Visuo-Spatial Ability, Effort and Affordance Analyses: Towards Building Blocks for Robot's Complex Socio-Cognitive Behaviors *

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Abstract

For the long term co-existence of robots with us in complete harmony, they will be expected to show socio-cognitive behaviors. In this paper, taking inspiration from child development research and human behavioral psychology we will identify the basic but key capabilities: *perceiving abilities*, *effort* and *affordances*. Further we will present the concepts, which fuse these components to perform multi-effort ability and affordance analysis. We will show instantiations of these capabilities on real robot and will discuss its potential applications for more complex socio-cognitive behavior.

When looked through the socio-cognitive window, the AI (Artificial Intelligence) hence the Artificial Agents should be able to take into account high level factors of other agents such as help and dependence, (Miceli, Cesta, and Rizzo 1995). Here the agents *social reasoning and behavior* is described as their *ability to gather information about others and of acting on them to achieve some goal*. Which obviously means such agents should not exist in isolation, instead must *fit in* with the current work practice of both people and other computer systems (artificial agents), (Bobrow 1991). While exploring this *'fit'*, works on social robots such as (Breazeal 2003), and survey of socially interactive robots such as (Fong, Nourbakhsh, and Dautenhahn 2003) altogether outline various types of social embodiment. This could be summarized as *social interfaces* to communicate; *sociable* robots, which engage with humans to satisfy internal social aims; *socially situated* robots, which must be able to distinguish between 'the agents' and 'the objects' in the environment; *socially aware* robots, situated in social environment and aware about the human; *socially intelligent* robots that show aspects of human style social intelligence.

Ability While exploring the key cognitive building blocks of these social embodiment, we get hints from the research on child development, such as (Carpendale and Lewis 2006). It suggests that visuo-spatial perception, i.e. perceiving others' ability to see and reach, comes out to be an important aspect of cognitive functioning. Very basic forms of social understandings, such as following others' gaze and pointing as well as directing others' attention by pointing, begin to revel in children as early as at the age of 12 months, (Carpendale and Lewis 2006). At 12-15 months of age children start showing the evidence of an understanding of occlusion of others' line-of-sight (Dunphy-Lelii and Wellman 2004), (Caron et al. 2002); and an adult is seeing something that they are not, when looking to locations behind them or behind barriers (Deak, Flom, and Pick 2000), for both: spaces (Moll and Tomasello 2004) and objects (Csibra and Volein 2008). Once equipped with such key cognitive abilities, children show basic social interaction behaviors, such as intentionally producing visual percept in another person by pointing and showing things and interestingly from the early age of 30 months, they could even deprive a person of a pre-existing percept by hiding an object from him/her (Flavell, Shipstead, and Croft 1978). Further studies such as (Rochat 1995), suggest that from the age of 3 years, children are able to perceive, which places are reachable by them and by others, as the sign of early development of allocentrism capability, i.e. spatial decentration and perspective taking. Evolution of such basic socio-cognitive abilities of visuo-spatial reasoning in children enable them to help, co-operate and understand the intention of the person they are interacting with.

Effort Perceiving the amount of effort required for a task is another important aspect of a socially situated agent. It play role in effort balancing in a co-operative task as well as provides a basis for offering help pro-actively. A socially situated robot should be able to perceive the effort quantitatively as well as qualitatively in a '*meaningful*' way understandable by the human. An accepted taxonomy of such '*meaningful*' symbolic classification of effort could be

Figure 1: Effort based taxonomy of reach action

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adapted from the research of human movement and behavioral psychology, (Gardner et al. 2001), (Choi and Mark 2004), where different types of reach actions of the human have been identified and analyzed. Fig. 1, shows taxonomy of such reaches involving simple arm-shoulder extension (arm-and-shoulder reach), leaning forward (arm-and-torso reach) and standing reach, which could easily be adapted to qualify the effort associated with other abilities and tasks.

Affordance In cognitive psychology, Gibson (Gibson 1986) refers affordance as what an object offers. Gibson defined affordances as all action possibilities, independent of the agent's ability to recognize them. Whereas in Human Computer Interaction (HCI) domain, Norman (Norman 1988) defines affordance as perceived and actual properties of the things, that determines how the things could be possibly used. He tightly couples affordances with past knowledge and experience. In robotics affordances has been viewed from different perspectives: agent, observer and environment; hence the definition depends upon the perspective, (Şahin et al. 2007). Irrespective of shift of definition, affordance is another important aspect for a socially situated agent for performing day-to-day cooperative human-robot interactive manipulation tasks. Affordance could be learnt (Gibson 2000) as well as could be used to learn action selection (Lopes, Melo, and Montesano 2007).

Contribution

Bottom-up Social Embodiment Approach Inspired from child developmental research and emergence of social behavior, we adapt the approach to grow the robot as "social" by developing basic key components, instead of taking 'a' complex social behavior and top down realizing its components. Our choice of bottom up approach serves the objective of this paper: *exploring and building a foundation for designing more complex socio-cognitive, by providing open 'nodes'* Below we describe the contribution of the paper reflecting this bottom up approach.

In this paper we will enrich the scope of *abilities*, *affordances* and *efforts* by incorporating the complementary aspects. Further we will fuse these components to develop new concepts to facilitate a more 'aware' human-robot interaction and interactive manipulation. Fig. 2 summarizes the concept building contribution of the paper. The scope of this paper is to describe the main constructs of the fig. 2, their significance and to illustrate the result for real human-robot interaction scenarios. Below we will first summarize the main conceptual contribution of the paper.

Perspective Taking to Perceive Non-Abilities As shown in the *visuo-spatial perspective taking* block of figure 2, we have equipped the robot to not only perceive what is visible and reachable, but also *which* object or place is deprived to be seen or reached by an agent and *why* (as shown in the sub-components: obstructed, unreachable, invisible and hidden).

Effort Hierarchy To qualify agent's effort in a human understandable and meaningful way, we have conceptualized an effort hierarchy, as shown in *effort analysis* block (fig. 2).

Multi-Effort Ability and Non-ability Analysis In the domain of Human-Robot Interaction, visuo-spatial perspective taking has already been studied. Specially the ability to perceive what other agent is seeing has been embodied and used in various ways, (Breazeal et al. 2006), (Trafton et al. 2005). But mostly the focus is on analyzing agent's abilities to see objects from the current state of the agent. As an attempt to make the robot more 'aware' about other agent's capabilities, by fusing *visuo-spatial perspective taking* with the *effort hierarchy*, we have developed the concept of *Mightability Analysis* as shown in fig. 2.

Agent-Agent Affordance Analysis We have enriched the notion of affordance by including inter-agent task performance capability, i.e. what an agent can afford to do for other agent (give, show...), as shown in *Affordance Analysis* block of fig. 2.

What an Environment Offers: Multi-Effort based Affordance Analysis We have incorporated effort and visuo-spatial abilities with affordances to equip the robot with rich reasoning about the environment (consists of agents and objects, places) could offer all together by incorporating different possible efforts of agents, as shown in Mightability based affordance analysis block. In this context we will introduce the concepts of *Taskability Graph*, *Manipulability Graph* and fuse them to construct *Object Flow Graph*. This will serve as a basis for generating shared plan, as well as for grounding the agent, action or object to the environmental changes.

The technical implementation detail of each component is beyond the scope of the paper, however we will illustrate the results in real human-robot interactive scenario. Next section will describe the concepts, and the instantiations, followed by the discussion on potential applications and conclusion.

Concept Description and Illustrative Instantiation

Perceiving Non-Abilities

We have identified three concepts about visibility of X (object or place) from an agent's perspective:

- *Visible*: X is directly seen by the agent.
- *Occluded*: X is in the field of view of the agent, but currently not seen, because some other object or agent is occluding it.
- *Invisible*: X is not in the field of view of the agent. So, either the agent will be required to put some effort or the X should be displaced.

Similarly for the ability to reach, corresponding concepts are:

- *Reachable*: agent can directly reach X just by stretching arm.
- *Obstructed*: X is withing the stretching arm reach region of the agent but currently the agent could not reach it, because some other object or the agent is obstructing it.

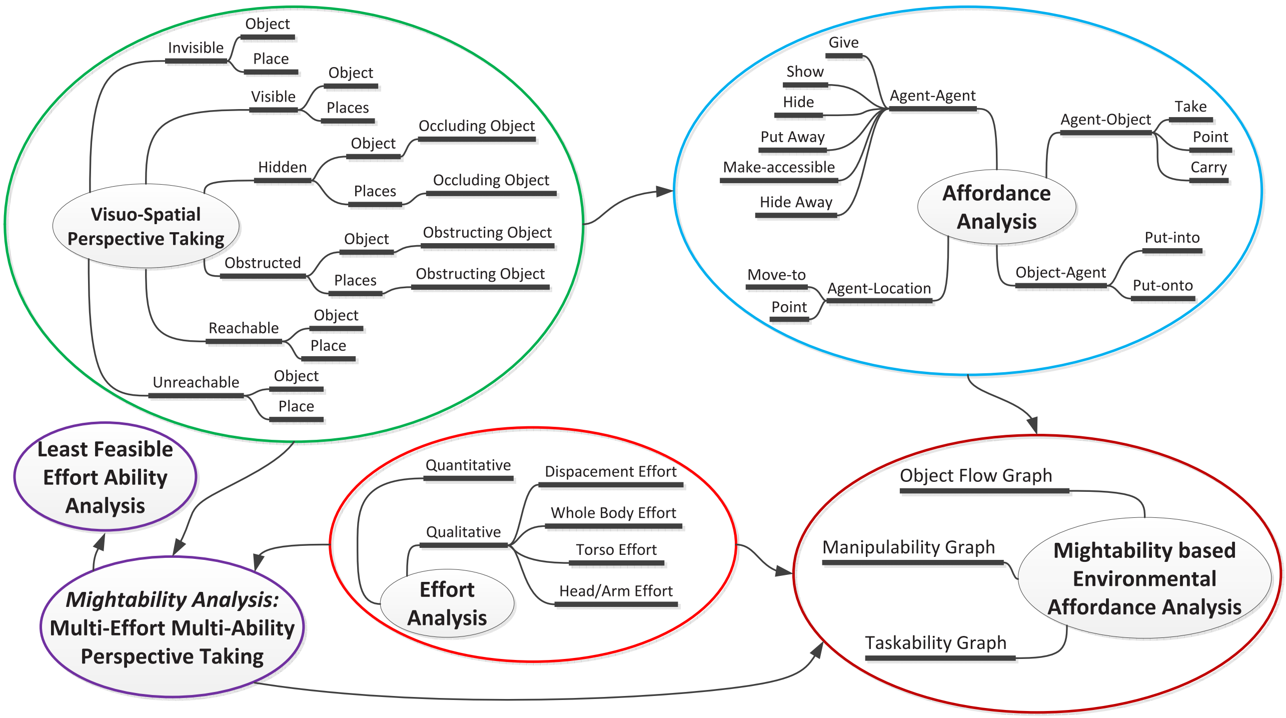


Figure 2: We have identified a subset of basic socio-cognitive abilities: Visuo-Spatial Perspective Taking, Effort Analysis, Affordance Analysis. We have enriched their scope and fused them to build a base, which will serve for developing complex socio-cognitive abilities for the robots to co-exist in human centered environment with better harmony.

- *Unreachable*: X is not withing reach region of the agent. So, either the agent will be required to put some effort or the X should be displaced.

Occluded and *Obstructed* differ from *Invisible* and *Unreachable* in the sense, for the former it is possible to produce the visual percept or facilitate the reach for agent *Ag* for object or Place *X* by making changes in the other parts of the environment without involving the *Ag* and *X*.

In (Pandey and Alami 2010), we have presented how the reachable and visible places by an agent are calculated. We will refrain from giving here the detail. In summary, from a given posture, for calculating the visible place, a ray tracing based approach is used from eye to the points in the workspace. And for calculating the reachable places, the arm-length with constraints of shoulder joints limits has been used. Below we will briefly describe the computation of complementary aspects: occluding (preventing to see something) and obstructing (preventing to reach something) objects.

If an agent *Ag* can not see an object *O*, which is otherwise in the field of view of Ag, the robot finds the occluding object, i.e. the objects which are depriving *Ag* to see *O*. For this a ray is traced back from the point $p \in P_i : i = 1...n$, uniformly samples on the object, to the agent's eye *E*. Then the points on the ray, which do not belong to free space and *O* are extracted. Further the objects belonging to these points are extracted, which in-fact are the occluding objects.

We say an object, which is within the arm length of the agent, to be obstructed from reaching if it fails the *basic* reachability test: if there are other objects on the line joining the shoulder joint and the object. This is an acceptable assumption, supported by human movement and behavioral psychology research, which suggests that our prediction to reach a target depends on the distance of the target relative to the length of the arm, (Rochat 1995), (Carello et al. 1989) and in-fact play as a key component in actual movement planning. We prefer to avoid performing more expensive whole body generalized inverse kinematics based reachability testing until the final stages of task planning, where it is really required. Hence obstructing objects are detected in similar way as explained earlier for occluding objects, where the ray is traced from object to the agent's shoulder. Similarly the occluding objects for hidden and unreachable places are found.

It is important to note that such perspective taking are performed from a particular state of the agent. That state could be the current state or a virtual state by applying a particular action, which will be clear in next section.

Effort Analysis

We have conceptualized an effort hierarchy based on the body part involved, as follows:

- *Head/Arm Effort*: Involves just turning the head around to see or just stretching out the arm to reach something.
- *Torso Effort*: Involves the upper body part only, e.g. lean torso forward, turn torso.
- *Whole Body Effort*: Involves whole body motion but no displacement, e.g. changing posture from sitting to standing or from standing to sitting, turning around the whole body.
- *Displacement Effort*: Involves displacement.

The symbolic level of effort increases from *Head/Arm* to *Displacement* effort. This effort hierarchy also grounds the agent's movement to a 'meaningful' effort. The robot further associates descriptors like left, right. As the robot reasons on 3D model of the agents with joints' information it further compares two efforts of same symbolic level, based on change in joint values or relative displacement.

Mightability Analysis: Multi-Effort Viuso-Spatial Perspective Taking

In (Pandey and Alami 2010), we have presented the concept of *Mightability Maps*, which stands for "*Might be Able to...*". There we used a set of virtual states of the agent to perform visuo-spatial perspective taking for points (cells in the workspace). In this paper we will more generalize the concept by using the *effort hierarchy* instead of predefined set of states as well as analyzing also for objects instead of just the points in the space. This we term as *Mightability Analysis*. The idea is to performs all the visuo-spatial reasoning shown in fig. 2, not only from the current state of the agent, but also from a sates, which the agent might attain if he/she/it will put a particular effort.

For performing Mightability Analysis, corresponding to each effort level there is a set of virtual actions. The robot applies A_V an ordered list of such virtual actions, to make the agent virtually attain a state and then estimates the abilities by respecting the environmental and postural constraints of the agent. Currently the set of virtual actions are:

$$A_V \subseteq \left\{ A_V^{head}, A_V^{arm}, A_V^{torso}, A_V^{posture}, A_V^{displace} \right\} \quad (1)$$

where,

$$A_V^{head} \subseteq \{Pan\_Head, Tilt\_Head\} \quad (2)$$

$$A_V^{arm} \subseteq \{Stretch\_Out\_Arm\,(left|right)\} \quad (3)$$

$$A_V^{torso} \subseteq \{Turn\_Torso, Lean\_Torso\} \quad (4)$$

$$A_V^{posture} \subseteq \{Make\_Standing, Make\_Sitting\} \quad (5)$$

$$A_V^{displace} \subseteq \{Move\_To\} \quad (6)$$

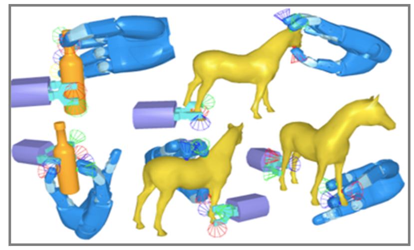


Figure 3: Agent-Object Grasp affordance: Autonomously generated grasp and analysis of simultaneous dual grasp.

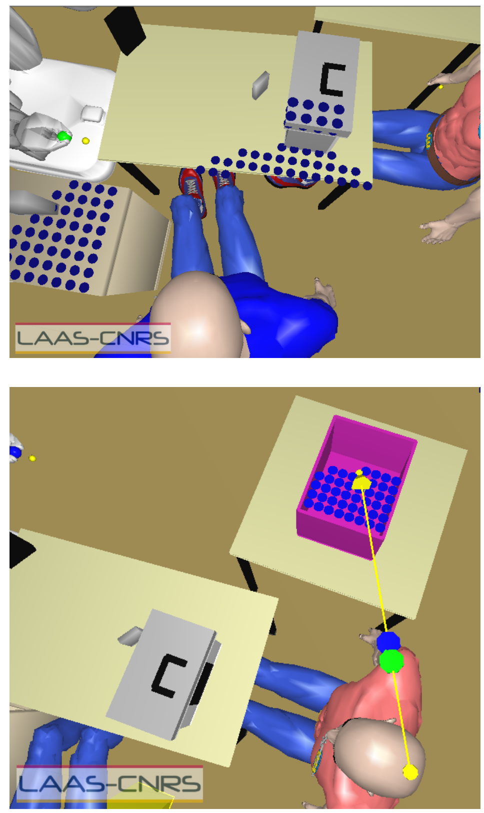


Figure 4: Object-Agent affordance. (a) Robot finds the places where the human on middle can put something onto. Note that the robot is able to find the top of the box also as a potential support plane. (b) Similarly it finds that something can be put into the pick trashbin and the places from where the human on right can put into. In both cases, the maximum allowed effort level was Arm Effort.

Affordance Analysis

As mentioned earlier, we have assimilated different notions of affordances as well as introduced the notion of "agent-agent affordance". As shown in fig. 2, we conceptualize four categories of affordance analysis:

(i) ***Agent-Object Affordance***: This suggests what an agent could potentially do to an object in a given situation and state. Currently the robot is equipped to find affordance to *Take*, *Point* and *Carry*. An agent *take* an object if there exists

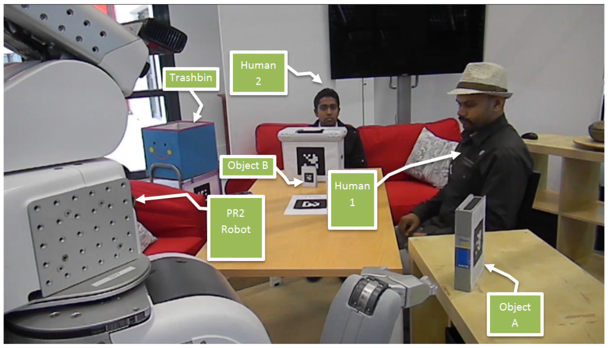


Figure 5: Example scenario with two humans, and a PR2 robot. There are different objects, reachable and visible by different agents with different effort levels.

at least one collision free grasp, and the object is reachable and visible from a given state of the agent. We have a dedicated *grasp* planner which could autonomously find set of possible grasps for the gripper/hand of robot/human, for 3D object of any shape (Saut, Sahbani, and Perdereau 2011). If the agent has to take an object from another agent, existence of simultaneous grasps, as shown in fig. 3 is tested. Another agent object affordance is to *point* to an object. In the current implementation an object is said to be *point-able* by an agent if it is *not hidden* and *not blocked*. The *blocked* is perceived in similar way as *obstructed* as explained earlier, but the test of whether the object is within the reach length of agent or not is relaxed. An agent can *carry* an object if he can afford to take it and the weight of the object is within acceptable range. Currently the weight information is manually provided as the object property.

Before moving further we would like to introduce fig. 5, which will be used to illustrate the main concepts through real results. The scenario shows two humans and a robot, PR2. The robot construct and update, in real time, the 3D model of the world by using Kinect based human detection and tag based object localization and identification through stereo vision, integrating in our 3D visualization and planning platform *Move3D*.

(ii) ***Object-Agent Affordance***: This type of affordance suggests what an object offers to an agent in a given situation, currently implemented for *to puton*, *to putinto* affordances. The robot autonomously finds *horizontal supporting facet* and *horizontal open side*, if exists, of any object. For this the robot extracts planar top by finding the facet having vertical normal vector from the convex hull of the 3D model of the object. The planner top is uniformly sampled into cells and an virtual small cube (currently used of dimension of (*5cm x 5cm x 5cm*)) is placed at each cell. As the cell already belongs to a horizontal surface and is within the convex hull of the object, so, if the placed cube collides with the object, it is assumed to be a cell of support plane. Otherwise the cell belongs to an open side of the object from where something could be put inside the object. Fig. 4a shows the automatically extracted places on which human on the middle can put something. Fig. 4b shows the places from where the human on the right can put something inside the pink trashbin. In this example, analysis has been done for the effort level of Arm Effort. Note that fig. 4 is 3D model built and updated online for a scenario similar to fig. 5

(iii) ***Agent-Location Affordance***: This type of affordance analysis suggests what an agent can afford with respect to a location. Currently there are two such affordances: can the agent move to a particular location and can the agent point to a particular location. For *move-to*, the agent is first placed at that location, tested for collision free placement and then existence of a path is tested. For *point-to* a location, similar approach is used as point to an object, discussed above.

(iv) ***Agent-Agent Affordance***: This type of affordance analysis suggests which agent can perform which task for which agent. Currently the robot is equipped to analyze the basic Human-Robot Interactive manipulation tasks: *Give*, *Show*, *Hide*, *Put-Away*, *Make-Accessible*, *Hide-Away*. For this it uses the *Mightability Maps* of the agents (Pandey and Alami 2010) involved. For a given effort level it solves the following expression to get the candidate points by performing set operation on Mightability Maps:

$$P_{place}^{Cnts} = \{p_j : p \equiv (x, y, z) \wedge (p_j \text{holds} \forall c_i \in \text{Cnts})\} \quad (7)$$

where j=1 to n, the number of cells. The set of effort constraints $Cnts = \{c_i : i = 1 \ldots m\}$ consists of tuple (m is number of constraints):

$$c_i = \langle \text{ability} : A_b, \text{agent} : A_g, \text{effort} : E_{A_b} = (true|false)\rangle \quad (8)$$

Where $A_b \in \{see,\ reach\}$. Depending upon the nature of the task and the desired/allowed effort level, the robot tests for existence of commonly reachable and/or commonly visible places for cooperative tasks like give, make-accessible, show, etc. Similarly it finds the places, which are reachable and visible for one agent but invisible and/or unreachable for another agent for competitive tasks like hide, put-away, etc.

Least Feasible Effort Analysis

For finding the least effort for an ability $A_b \in \{see,\ reach\}$, the robot sequentially applies the virtual actions presented in eq. 1 starting from the least effort level, until the desired ability for that agent becomes true for the object or place of interest. As shown in fig. 6a, the robot finds that the human on the right Might be able to see the small tape (object B in fig. 5, which the robot finds to be hidden from the human's current perspective and the occluding object is the white box), if he will put at least the *Whole Body Effort*. As shown, the robot finds that the human will be required to stand up and lean forward to see the small tape. The same human might be able to even reach another object with *Displacement Effort* 6b, by moving to a place and then leaning forward. The another human on the middle has to at least put *Torso Effort* to reach the black tape in front of him, as he is required to just lean forward.

Mightability Based Affordance Analysis

As long as the robot reasons only on the current states of the agents, the complexity as well as the flexibility of cooperative task planning is bounded in the sense if the agent cannot

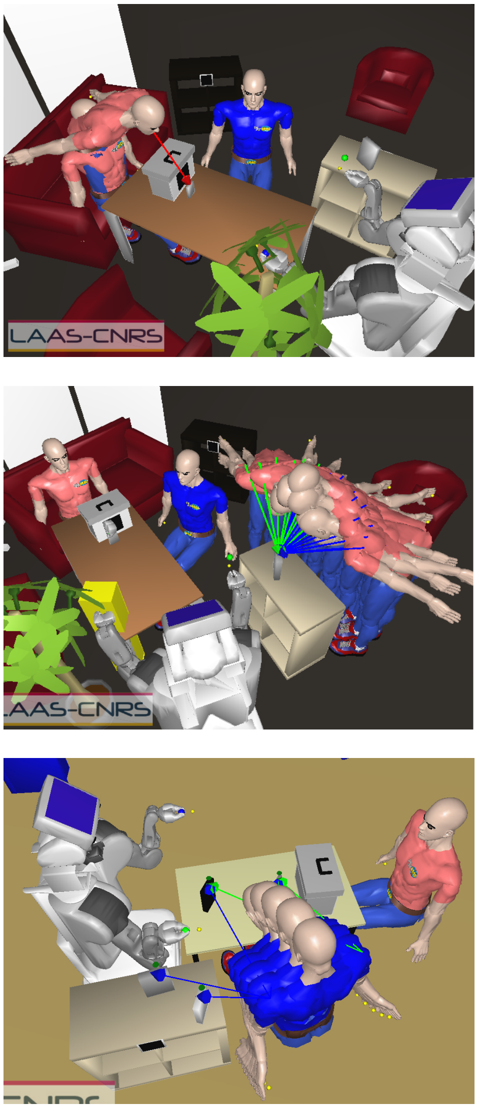
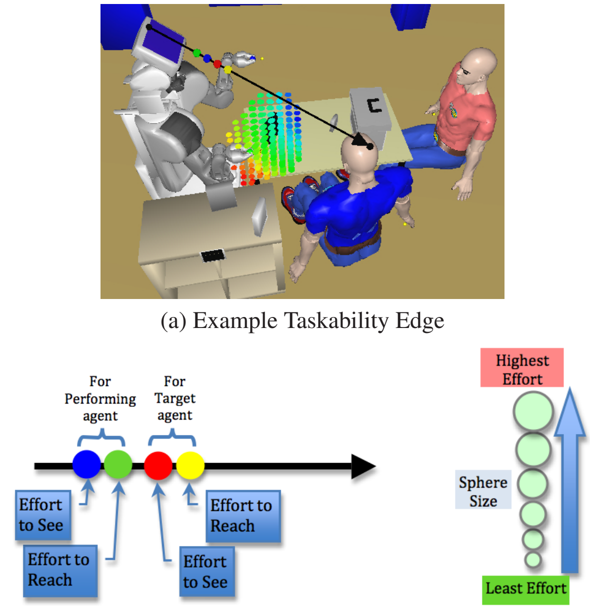


Figure 6: Least feasible effort analysis: (a) Whole Body Effort to see the small tape by the human 2 of fig. 5, who is currently sitting on the sofa. (b) Displacement Effort to reach another tape by human 2. (c) Torso Effort to reach black tape by another human.

reach an object from current state, it means that agent cannot manipulate that object; similarly if the agent cannot give an object to another agent from his current state it means he will not. But thanks to Mightability Analysis our robot is equipped with rich reasoning of agents' abilities from multiple states. This introduces another dimension: *effort* in the cooperative manipulation task planning, as theoretically every agent would be able to perform a task, only the effort to do so will vary. This section will introduce the concepts of different graphs which could easily incorporate effort in planning for help and cooperation.

Taskability Graph Taskability graph represents *agent-agent affordances* for different tasks. An edge of taskability graph is directed from the *performing agent* and the *target agent* and found based on maximum allowed effort levels of both agents, and the requirement to balance the mutual effort, or to reduce the effort of one of the agent. Each edge consists of the name of the task, the corresponding effort levels of the agents involved, the candidate places where the task could be performed, based on the allowed effort. Fig. 7 shows one edge of taskability graph, corresponding to the affordance of PR2 to give an object to the human on the middle. The colored point cloud shows the candidate places for the task.



(a) Example Taskability Edge

(b) Edge Description

(c) Effort Sphere

Figure 7: Explanation of a taskability edge: bigger the sphere size, greater the effort to see and reach.

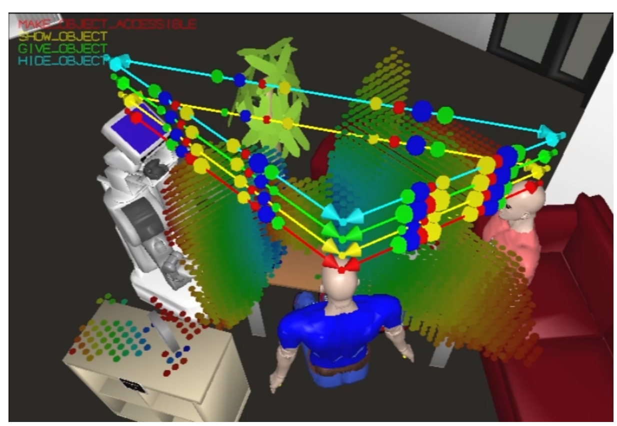


Figure 8: Taskability Graph for different tasks for real scenario of fig 5 based on effort balancing assuming equal social status and maximum allowed effort levels for each agent as *Arm Torso Effort*

Fig. 8 shows the taskability graph for 4 different tasks: Give, Show, Hide, Make Accessible, for scenario of fig. 5 among all the agents in the environment. Assuming equal social status for all the agent, the planner starts checking for the feasibility of the task by testing for equal effort levels for each agent, starting from the least effort level. To illustrate that the situation and desire of individual can be incorporated in the generation of such grasp, we have restricted the maximum desired effort level of each agent as Torso Effort as they are sitting around a table and not willing to stand or move. Hence, in the corresponding taskability graph, between human 2 and PR2 robot there is no possibility of give and make accessible tasks, as there was no commonly reachable places with this effort level. This is reflected from the taskability graph, having only two edges between them, for hide and show tasks, where common reachab places by both agents are not required.

Manipulability Graph As *Taskability Graph* encodes what an agent might be able to do for another agent, *Manipulability Graph* represents agent-object and object-agent affordances. Currently the robot construct Manipulability Graphs for three tasks: *Take*, *Putonto*, and *Putinto*, as explained in affordance analysis section.

Fig. 9 shows the manipulability graph encoding the ability and efforts for *take* and *putinto* affordances. To show that different maximum effort levels can be assigned for different affordances, we provided maximum allowed effort for *take* as *Displacement Effort* whereas for *putinto* it has been assigned as *Torso Effort*. Hence the resulted graph shows that human 2 can take the object on the right of the robot and also can put something into the trashbin. But the human 1 can not put something into trashbin. Each edge shows the corresponding efforts to see and reach the objects by green and blue spheres. Note the difference among the effort levels of all the agents to take the objects, e.g. one on the right of the robot, successfully encoded in the Manipulability Graph.

Object Flow Graph By combining Taskability Graphs and Manipulability graphs, we have developed the concept of *Object Flow Graph* (OFG). It encodes all the possible ways in which objects could be manipulated among the agents and across the places. Fig. 10 shows the *OFG* of the current scenario of fig. 5. For constructing *OFG*, following rules are used: (i) Create unique vertices for each agent in the environment and for each object in the environment. (ii) For each edge *Et* of taskability graph from performing agent *PA* to target agent *TA*, introduce an intermediate virtual vertex *Vt* and split *Et* into two edges, *E1*, connecting *PA* and *Vt*; and edge *E2*, connecting *Vt* and *TA*. The direction of *E1* and *E2* depends upon the task: if the task is to give or make accessible, *E1* will be directed inward *Vt* and *E2* will be directed outward from *Vt* towards the *TA*. If the task is to hide or just show the object, *E2* will be directed towards the *Vt* from *TA* also. This ensure that for hide or show tasks, the object will not flow further from the performing agent and *E2* is for the purpose of grounding the task corresponding to that *Vt* and *TA*. (iii) For each edge *Emt* of manipulability graph to take an object, an edge is introduced in the *OFG* directing from the object to the performing agent. (iv) For each edge *Emp* of manipulability graph for putinto and puton affordances, an edge is introduced in the *OFG* from the performing agent to the container object or supporting place. Rule (ii) encodes the flow of object between two agents and rules (iii) and (iv) encode the possible flow of object corresponding to pick, putinto, puton tasks. Further each edge will have a weight depending upon the efforts of the performing and the target agents in the parent graphs.

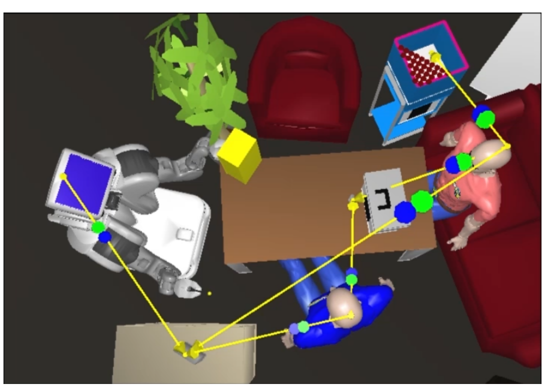


Figure 9: Manipulability Graph to take-object and for Putinto affordance with maximum allowed effort levels as Displacement and Torso Efforts respectively.

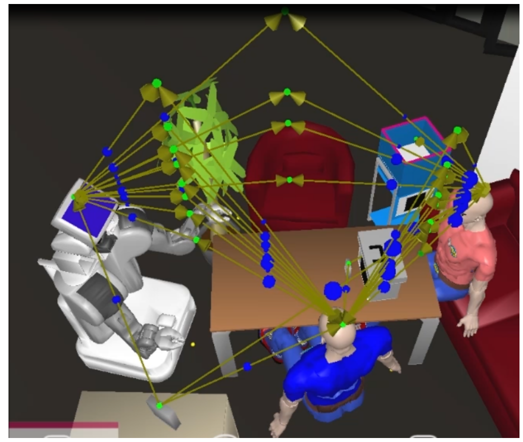


Figure 10: Object Flow Graph

The novelty of object flow graph is: *(i)* It transforms a human-robot interactive object manipulation task planning problem into a graph search problem. *(ii)* It provides capability to reason on human/agents effort levels, and *(iii)* It facilitates easy incorporation of preferences and social constraints in terms of desired/acceptable efforts.

Potential Applications

Once the robot is equipped with the capabilities to analyze the potential flow of the object, i.e. has the *Object Flow Graph*, it could be used for variety of purposes: To generate a shared cooperative plan for the task, to ground the changes to the agent and the actions. For example if the task is to throw the object A of fig. 5 in the trashbin, the planner has to just find the node corresponding to object A, and the node corresponding to the trashbin. Then simply a shortest path search algorithm between both nodes will give a plan to perform the task. The planner can have different paths by varying the desired criteria for overall or individual effort. Similarly different constraints could be introduced, such as making sure to involve an agent in the planned cooperative task, or to exclude an agent, and so on. If an agent is having back problem, just by restricting his effort level to *Arm Effort* will automatically propagate this in the framework and his involvement will be restricted to the tasks affordable by him. Similarly *OFG* could be used for grounding environmental changes, to the probable agents and actions.

Conclusion and Future Work

We have explored key components for developing complex socio-cognitive behaviors. From the needs of human robot interaction, we have enriched the robot's capabilities to analyze *abilities*, *effort* and *affordances* in a *human understandable* manner. We have also introduced the notion of *agent-agent affordances* and importance of *perceiving non-abilities*. Further we have fused them to develop the concepts of *Mightability analysis*, and to build *object flow graph*, which converts effort based task planning problem into graph search problem. All these make the robot more 'aware' about the agent, and agent's capabilities. An interesting future work is integrating such rich knowledge with the high level task planners, such as (Alili, Alami, and Montreuil 2008) to effectively solve complex tasks cooperatively.

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