligence (AI) technologies (Umbrico et al. 2020b). It specifically pursues a tight interaction between semantic and acting technologies by integrating a semantic (ontology-based) module with a (deliberative) planning and execution module. The semantic module provides the acting module with contextual knowledge suited to synthesize personalized stimulation plans. Fig. 2 shows a conceptual view of the cognitive architecture and the modules.

The elements composing the *Ontology-based Representation and Reasoning* module realize the cognitive functionalities that allow a robot to internally represent information about assistive scenarios and reason about the resulting *knowledge*. The *Belief Reasoning & Updates* element builds and maintains the resulting internal knowledge. This knowledge instantiates the defined ontology providing a semantic representation of user profiles and stimulation capabilities of a robot. The *Contextual Reasoning* element analyzes the "robot belief" to *infer* additional knowledge about the specific (physical or cognitive) *impairments* of a person and *stimulation opportunities* enabled by robot *stimulation capabilities*. The *Reasoning about Preferences* element further analyzes the internal knowledge in order to performs a *match making* between inferred impairments and stimulation opportunities and identify a number of correlated stimulation actions. This element realizes a kind of standard *recommender system* (Ricci, Rokach, and Shapira 2011) extracting *recommendations* about assistive behaviors from knowledge. These recommendations *suggest* to the decision making module a number of stimulation actions suited to the particular needs of an assistive scenario and therefore support the synthesis of personalized assistive behaviors. Finally, the elements composing the *Decision Making and Problem Solving* module are responsible for the actual synthesis and execution of personalized assistive behaviors. The *Decision Making* element receives as input recommendations from the "semantic module" and synthesizes a personalized assistive plan. Such a plan is then then "dispatched" and the related stimulation actions are executed by the *Assistance Execution* element which is in charge of actually administrating planned stimuli to a patient. While the acting part of the architecture relies on consolidated planning and execution technologies (Umbrico et al. 2018; Pellegrinelli et al. 2017), the novel contribution of the paper specifically focuses on the semantic part of the architecture. Next sections describe technical details concerning the knowledge representation and reasoning functionalities developed to support the described scenario.

3 Representing Health Status and Stimuli

The use of ontology supports the realization of flexible knowledge processing mechanisms based on a well defined logic formalism. As show in some recent works like e.g., (Bozcuoğlu et al. 2019; Borgo et al. 2019; Tenorth and Beetz 2017; Awaad, Kraetzschmar, and Hertzberg 2015), the use of ontology is a key aspect to endow robots (and more in general artificial agents) with the necessary cognitive capabilities to realize *self-awareness* and autonomously evaluate *opportunity* of interactions with the environment and therefore achieve *behavioral qualities* like e.g,. *flexibility*, *proactivity*, *personalization* and *adaptation* that are crucial in many real-world scenarios.

Following the classification proposed by (Guarino 1998), we propose a *domain ontology* characterizing the health-related needs of patients and the *stimulation opportunities* determined by the assistive *capabilities* of a robot. In order to foster integration with other ontological models and to use a structured and consolidated theoretical background (Jansen and Schulz 2011; Studer, Benjamins, and Fensel 1998; Gruber 1995) we ground our model on DOLCE [2] which is a well-known foundational ontology. The domain ontology and the resulting internal knowledge of the robot have been realized using standard semantic technologies. The ontology (TBox) is written in OWL (Antoniou and van Harmelen 2004) and it has been defined using Protégé [3], a well known free and open-source ontology editor. The internal knowledge (ABox) of the robot and related knowledge-processing mechanisms have been developed using the open-source Java library Apache Jena [4].

Although the *inspiring assistive scenario* specifically focuses on cognitive stimulation, for sake of generality the proposed ontology deals with general health-related needs of a person (either cognitive or physical) and general stimulation capabilities of stimuli. Therefore, the developed knowledge processing mechanisms can address a wider range of stimulation scenarios like e.g., physical rehabilitation.

3.1 ICF-based Representation of User Profiles

A user profile characterizes all the information a robot needs to represent and *reason* about the health state of a patient. We propose an ontological model of the *International Classification of Functioning, Disabilities and Health* (ICF) which has been introduced by WHO (World Health Organization 2001). It interprets *functioning* as a dynamic interaction among the health condition of a person, environmental factors and personal factors. Functioning and disability denote respectively the positive and negative aspects of functioning from a biological, individual and social perspective.

[2] http://www.loa.istc.cnr.it/dolce/overview.html
[3] https://protege.stanford.edu/
[4] https://jena.apache.org/index.html

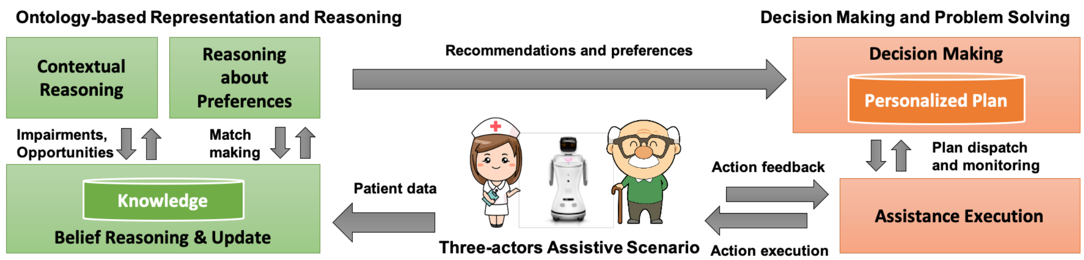

Figure 2: Integrated view of the knowledge processing mechanisms within the KOaLa cognitive architecture

Thus, ICF defines a scientific, operational basis to describe health and health-related states.

The classification is organized into two parts. A first part deals with *functioning and disabilities* while the other part deals with *contextual factors*. These two parts are then further organized into two components. The components *body functions* and *body structure* belong to the part concerning functioning and disabilities. The components *environmental factors* and *personal factors* belong to the part concerning contextual factors. Each ICF component consists of multiple domains, and each domain consists of categories that are the entities of the classification.

Concerning the objectives of our work, we integrate ICF concepts into DOLCE formalism to characterize health state of patients and stimulation capabilities of robot actions. We specifically focus on *body functions and structure* and *activity and participation* parts of ICF. The former part supports the description of the functioning of a person and is useful to characterize the physical and cognitive impairments of a patient. The latter part describes the functioning of a person with respect to his/her behaviors and abilities of interaction with the environment.

Taking into account the theoretical background of DOLCE, ICF concepts can be interpreted as *qualities* characterizing cognitive and physical aspects of a person (i.e., *functioning qualities*). The concept `DOLCE:Quality` models any aspect of an *entity* which cannot exist without that entity (e.g., the way a surface of a physical object looks like). Following this interpretation, we have defined the concept `FunctioningQuality` as a specialization of `DOLCE:Quality` with the aim of characterizing functioning aspects of a `DOLCE:Person`. The concept `FunctioningQuality` represents the *root element* of the integrated ICF taxonomy and therefore it is further specialized in a number of sub-concepts like e.g. `AttentionFunction`, `MemoryFunction` or `CalculationFunction`, that model the considered elements of ICF. Figure 3 shows the defined taxonomy of functioning qualities of a `DOLCE:Person`.

Also, our aim is to *evaluate* the functioning qualities of a patient and therefore we leverage the `DOLCE:Quality`-`DOLCE:Region` distinction of DOLCE in order to reason and contextualize the individual health-related aspects of a `DOLCE:Person` (i.e., functioning qualities). According to DOLCE, the concept `DOLCE:Region` models any dimensional space which can be used as a value for a quality of

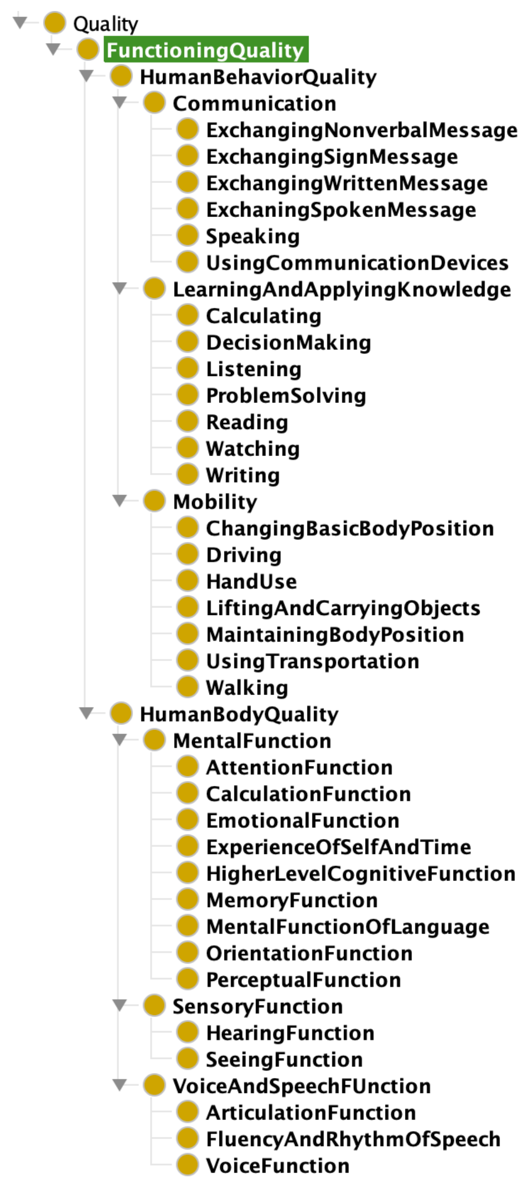

Figure 3: Taxonomy of functioning qualities

an entity of the domain. We use ICF to extend this concept and define a dimensional space to measure the functioning qualities of a patient.

The ICF framework proposes a general qualifier to measure the extent of an impairment which is defined within the range $[0, 6]$. The value 0 means *no impairment* (0-4%). The value 1 means *soft impairment* (5-24%). The value 2 means *medium impairment* (25-49%). The value 3 means *serious impairment* (50-95%). The value 4 means *full impairment* (96-100%). Finally, the values 5 and 6 represent the impossibility of measuring a quality. We define the concept `FunctioningRegion` as sub-concept of `DOLCE:Region` and define *data properties* associating the *outcomes* of possible measurements.

Given these qualities and the associated dimensional space, we define the concepts needed to associate measurements of functioning qualities to a patient. Namely, the ontology should define concepts that allow us to *describe* the physical and cognitive state of a person at a particular point in time. We define the concept `Profile` as sub-concept of `DOLCE:Description` and therefore as a "descriptive context" of the functioning qualities of a `DOLCE:Person`. A profile is composed by a number of `Measurement` (specialization of `DOLCE:Diagnosis`) that represent *descriptions* of *situations* concerning a particular *functioning quality* of a `DOLCE:Person`. Each individual of `Measure` associates an individual of `FunctioningQuality` to an individual of `FunctioningRegion`, expressing the outcome of the measurement within the ICF bound $[0, 6]$. A user profile instance can be seen as a Knowledge Graph associating a patient instance to a number of *values* each of which measures a specific functioning quality of a patient.

$$\begin{aligned}\texttt{Profile} \sqsubseteq \; & \texttt{Description} \sqcap \\ & \exists\, \texttt{describes.Person} \sqcap \\ & \exists\, \texttt{hasPart.Measure}\end{aligned} \tag{1}$$

$$\begin{aligned}\texttt{Measure} \sqsubseteq \; & \texttt{Diagnosis} \sqcap \\ & \exists\, \texttt{hasConstituent.Person} \sqcap \\ & \exists\, \texttt{isRelatedTo.Profile} \sqcap \\ & \exists\, \texttt{measures.FunctioningQuality} \sqcap \\ & \exists\, \texttt{outcome.FunctioningRegion}\end{aligned} \tag{2}$$

According to ICF, impairments represent problems concerning the functioning or the structure of body and therefore they mean loss of functioning. Each measurement outcome stored with a profile denotes the *level of impairment* of a patient with respect to a particular functioning quality. An assistive robot processes the information about the profile of a patient and autonomously *infers* her *impairments*. Given the measured functioning qualities of a patient an assistive robot is thus autonomously capable of identifying aspects that need assistance and therefore recognize the *situation of impairments* that characterize the cognitive state of a patient.

To support such reasoning mechanisms the ontology defines the concept `Impairment` as specialization of `DOLCE:Situation`. Taking into account the semantics of `DOLCE:Situation`, an `Impairment` represents a *view* on the `Profile` of a patient *satisfying* some condition on some `FunctioningQuality` and therefore it can be *inferred* through the following rule:

$$\begin{aligned}\forall\, x,y,w,z.\ \exists\, i.\ (&\texttt{Measurement(x)} \wedge \\ &\texttt{measures(x,y)} \wedge \\ &\texttt{hasConstituent(x,w)} \wedge \\ &\texttt{FunctioningQuality(y)} \wedge \\ &\texttt{Person(w)} \wedge \\ &\texttt{hasOutcome(x,z)} \wedge \\ &\texttt{hasICFScore(z)} > 0 \wedge \\ &\texttt{hasICFScore(z)} < 4 \rightarrow \; \texttt{Impairment(i)} \wedge \\ &\qquad \texttt{concerns(i,w)} \wedge \\ &\qquad \texttt{concerns(i,y)} \wedge \\ &\qquad \texttt{satisfies(i,x)})\end{aligned} \tag{3}$$

This rule defines `Impairment` as any situation where the measured outcome `hasICFScore(z)` of a functioning quality is included in the set $\{1, 2, 3\}$. It characterizes as `Impairment` any situation of *soft*, *medium* and *serious* impairment of a functioning quality. Following this semantics, an assistive robot can analyze the profile of a patient and autonomously *infer* the impairments that can be addressed by a *personalized stimulation plan* (rule (3) excludes full impairments from the considered situations): The described ontological concepts define the *semantics* needed to represent and reason about the physical and cognitive state of a patient and identify the aspects that require assistance. Next subsections defines the ontological concepts that allow to contextualize this knowledge and identify the set of stimuli that can actually address the health needs of a person.

3.2 Affordances of Functional Capabilities

In addition to the cognitive and physiological state of a person, the ontology characterizes the "capabilities" of an assistive robot by taking into account the capabilities of available stimuli and related stimulation actions. On one hand, the ontology characterizes the "functional features" of available stimuli. On the other, the ontology defines a semantics to correlate functional capabilities of stimuli and the profile of a person so that knowledge processing mechanisms can evaluate and reason about the *relevance* of a particular stimulus (e.g., a cognitive exercise) with respect to the *impairments* of a person.

The ontology characterizes the capabilities of available stimuli so that an assistive robot can know which are the functioning qualities a particular type of stimulation can support. For the sake of flexibility, it is crucial to represent this knowledge in a general way and therefore independently from the specific "nature" of considered stimuli and related stimulation actions. It is crucial to model stimuli as "black boxes" focusing on their "external qualities" (i.e., their stimulation capabilities) regardless of their specific "shape" and, so to say, "implementation details". We take inspiration from the *Taxonomy of Functions* introduced in manufacturing domains (Borgo et al. 2014; Borgo et al. 2009). It defines different types of function an agent can perform in the environment according to the *effects* these functions have on the *qualities* of the entities of a domain (e.g., the physical objects of the environment).

The classification of functions in terms of their effects supports a clear separation between the capabilities of an

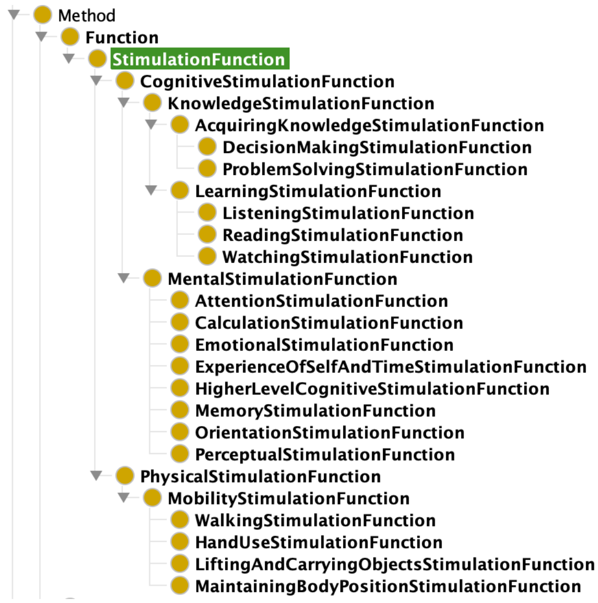

Figure 4: Taxonomy of stimulation functions

"acting entity" of a domain and the concrete implementation (instance) of such an entity. This distinction enables flexible reasoning mechanisms that can dynamically determine *which* functions can be performed and *how* according to the contextual knowledge of an agent, as shown for example in (Borgo et al. 2019; Borgo et al. 2016).

Following this interpretation, we define the concept of `StimulationFunction` to characterize the capabilities of stimuli (and therefore the overall stimulation capabilities of an assistive robot) in terms of their effects on the functioning qualities of an assisted person. Specifically, the ontology defines a `StimulationFunction` as a particular type of `DOLCE:Method` describing procedures that have some *effects* on some functioning quality of a person and is part of the description of some *stimulus*.

$$\begin{aligned}\texttt{StimulationFunction} \sqsubseteq\ & \texttt{Method} \sqcap \\ & \exists\, \texttt{isPartOf.Stimulus} \sqcap \\ & \exists\, \texttt{hasEffectOn.FuncQuality}\end{aligned} \tag{4}$$

Figure 4 shows the elements of the defined taxonomy of stimulation functions. This taxonomy is integrated with the taxonomy of functioning qualities of Figure 3. It can be noticed that, these two taxonomies share the same background formalism based on ICF. This choice and the association of these functions with the known stimuli allow an assistive robot to reason about its *stimulation capabilities* and the assistive scenarios it can actually support.

Concerning the relationship between the stimulation capabilities of a robot and the profile of a patient, the ontology defines a semantics to combine this knowledge and thus *infer* the resulting opportunities of assistance. We consider the concept of *affordances* which has been defined by Gibson as "opportunities for actions" (Gibson 1977). The original definition of affordances given by Gibson has been refined by many researchers and used in several works with the aim of improving the *flexibility* of robot behaviors. (Bozcuoğlu et al. 2019; Awaad, Kraetzschmar, and Hertzberg 2015) are just some relevant examples of works pursuing the use of this concept to reason about robot action opportunities like e.g., object manipulation actions of a robot.

Although Gibson's definition concerns mainly opportunities of actions "enabled" by objects, we borrow this concept to characterize *opportunities of stimulation* enabled by the stimulation capabilities of an assistive robot. In the context of Robotics, researchers agree that robot flexible behaviors can be achieved by interpreting the concept of affordances as a *relationship* between the properties of objects and (interaction) capabilities of a robot. The concept of affordances should not be considered a property of an object but rather it should represent opportunities of action in a particular situation. In other words, it represents a relational concept contextualizing properties of objects with skills and capabilities of robots to dynamically infer actions (opportunities) that can be performed in a particular context (scenario).

This flexible and general interpretation of affordances is well suited for our objectives to generally characterize the opportunities of stimulation in a particular assistive scenario. Following this interpretation, the ontology introduces the concept of `Affordances` as a particular type of `DOLCE:Role` to emphasize the pursued relational semantics. Then, the concept `StimulationOpportunity` is defined as a particular type of `Affordances` correlating exactly one impairment situation concerning some functioning quality of a person and exactly one stimulation function of an assistive robot, supported by some (known) stimulus.

$$\begin{aligned}\texttt{StimOpportunity} \sqsubseteq\ & \texttt{Affordances} \sqcap \\ & \exists!\, \texttt{classifies.Impairment} \sqcap \\ & \exists!\, \texttt{classifies.StimFunction}\end{aligned} \tag{5}$$

A stimulation opportunity is modeled as a contextual knowledge depending on the actual impairment situations characterizing the physical and cognitive state of a person and, on the actual capabilities of an assistive robot to stimulate and assist these impairments. In this way, an assistive robot can reason on its contextual knowledge to dynamically infer the set of stimuli whose capabilities (i.e., the associated stimulation functions) enable stimulation opportunities and therefore "can afford" the impairment situations characterizing the health state of a person.

$$\begin{aligned}\forall\, x,y,w,z.\ \exists\, o.\ (&\texttt{Impairment(x)} \wedge \\ &\texttt{FuncQuality(y)} \wedge \\ &\texttt{concenrs(x,y)} \wedge \\ &\texttt{StimFunction(w)} \wedge \\ &\texttt{hasEffectOn(w,y)} \wedge \\ &\texttt{isPartOf(w,z)} \wedge \\ &\texttt{Stimulation(z)} \rightarrow \texttt{StimOpportunity(o)} \wedge \\ &\qquad \texttt{classifies(o,x)} \wedge \\ &\qquad \texttt{isRelatedTo(o,y)} \wedge \\ &\qquad \texttt{isRelatedTo(o,w)} \wedge \\ &\qquad \texttt{canAfford(z,x)})\end{aligned} \tag{6}$$

The concept of affordances is central and supports reasoning capabilities that are necessary to contextualize *known* stimulation exercises with respect to the profile of a patient and therefore related cognitive needs.

Following the rule above, knowledge processing mechanisms analyze the set of detected `Impairment` of a person, the set of `SimulationFunction` of known stimuli (`Stimulus`) and *infer* the resulting set of `StimulationOpportunity`. According to the inferred opportunities, it is possible to contextualize the affordances of known stimuli and thus the ones that can *affords* the actual impairments of a person.

4 From Knowledge to Recommendations

Given the inferred set of situation opportunities, it is possible to extract the set of stimuli that best address the impairments of a person. A person can have several impairments and there can be a significant number of stimuli that can address the total impairments of a person. Also, a particular stimulus can address a multitude of impairments, according to the associated stimulation functions. According to this knowledge, an assistive robot can extract the set stimuli that *best fit* the specific needs of a person. A knowledge reasoning mechanism is in charge of *ranking* the inferred stimuli and extracting *recommendations* about a set of stimuli suited for the synthesis of a personalized stimulation plan.

We have developed a "semantic-based" recommendation system (Ricci, Rokach, and Shapira 2011) for the extraction of such stimuli. We use the ICF framework as basic formalism for analyzing relationships between user profiles and stimulation capabilities of available stimuli. Specifically, the recommendation system takes into account the taxonomy of functioning qualities of Figure 3 and the functioning aspects addressed by known stimuli (i.e., the stimulation functions of Figure 4). The relationships between the inferred stimuli and the ICF-based functioning qualities of the taxonomy are represented by means of an *incidence matrix*.

$$A_{m,n} = \begin{bmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,n} \\ a_{2,1} & a_{2,2} & \dots & a_{2,n} \\ \dots & \dots & \dots & \dots \\ a_{m,1} & a_{m,2} & \dots & a_{m,n} \end{bmatrix} \tag{7}$$

Number of columns n is the number of the elements of the taxonomy used to profile a person. Each column of the matrix is associated to a specific functioning quality of the taxonomy. Number of rows m instead is the size of the set of stimuli extracted from the inferred stimulation opportunities.

The ontology associates stimuli to the taxonomy of functioning qualities through stimulation functions. As shown in the previous section, this ontological knowledge is used to *contextualize* stimulation capabilities with the health status of a person through inferred stimulation opportunities. Each row of the matrix A is associated to one of these stimuli and characterizes its correlations with the taxonomy. A value of the matrix $A(i, j) = 1$ denotes that the i-th stimulus *can afford* the functioning quality represented by the j-th element of the taxonomy. A value of the matrix $A(i, j) = 0$ instead denotes that the i-th stimulus *cannot afford* the functioning quality represented by the j-th element the taxonomy.

Let us suppose that a number k of user profiles are stored into the knowledge base of an assistive robot. Such knowledge can be represented as a *profile matrix*.

$$V_{n,k} = \begin{bmatrix} v_{1,1} & v_{1,2} & \dots & v_{1,k} \\ v_{2,1} & v_{2,2} & \dots & v_{2,k} \\ \dots & \dots & \dots & \dots \\ v_{n,1} & v_{n,2} & \dots & v_{n,k} \end{bmatrix} \tag{8}$$

The elements of this matrix represent for each stored profile the stored measurement outcomes associated to the functioning qualities composing the taxonomy of the ontology. Each element of the matrix $V(i, j) \in [0, 4]$ characterizes the functioning level of the i-th quality of the taxonomy with respect to the j-th profile of the knowledge base.

Since both matrices rely on the ICF-based taxonomy of functioning qualities, it can be observed that the number of columns of the matrix $A_{m,n}$ is equal to the number of rows of the profile matrix $V_{n,k}$. Thus, we can combine the incidence matrix $A_{m,n}$ with the profile matrix $V_{n,k}$ in order to obtain a *ranking matrix* $R_{m,k}$ expressing a number of recommendations. A value $R(i, j) \in \mathbb{R}_0^+$ of the ranking matrix specifies a *rank* denoting the "relevance" of the i-th known stimulus to the j-th stored profile. The higher the rank the more the stimulus is relevant for a particular profile.

Without loss of generality, we can consider the particular case where only one profile is stored into the knowledge base of an assistive robot. In this case, the equation below computes a *ranking vector* R_m (i.e., a ranking matrix $R_{m,k}$ where $k = 1$) representing the "relevance" of known stimuli with respect to the heal needs of the assisted person.

$$\begin{aligned} R_{m,1} = A_{m,n} \times V_{n,1} &= \begin{bmatrix} a_{1,1} & \dots & a_{1,n} \\ a_{2,1} & \dots & a_{2,n} \\ \dots & \dots & \dots \\ a_{m,1} & \dots & a_{m,n} \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ \dots \\ v_n \end{bmatrix} \\ &= \begin{bmatrix} a_{1,1}v_1 + \dots + a_{1,n}v_n \\ a_{2,1}v_1 + \dots + a_{2,n}v_n \\ \dots \\ a_{m,1}v_1 + \dots + a_{m,n}v_n \end{bmatrix} = \begin{bmatrix} r_1 \\ r_2 \\ \dots \\ r_m \end{bmatrix} \end{aligned} \tag{9}$$

The higher the value r_i, the higher the *relevance* of the i-th stimulus with respect to the *impairments* of a person. High ranking values r_i entail that the associated i-th stimulus can afford aspects of a person representing medium/serious impairments but also that they can afford a multitude of impairments. Given a ranking vector R_m, it is possible to select a number h of stimuli that best fit the profile of a person (i.e. *best recommendations*) by extracting from R_m the indices of the h highly ranked stimuli. Then, these recommendations are passed to the deliberative components of Figure 2 as input in order to synthesize a *personalized stimulation plan*.

Next section describes an experimental evaluation "stressing" the described knowledge representation and reasoning capabilities. The experiments show the capability of representing and reasoning on impairments and stimulation opportunities in different assistive scenarios, consisting of different user profiles and different stimuli.

5 Experimental Evaluation

The experiments evaluate the technical feasibility and the performance of the developed reasoning mechanisms. They assess the capabilities of analyzing knowledge about *functioning qualities* and *impairments*, recognizing *stimulation opportunities* and producing *recommendations* coherent with health conditions of patients. The following subsections describes: a) the rationale of the designed experiments and analyzes the obtained results; b) some interesting capabilities of the proposed approach with respect to *explainability*. Indeed, the proposed semantics can also explain stimulation plans to assisted persons as well as provide health-care professionals with supporting information.

5.1 Experimental Result Analysis

Experiments have been designed to *stress* the reasoning and personalization capabilities of the presented approach. To this aim, a number of randomly generated patient profiles and a number of randomly generated sets of stimuli have been considered. Patient profiles have been generated on top of the defined taxonomy of functioning qualities. For each element of the taxonomy the procedure randomly computes a *score* within the ICF bound $[0, 6]$. Similarly, the sets of stimuli (i.e., the sets of known portfolios) have been generated on top of the defined taxonomy of stimulation functions in order to define their stimulation capabilities. Each stimulus is associated with a maximum number of 5 distinct stimulation functions.

Following these specifications, 10 random profiles of patients and 18 random sets of stimuli have been generated. Each set is composed by a growing number of stimuli, from a minimum of 10 to a maximum of 500. Given this "dataset" we have made a run for each couple *profile - set of stimuli* for a total of 180 runs whose results are shown in Table 1 [5].

The table shows an average of the obtained results, grouped by sets of stimuli. Each row i of the table shows the average of the results obtained by all the profiles on the i-th defined set of stimuli. Each row shows also the average number of inferred *impairments*, the average number of inferred *stimulation opportunities*, the number of generated *recommendations* (together with the average number best recommendations) and the average *reasoning time* for knowledge inference and recommendations. In particular, the column *Recommendations* shows the average number of stimuli extracted. These are all the stimuli j whose ranking value is positive i.e. $r_i > 0$. The column *Best Recommendations* instead shows the average number of the most relevant stimuli extracted. They are all the stimuli whose ranking value is higher than a certain *threshold*. The threshold is computed dynamically by taking into account the maximum ranking value r_{max} obtained for a particular profile. Given this value r_{max}, the threshold value is defined as $(r_{max}/2) + 1$. Comparing the results of the two columns it can be noticed the higher selectivity of best recommendations. Furthermore, it can be observed that the average number of *inferred stimulation opportunities* grows with a growing number of known stimuli and associated stimulation functions. In fact, the higher the number of stimuli an assistive robot knows, the higher the number of stimulation capabilities and therefore the number of stimulation opportunities a robot *can afford*.

[5]Experiments ran on a MacBook Pro with 2,8 GHz quad-core CPU and 16 GB RAM.

A higher number of stimuli and a higher number of possible stimulation opportunities entail a higher number of combinations and knowledge to be processed to extract recommendations. The columns *Inference Time* and *Recommendation Time* show respectively the average time needed to infer impairments and stimulation opportunities and the average time needed to generate recommendations. The *reasoning time overhead* concerning the impairments inference can be considered *constant* because the "size" of patient profiles depends on the "size" of the taxonomy of functioning quality which does not change.

The number of known stimuli instead can affect the performance of knowledge processing mechanisms. A higher number of stimuli (and associated stimulation functions) determines a higher number of stimulation opportunities (i.e., more inference). As it can be seen the performance trend is quite efficient and feasible for concrete deployment in realistic assistive scenarios. The developed knowledge processing mechanisms indeed take a total average time of *700 milliseconds* in the worst case.

Finally, the column *Impairments* shows the average number of inferred impairments for the generated profiles. It does not change over the runs because the set of profiles is the same. Thus, Table 2 shows a more detailed view which considers the number of inferred impairments for each randomly generated profile. The table shows both the number of inferred impairments and the number of "expected impairments", according to the data of the associated profile. This shows the *accuracy* of the reasoning approach and specifically shows its capability of inferring all the expected impairments for all the generated profiles.

5.2 Toward Explainability

Concepts and rules defined within the ontology can be used to *explain* robot behaviors to patients and health professionals. As an example, we consider two *explainable behaviors* that can be "easily" realized on top of the defined semantics.

Why do I need this exercise? Let us consider a patient who constantly receives a number of "requests" from an assistive robot, asking to perform some cognitive or physical exercise (stimuli). It may happen that such a patient wants to know (or does not remember) why such exercises are necessary. A patient would therefore ask the robot for explanations about the need of performing a particular exercise. A robot can answer to the patient by leveraging the ontology in order to explain the relationships between the exercises and her health state . Knowledge reasoning mechanisms can thus "navigate" robot knowledge to identify the (inferred) impairments that originated the stimulation opportunities *afforded* by the considered exercises. Given such impairments, a robot can provide a patient with an explanation showing the functioning qualities that are stimulated by the exercise.

Is there any impairment the robot cannot afford? A health-care professional wants to know if the synthesised stimulation plans address all the impairments of a patient

Stimuli	Impairments	**Opportunities**	**Recommendations**	Best Recommendations	**Inference Time**	Recommendation Time
10	15	**42.00**	**9.50**	4.70	**25.50 ms**	2.90 ms
20	15	**63.40**	**18.70**	7.30	**19.50 ms**	3.20 ms
30	15	**123.30**	**28.90**	13.70	**24.40 ms**	4.70 ms
40	15	**206.50**	**39.00**	17.70	**30.80 ms**	5.50 ms
50	15	**191.00**	**44.70**	16.70	**31.70 ms**	6.20 ms
60	15	**246.40**	**58.60**	22.30	**36.60 ms**	7.20 ms
70	15	**314.20**	**66.70**	28.40	**42.20 ms**	8.20 ms
80	15	**330.70**	**76.60**	29.10	**48.00 ms**	8.30 ms
90	15	**399.80**	**85.30**	34.70	**53.30 ms**	9.10 ms
100	15	**399.50**	**93.00**	35.90	**57.40 ms**	9.70 ms
150	15	**645.70**	**142.70**	47.50	**100.60 ms**	14.20 ms
200	15	**868.20**	**191.60**	69.80	**154.50 ms**	17.90 ms
250	15	**1060.60**	**233.60**	80.70	**215.90 ms**	22.30 ms
300	15	**1238.60**	**285.80**	92.30	**293.10 ms**	26.20 ms
350	15	**1465.90**	**334.30**	113.60	**379.80 ms**	29.90 ms
400	15	**1661.00**	**378.50**	106.50	**467.10 ms**	33.60 ms
450	15	**1840.80**	**427.90**	130.70	**579.40 ms**	37.20 ms
500	15	**2070.20**	**475.40**	137.70	**697.50 ms**	42.30 ms

Table 1: Results of the experimental evaluation

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Profile 6	Profile 7	Profile 8	Profile 9	Profile 10
Impairment	9/9	16/16	16/16	21/21	15/15	11/11	13/13	18/18	16/16	15/15

Table 2: Impairments inferred on the generated profiles

and may ask for explanations. The robot can answer to the question by comparing the inferred impairment of a patient and the ones associated to the inferred stimulation opportunities (i.e., the *afforded* impairments). The set obtained from the difference between the set of inferred impairments and the set of afforded impairments represents all the (inferred) impairments that are not afforded by the robot. If this set is not empty then, the robot can answer by showing the set of impaired functioning qualities the robot cannot support, according to its stimulation capabilities.

6 Conclusions

This paper presents an ontology-based representation and reasoning approach supporting the synthesis of personalized robotic assistance. A novel aspect of the work concerns the use of the concept of *affordances* and *function*, that are typically used in robotics and manufacturing domains, in the domain of robotic assistance. The work propose an interpretation of these concepts based on the ICF classification and therefore on the functioning properties of a person. Knowledge reasoning mechanisms analyze health knowledge about patients to infer impairments, stimulation opportunities and accordingly extract suited stimulation actions (i.e., *recommendations*). Experiments show technical feasibility and performance of the developed approach.

Future works will further investigate *explainability capabilities* as well as evaluate this technology with real patients and health-care professionals. In this regard, the work (De Benedictis et al. 2020) represents a first concrete step toward the deployment of this technology. It presents the integration of model-based and model-free technologies to realize dialogue agents capable of administrating cognitive exercises to patients. The pursued approach resemble the distinction between System 1 and System 2 (Tversky and Kahneman 1974; Kahneman and Tversky 1984) referred in cognitive sciences and cognitive architectures. A *slow* long-term module implements the presented approach to synthesize a personalized stimulation plan. A *fast* short-term module realizes dialogue-based functionalities to execute a stimulation plan by actually interacting with a patient.

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