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Mightability Maps: A Perceptual Level Decisional Framework for Co-operative and Competitive Human-Robot Interaction

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***Abstract*—Interestingly Humans are able to maintain rough estimations of visibility, reachability and other capabilities of not only themselves but of the person they are interacting with. Studies in neuroscience and psychology suggest that from the age of 12-15 months children start to understand the occlusion of others line-of-sight and from the age of 3 years they start to develop the ability, termed as *perceived reachability* for self and for others. As such capabilities evolve in the children, they start showing intuitive and proactive behavior by perceiving various abilities of the human partner.**

Inspired from such studies, which suggest that *visuo-spatial perception* plays an important role in Human-Human interaction, we propose to equip our robot with the capabilities to maintain various types of reachabilities and visibilities information of itself and of the human partner in the shared workspace. Since these analyses will be basically perceived by performing a virtual action onto the agent and roughly estimating what that agent *might be able* to 'see' and 'reach' in 3D space, we term these representations as *Mightability Maps*.

By applying various set operations on *Weighted Mightability Maps*, robot could perceive a set of candidate solutions in real time for various tasks. We show its application in exhibiting two different behaviors of robot: co-operative and competitive. These maps are also quick to compute and could help in developing higher-level decisional capabilities in the robot.

I. INTRODUCTION

WE, the Humans, have the capability to perceive (imagine) various abilities of ourselves as well as of others in various situations. Suppose Jack and Jill are sitting around a table, cluttered with different objects, occluding their field of vision and restricting their reach, as shown in fig. 1. Suddenly Jack asks to Jill "*please put the bottle near me*". Jill picks and puts the bottle at an 'appropriate' place on the table where Jack could not only 'easily' see the bottle but also could 'easily' reach to the bottle. Now Jill counter commands: "*show me your cup*". Jack picks and holds the cup in the way Jill can 'easily' see it. Interestingly, neither Jill nor Jack took any pain in performing their tasks. The more interesting fact is, however Jack was aware that if he will stand up and lean forward, he might be able to reach the bottle, but he was also aware that not only Jill could 'easily' reach the bottle, but also she shares an 'easily' reachable space with him. Similarly Jill was also aware that if she would stand up she might be able to see the cup, but she also chose the 'easy' way to see the cup, by perceiving Jack's capability. This suggests that they have some perception about the places, which could be reachable and visible by both, even before performing the actual task. For measuring such capabilities and assigning the level of 'ease', they basically associated and executed virtual actions (stand up, bend, move, etc.) on the agents and then perceived different abilities. This points out following 3 important issues about the day-to-day Human-Human interactions:

Fig. 1. Typical Human-Human interaction scenario.

(i). Maintaining various types of abilities (reachability, visibility, ability to grasp, etc.) of self and of others.

(ii). Assigning macro level 'ease' or 'comfort' to such abilities (reachable without leaning forward, visible without turning, etc.) and finalizing mutual comfort level for performing a task.

(iii). Assigning micro level comfort (reachable without leaning but also *near current position of the hand*, visible without turning but also *at sufficient distance from the eye as well as close to the axis of current focus of person,* etc.)

This paper will mainly focus on issue (i), i.e. maintaining various types of visibility and reachability, which our robot will perceive by performing different types of virtual actions on itself and on the human partner. This in fact could help in developing the higher-level decisional capabilities in the robot. Although in the framework presented in this paper, there are dedicated steps to incorporate points (ii) and (iii), but separate studies are required to finalize the optimal comfort, which depends upon the mental and physical states of the agents, the task as well as the role (partner, slave, friend, boss, etc.) of the agents.

In this paper we will confine ourselves to two abilities: Visibility and Reachability. Visuo-spatial perception is an important aspect of cognitive functioning such as accurately reaching for objects, shifting gaze to different points in space, etc. Studies in psychology and neuroscience, such as [1], 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. Moreover, it is not sufficient to know which objects are visible, but also which space in 3D is visible to an agent. Imagine the case when we need to find place in 3D space to show or hide something from others. At 12–15 months of age children

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also show evidence of an understanding of occlusion of others line-of-sight [9], [10]; and an adult is seeing something that they are not when looking to locations behind them or behind barriers [11], [12]. Evolution of such abilities of visuo-spatial reasoning in children enable them to help, co-operate and understand the intention of human partner.

Inspired from such evidences from neuroscience and psychology, in this paper we propose to equip our robot with such basic yet important capabilities of maintaining spatial and visual abilities of itself and of the human partner. This will facilitate the robot to behave more intuitively and to solve tasks both in co-operative and competitive scenarios.

Representation of reachable and manipulable workspace has already received attention from various researchers. In [5], the kinematic reachability and directional structure for the robot arm has been generated. Although, it is an offline process, such representation has been shown useful in generation of reachable grasp [6]. In [7], an offline technique for mapping workspace to the configuration space for redundant manipulator has been presented based on the *manipulability measure*. In [8], a Monte Carlo based randomized sampling approach has been introduced to represent the reachable workspace for a standing humanoid robot. It stores the true or false information about the reachability of a cell by using the inverse kinematics. However none of these works focus on such analysis with different postural and environmental constraint as well as they don't estimate such abilities of the human partner, which is one of the important aspect for decision making in a Human-Robot Interaction scenario.

Regarding the visual aspect of visuo-spatial reasoning, there have been works in the field of robotics mainly on perspective taking. Perspective taking has been shown useful in learning [17], in action recognition [16], in human-robot interaction [18] as well as for shared attention [15]. However, most of such works answer to the question: "which object is visible?" not "which spaces in the 3D are visible?", which in fact is a complementary issue.

In psychology [19], [20], in Human-Computer Interaction [21] and in Robotics [22], [23], term affordance is used, which basically associates with object in the environment from the perspective of task and/or agent. In our knowledge no significant work has been published, in which the robot analyzes various types of visibility and reachability of itself as well as of human partner and combines them for various decision-making. In this paper we propose the term *Mightability Map* as the representation of various perceived abilities of the agents in 3D.

Next section proposes the concept of Mightability Maps and their computation. Section III will show their use for performing co-operative tasks like "making accessible" and "showing" something to the human as well as competitive task like "hiding" something from the human, by our Humanoid robot HRP2. Various potential applications of our proposed *Mightability Maps* will be discussed in section IV, followed by conclusion and future works.

II. Mightability Map : The perceived ability

A. Mightability Map

The main motivation behind the present work is to maintain a set of knowledge about different abilities, as humans do, which: (i). could be fast to compute, (ii). should not underestimate any ability, so that robot will not fail to find a solution for a task if one exists, (iii). provides a relevant basis for semantic reasoning capability, (iv). is independent to the nature of the task/human activity, which might not be known in advance and even help the robot to predict it, (v). facilitates robot to behave/communicate more intuitively in real time with the human partner.

Since, various abilities of the agent will be perceived by applying some virtual actions on it, hence it will inherit overestimation/uncertainty for the sake of not being underestimated. We term it as Mightability (for *Might be Able*, a rough estimation) Map (for representing in 3D grid).

Each Mightability Map will answer to a particular question about the perceived ability, for example "if the human will lean forward, he/she *might be able* to *reach* these places", "if robot/human will turn around it/he/she *might be able* to *see* these places", etc.

B. Perceived Reachability

From the studies in [2], [3], [4] the general agreement is that, the prediction to reach a target with the index finger depends on the distance of the target relative to the length of the arm, which slightly overestimates by 10% of the actual arm length, but plays as a key component in actual movement planning. So, we will also use the length of the arm to estimate the reachability boundary for the given posture of the human and the robot. An agent can show reaching behavior to touch, grasp, push, hit, point or take some object from inside some container, etc. Hence, having a perceived maximum extent of the agent's reachability even with some overestimation will be acceptable as the first level of estimating the ability, which could be further filtered by the nature of the task as well as more rigorous kinematics and dynamics constraints, as shown in section III.

In the studies of human movement and behavioral psychology, [13], [14], different types of reach action of the human has been identified and analyzed. Ranging from a reach involving simple arm extension (arm-only reach), shoulder extension (arm-and-shoulder reach), leaning forward (arm-and-torso reach) and standing (standing reach).

Fig. 2. Taxonomy of reach actions:(a) arm-shoulder reach, (b) arm-torso reach, (c) standing reach.

Fig. 2 illustrates taxonomy of such reach actions. We have augmented various other reachability analyses to the set studied in [13]: reaching by turning around only and reaching by turning around and then leaning forward, for sitting as well as for

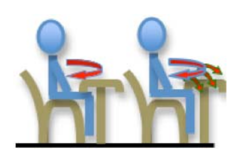


Fig. 3. (a) Turn around reach, (b) turn around and lean reach.

standing, as shown in fig. 3. Furthermore, the robot distinguishes the places, only reachable by left hand or right hand or by both hands of the agent. Fig 4 shows few interesting observations. If human is sitting close to the table, he will be able to lean less as compared to sitting away from the table, hence sometimes regions reachable in former case will be less as shown in fig 4(a) & (b). Similarly human might not be able to reach the table, which is too low, without leaning forward, fig 4(c). While generating the Mightability Maps, we will also take into account such postural (Sitting, standing) and 3D environmental (table, chair, etc.) constraints. The robot computes such abilities in 3D workspace in the following manner:

Fig. 4. Human closer to the table (a), could lean less compared to sitting away from the table (b). Table is too low to be reached without leaning (c).

Robot has the kinematic structures of itself and of the human. The joint limits of shoulder, neck and waist of HRP2 robot and of human have been adapted from [24]. The information about the human position, orientation and the 3D structure of the environment, fig. 5(a), is continuously updated in our 3D representation and planning platform, Move3D, fig. 5(b), which facilitates the robot to check self and external collisions for itself, for human model as well as for objects. Robot constructs a 3D workspace (red box in fig. 5(b), dimension of *3m x 3m x 2.5m* for current scenario) and divides it into cells, each of dimension *5cm x 5cm x 5cm*.

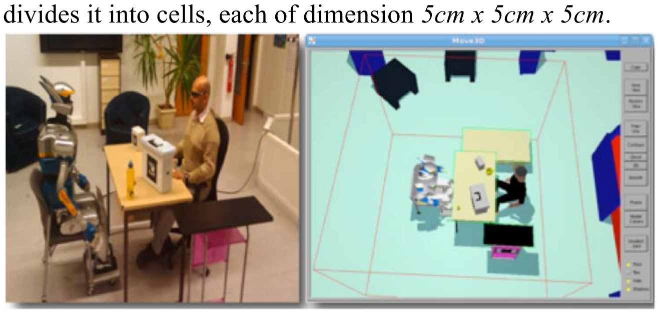
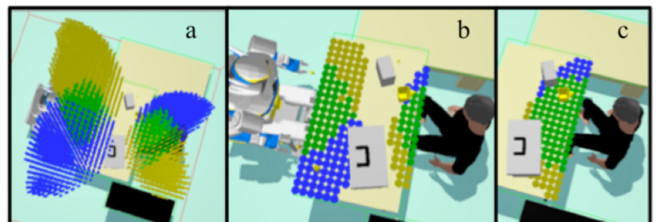


Fig. 5. (a) Experimental setup (b) 3D map of environment, which the robot maintains and uses for decision making and planning.

First, the robot calculates the arm-shoulder reach. For this robot stretches the hand of the 3D model of human by permissible limit of each shoulder's yaw and pitch joints and computes which cells in the 3D grid are reachable by human just by using the length of the arm from the shoulder to finger. Then the robot virtually leans the human model by its torso incrementally until the torso collides with the table or any other object or the maximum limit of human waist pitch joint has been reached. Then from these new virtual positions of the human, robot again calculates the reachability in 3D as explained earlier. Next, the robot turns the torso of the human model at its current position until collision or maximum limit of human waist yaw is reached, to calculate the reaching by turning-around. Similarly the reachability of turning-around-and-leaning is computed. Robot also calculates all these reachabilities in 3D by virtually making the human standing as well as for itself.

Fig. 6(a) shows the arm-shoulder reachable cells in 3D for the humanoid robot HRP2 and human from their current positions and orientations. Robot also distinguishes among the cells, which could be reached only by left hand (yellow), only by right hand (blue) and by both hands (green). Fig. 6(b) show similar cells belonging to table surface. It could be easily seen that there is no common reachable region on table if neither of them will lean forward. Fig. 6(c) shows reachability of human on table but with maximum possible leaning forward. Clearly the human might be able to reach more regions. The robot is also able to perceive that if human will turn and lean he will be able to reach some parts of the side by tables of different heights as well, as shown in fig. 6(d). Note that at this level all the cells in 3D, which are reachable, are estimated, irrespective of the fact: is there any object or it is free space, because as mentioned earlier, robot should be able to predict reachability for a range of tasks.



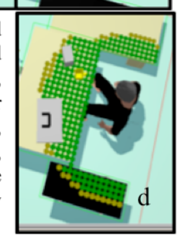


Fig. 6. Sitting arm-shoulder reachability in 3D (a) and on table surface (b) from the current position and without leaning for the robot HRP2 and the human, (c) arm-torso reach on table by leaning forward for human, human might be able to reach more regions, (d) turnaround and leaning reachability for human, human might be able to reach some parts of the side by tables. (All calculations are done in 3D), (Yellow only by left, blue only by right, green by both hands).

C. *Perceived Visibility*

For calculating the visibility, from the current position and yaw and pitch of the head, robot finds the plane perpendicular to the axis of field of view. Then that plane is uniformly sampled to the size of a cell of the 3D grid of Mightability Map. Then as shown in fig. 7, a ray is traced from the eye/camera of the agent to each such sample on the plane. If an obstacle is found on the way, all the cells of the corresponding Mightability Map till the obstacle (green arrow) is marked as visible and rest of the cells on the ray till the plane (red arrow) is marked as invisible. Different types of virtual actions, which the robot performs on the agent to perceive various visibility based Mightability Maps are: only turn the head, left and right, till the neck joints limits, turn the torso left and right until collision or till waist yaw limit and then turn the head till the neck joints limits, both for sitting and standing.

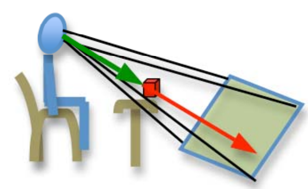


Fig. 7. Calculation of visibility

Red circles in fig. 8(a) shows the visibility of the human from his current position and head orientation for the cells of corresponding 3D Mightability Map, which are on the table plane. Note the invisible regions because of the objects. The blue cells in fig. 8(b) show the visibility in 3D for the HRP2

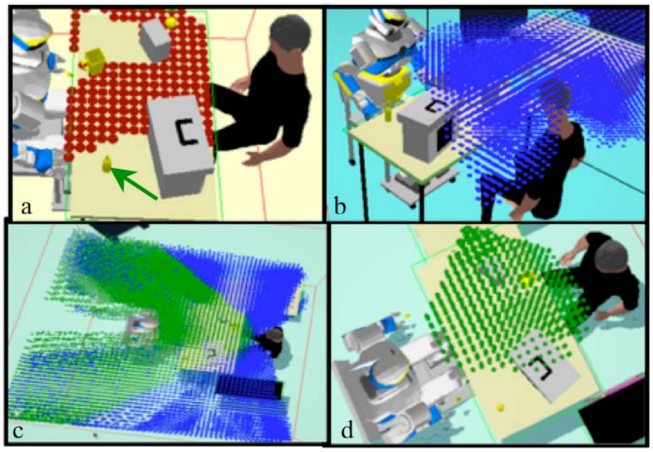


Fig. 8. Current visibility of human on table surface (a) and of HRP2 in 3D (b). (c) Current and turning the head around visibility of human without turning torso. (d) Common current visibility of human and robot in 3D.

robot for its current orientation of head. Fig. 8(c) shows the current visibility (green cells) as well as the visibility when human will turn its head without turning the torso (blue cells) in 3D. Fig. 8(d) shows the current common visibility of HRP2 and human in 3D. As the ranges of HRP2 camera and human eye are different, the corresponding Mightability maps will not be symmetric.

D. *Perceived Mightability Maps and Computation Time*

Table I summarizes different types of perceived Mightability Maps for reachability and visibility computed by the robot for itself as well as for the human. Note that depending upon the type/structure of the robot, few of them will not be applicable for a particular robot. Table II shows time for calculating various Mightability Maps for the human and the HRP2 humanoid robot used in current experiment. It also shows the time for one time process of creating and initializing cells of the 3D grid to discretize the workspace with various information like cells which are obstacle free, which contains obstacles, which are the part of the horizontal surfaces of different tables, etc. Note that it took 1.6 seconds to create and initialize 3D grid consisting of 180000 (60x60x50) cells, each of dimension 5cm x 5cm x 5cm, hence 0.000009 seconds for a single cell. As most of

TABLE I
VISUO-SPATIAL PERCEIVED 3D MIGHTABILITY MAPS

Visibility for Human and Robot	**Reachability for Human and Robot**
From **C**urrent head orientation, (C)	Arm-shoulder reach from **C**urrent position, (C)
Virtually **T**urning head **S**traight, (T_H_S)	Arm-torso reach by virtually **L**eaning **T**orso until collision or waist's pitch joint limit is reached, (L_T)
Virtually **T**urning the **H**ead around, **L**eft and **R**ight, until neck's yaw joint limit is reached, (T_H_L), (T_H_R)	Arm-shoulder reach by virtually **T**urning **T**orso around, **R**ight and **L**eft, until collision detected or waist's yaw joint limit is reached, (T_T_L), (T_T_R)
Virtually **T**urning the **T**orso **L**eft and **R**ight, until collision or waist's joint limits are reached and then turn **H**ead until neck's yaw joint limit is reached, (T_T_H_L), (T_T_H_R)	Arm-torso reach by virtually **T**urning **T**orso around, **L**eft and **R**ight, and **L**eaning until collision detected or waist's yaw and pitch joint limits are reached, (T_T_L_L), (T_T_R_L)
Virtually **S**tanding and applying same actions as above, (S_C), (S_T_H_S), (S_T_H_L), (S_T_H_R), (S_T_T_H_L), (S_T_T_H_R)	Virtually **S**tanding and applying same actions as above, (S_C), (S_L_T), (S_T_T_L), (S_T_T_R), (S_T_T_L_L), (S_T_T_R_L)

TABLE II
CALCULATION TIME FOR MIGHTABILITY MAPS IN SECONDS (S)

3D grid creation and initialization (one time process)	**1.6**
3D visual Mightability Maps for Human	0.146
3D visual Mightability Maps for HRP2 Robot (excluding making the robot virtually standing)	0.089
3D spatial Mightability Maps for Human	0.128
3D spatial Mightability Maps for Robot (excluding making the robot virtually standing)	0.083
Total Time for all Mightability Maps' calculation (excluding one time 3D grid creation and initialization process) = **0.446 seconds**	

the time at a given moment, practically the changes in the environment will affect a fraction of the 3D grid, like movement of objects on the table and/or change in position of some body parts of the agents, the Mightability Map set could be updated quickly. Table II also shows that for an average scenario as shown in fig. 5 it takes about 0.446 seconds to calculate all the Mightability Maps for the human and the robot, once the 3D grid is initialized.

III. APPLICATION, EXPERIMENTS AND RESULTS

A. *Representing Information from Mightability Maps*

The Mightability Map computed for Human and for Robot will have prefix '*MH*' and '*MR*' respectively, which will be followed by '*V*' or '*S*' for visual or spatial aspects. Then the acronyms of map type used in the table I will be added as suffix. For example, the spatial Mightability Map for perceiving the human reach by turning right and leaning will be represented by *MHST_T_R_L*. The set of all the Mightability Maps for human is represented as:

$MH = \{m : m \in MHV \vee m \in MHS\}$, where,

$$MHV = \{MHV\_C, MHV\_T\_H\_S, MHV\_T\_H\_L, MHV\_T\_H\_R, MHV\_T\_T\_H\_L, MHV\_T\_T\_H\_R, MHV\_S\_C, MHV\_S\_T\_H\_S, MHV\_S\_T\_H\_L, MHV\_S\_T\_H\_R, MHV\_S\_T\_T\_H\_L, MHV\_S\_T\_T\_H\_R\} \quad and$$

$$MHS = \{MHS\_C, MHS\_L\_T, MHS\_T\_T\_L, MHS\_T\_T\_R, MHS\_T\_T\_L\_L, MHS\_T\_T\_R\_L, MHS\_S\_C, MHS\_S\_L\_T, MHS\_S\_T\_T\_L, MHS\_S\_T\_T\_R, MHS\_S\_T\_T\_L\_L, MHS\_S\_T\_T\_R\_L\}$$

The set of all the Mightability Maps for robot, *MR*, is represented in similar manner.

Since, as mentioned earlier, for exhibiting various co-operative as well as competitive behaviors, the Mightability Maps not only encode information about what an agent might be able to do, but also what he/it might not be able to do. So, an operator '*val((x,y,z),M)*', returns 1 (might be able) or 0 (might not be able) for a particular cell (x,y,z) of a particular Mightability map *M*. Hence, for example the set of all cells, to which the human *might be able* to arm-shoulder-reach from his current position, will be denoted as:

$$MHS\_C\_True = \{(x,y,z) : (x,y,z) \in MHS\_C \wedge val((x,y,z), MHS\_C) = 1\}$$

B. *Using Mightability maps*

Fig. 9 illustrates how such Mightability Map could be potentially used to get a fast and optimal solution for various tasks. We will describe the steps in fig. 9, in the context of a particular task for the robot: *Make the yellow bottle (shown as green arrow in fig. 8(a)) accessible to the human*.

By analyzing various Mightability Maps, which are quick to compute, robot will have a rough estimate about reachability and visibility, from the perspective of both agents. Robot will be able to know that, if it will ask human to stand up and lean, human will be able to see as well as reach the bottle. Alternatively, robot will be also aware that it could also reach the bottle and make the bottle visible and reachable to human by putting it 'somewhere' on the table near the human. As mentioned earlier deciding upon the mutual balanced comfort level for achieving a particular goal requires separate investigation. Fig. 9(b) shows such decision making step on macro level comfort. We will simplify this step by assuming that robot is cooperating the human as a partner and it will take the bottle and put it on any of the tables, at a '*place*', which is:

(i) directly arm-shoulder reachable by robot from its current position (needs *MRS_C*),

(ii) AND visible by robot without any need for turning the torso (needs *MRV_T_H_S, MRV_T_H_L, MRV_T_H_R*),

(iii) AND *either* arm-shoulder reachable by the human from his current position (needs *MHS_C*), *or* reachable by the human by only leaning forward (needs *MHS_L_T*),

(iv) AND in human's current field of view (needs *MHV_C*).

With such criteria, robot will get a subset of relevant Mightability maps as shown in the fig. 9(c). In our case, it will be *MRS_C, MRV_C, MRV_T_N, MHS_C, MHS_L_W* and *MHV_C*. Now the next step is to apply various set operations, fig. 9(d), on these relevant Mightability maps to get the set of candidate cells. For our case the set of candidate cells will be given by:

$$Raw\_Candidate\_Cells = \{(x,y,z):(x,y,z) \in (MRS\_C\_Ture \bigcap (MRV\_T\_H\_S\_True \bigcup MRV\_T\_H\_L\_True \bigcup MRV\_T\_H\_R\_True) \bigcap (MHS\_C\_True \bigcup MHS\_L\_T\_True) \bigcap MHV\_C\_True)\}$$

where, *MRS_C_True* is set of cells of Mightability map *MRS_C*, having value 1, which is denoted as:

$$MRS\_C\_True = \{(x,y,z):(x,y,z) \in MRS\_C \wedge val((x,y,z), MRS\_C) = 1)$$

and similarly for others.

Since, the task is to put the bottle on any of the table, the final set of candidate cells is further reduced:

$$Raw\_Candidate\_cells\_to\_Put = \{(x,y,z):(x,y,z) \in Raw\_Candidate\_Cells \wedge (x,y,z) \in \bigcup_{i=1}^{n} surface\_of\_table_i\}$$

where n is the total number of tables in the workspace and $surface\_of\_table_i$ represents the horizontal supporting plane of table i in the environment, information about which is already encoded in the 3D grid during the process of creation and initialization.

Hence, the robot quickly gets a set of raw candidate cells, fig. 9(e), within which the feasible solutions will lie if exist. Also as table III shows, the search space for the rigorous testing for finding the final solution has been significantly reduced, from *144000* cells of the entire workspace to only *8* cells in the candidate search space. Now micro level weights could be assigned, fig. 9(f), within the candidate search space, to get a weighted candidate cells, fig. 9(g). As discussed in section I, assigning such weights depend on various criteria and need investigation, we will assign two intuitive measures of preferences for the candidate cells to put the bottle: (i) Assign higher weights for the points which

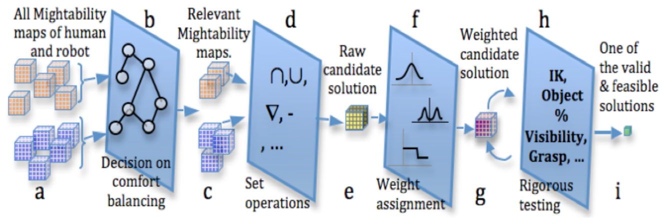


Fig. 9. Steps for finding a solution: (a) Initial Mightability Maps, (b) macro level Decision making, (c) relevant Mightability Maps, (d) set operations, (e) raw candidate solution set, (f) micro level weight assignment, (g) set of weighted candidate points, (h) applying rigorous and expensive tests on reduced search space, (i) the final optimal solution of highest weight.

are along the front axis of the human torso, by 2D Gaussian distribution centered at a distance of *d1* (we have chosen *d1=0.35 m*) from the human along this axis, to avoid putting very close to the human, (ii) then add higher weights for the points which are near to the current position of the bottle, by Gaussian distribution centered at bottle's position.

After having a set of weighted candidate points, robot performs various feasibility tests on each point in the order of highest to lowest weights, fig. 9(h). For the current task, the robot performs following tests: (i) Does there exist any feasible configuration for the robot to grasp the bottle, which also satisfies the task constraints? (ii) Will the bottle be 'sufficiently' visible to the human if put at that point? (iii) Does there exist a collision free trajectory to put the bottle at that point respecting the kinematic and dynamic constraints? We have dedicated modules for all these feasibility analyses.

In the current implementation, we use the first candidate-weighted point, which passes all the above-mentioned rigorous and computationally expensive tests, as the final point for performing the current task, fig. 9(i). If all these tests have to be performed for all the cells in the workspace, it would have been very expensive, which often either leads to offline processing or to some randomized approaches, generating 'a solution' not necessarily the optimal one. Our approach by delaying various expensive tests till later steps of decision making diminishes the necessity of such offline or random processing. Hence, Mightability Maps, as a decisive and reasoning tool on the candidate search space, greatly reduce the search space for a particular task and the robot could quickly converge to the most preferred solution, which is 0.34 s for current example, as shown in table III.

C. Experimental Setup and Testing

We have tested our approach both in simulation and on real humanoid robot HRP2. Experimental setup consists of 3 tables of different heights and the human and robot sitting around the table. 3D map of the static environment is known to the robot. Acquisition of the dynamic objects such as the big and small boxes and the cup is done by stereo-vision based tag identification system through robot's camera. For tracking the human and the bottle to be manipulated by robot, markers based motion capture system is used. We filter out data of those markers, which are not in the field of view of robot, to avoid the impression of bird's eye view. 3D model of the environment is maintained in real time in Move3D, an integrated 3D representation and planning

Fig. 10. Making the bottle accessible to the human, (a) Grasping the bottle by planning collision free path (b) final place where the robot is putting the bottle so that human can access it.

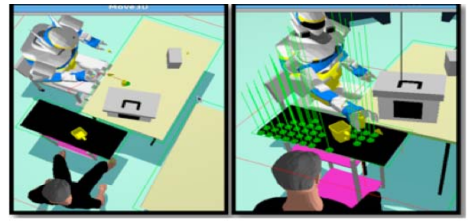


Fig.11. (a) Initial position of the bottle (b) Candidate cells (green circles), their relative weights (length of green lines) and the final place to put the bottle.

Fig. 12:(a) Candidate points in 3D to show the bottle, which was actually hidden from human (b) Robot showing the bottle at the feasible place.

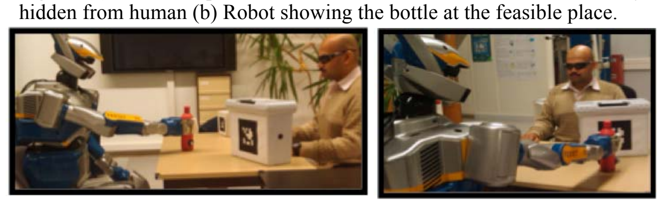


Fig. 13. Hiding the bottle from the human. (a) Initial position of bottle, (b) final position of the bottle hidden from human.

platform developed at LAAS-CNRS. Human gaze is simplified to the human head orientation and the length of human arm is fix in current implementation.

Fig. 10 shows robot performing the task of making the bottle accessible to the human, as explained earlier.

Fig. 11 shows a different scenario, in which human is sitting in front of another table on the right side of the robot. Fig. 11(b) shows the candidate cells (green circles) and their relative weights (length of green lines). The feasible and most preferred solution lies on the table other than the table on which initially the bottle was. As the Mightability Maps contain the visuo-spatial information of the 3D workspace volume, robot easily associates the surface of the other table with the candidate solution to finally put the bottle at a place where the human can easily see and access it.

To show the generic applicability of the Mightability Maps, robot performs another experiment to *show the bottle to the human* by holding it at an appropriate place in space. A similar formulation for this task has been done but by relaxing few criteria. It is no loner necessary to be reached by human as well as the solution need not to be lying on the table surface. Hence the set of candidate cells will be:

$$Raw\_Candidate\_Cells\_to\_Show = \{(x,y,z):(x,y,z) \in (MRS\_C\_Ture \cap (MRV\_T\_H\_S\_True \cup MRV\_T\_H\_L\_True \cup MRV\_T\_H\_R\_True) \cap (MHV\_C\_True \cup MHV\_T\_H\_S\_True))\}$$

The yaw and pitch of the human head to see the point has been used as parameters for assigning the micro level weights. Fig. 12(a) shows the initial position and the set of weighted candidate points and fig. 12(b) shows final position at which the robot is showing the bottle to human.

In the next task the robot has to exhibit the competitive behavior of *hiding the bottle somewhere on the table*, so that the human could *neither see* it *nor reach* it from the *sitting position*, but it should be *visible* and *reachable* to the human if he *stands up*. The candidate points for this task will be:

$$\begin{aligned} Raw\_Candidate\_Cells\_to\_Hide = ((x,y,z):(x,y,z) \in ((MRS\_C\_Ture \cap \\ (MRV\_T\_H\_S\_True \cup MRV\_T\_H\_L\_True \cup MRV\_T\_H\_R\_True) \\ \cap (MHS\_S\_C\_True \cap MHV\_S\_L\_T\_True)) - ((MHV\_C\_True \cup MHV\_ \\ T\_H\_S\_True \cup MHV\_T\_H\_L\_True \cup MHV\_T\_H\_R\_True \cup MHV\_ \\ T\_T\_H\_L\_True \cup MHV\_T\_T\_H\_R\_True) \cup (MHS\_C\_True \cup MHS\_ \\ L\_T\_True \cup MHS\_T\_T\_L\_True \cup MHS\_T\_T\_R\_True \cup MHS\_T\_T\_ \\ L\_L\_True \cup MHS\_T\_T\_R\_L\_True)) \wedge (x,y,z) \in \bigcup_{i=1}^{n} surface\_of\_table_i) \end{aligned}$$

Note that the set of visible and reachable points from the sitting position of the human have been subtracted to get the set of points which are exclusively visible and reachable when the human will stand up. Fig. 13 shows the robot grasping and hiding the bottle by putting it behind the box.

Table III shows the candidate number of cells at the step (e) of fig 9, which is significantly less than the total number of cells in the workspace. Also the time to obtain the highest weighted feasible solution is reasonably acceptable for Human-Robot Interaction, which includes all the steps from fig. 9(a) till 9(i), including the iterative loop between 9(g) and 9(h), once the Mightability Maps have been calculated.

IV. Discussion and Potential Applications

In the current implementation robot uses Mightability Maps to find a solution for a particular task, assuming that the robot knows the semantic of the task. But the proposed Mightability analysis in its form of points in 3D space or extended form of object level Mightabilities, could be used as predicates for learning a variety of task in terms of '*effects*' to be achieved for a particular task. For example from Human-Human demonstrations robot could learn that making accessible means the object should be visible and reachable to the human. Similarly these ananlyses could be used to monitor, understand and predict the actions/changes an agent might be able to do as well as to predict the agent who might have performed a particular action/change in the environmrnt about which the robot was oblivious.

As these Mightability Maps are fast to compute, they could also be stored as facts in chronicle based decision systems for higher-level reasoning. As the robot quickly gets a set of candidate solutions, some external planner or

TABLE III
REDUCTION IN SEARCH SPACE AND TIME FOR VARIOUS TASKS

Initial Total Number of Cells in Workspace = **144000**

Task (HRP2 for Human)	**Ref. Fig.**	**Significantly Reduced Search Space (final number of candidate cells)**	**Time to get the first feasible solution of maximum weight**
Make bottle accessible	10	8	0.34 *seconds*
	11	33	0.52 *seconds*
Show bottle	12	414	0.33 *seconds*
Hide bottle	13	42	0.28 *seconds*

decision making system could iterate/query on the presented basic framework to find an alternative solution or to maintain a ranked set of multiple solutions. Such Mightability analyses could also be used for development of shared plan, as well as bridging the gap between the symbolic and geometric planners [25]. Such understanding of various abilities of itself and of human partner could also be used to enhance the verbalized interaction capabilities of the robot with the human partner as well as the proactive behavior of robot in Human-Robot interaction.

V. Conclusion and Future Work

We have introduced the concept of *Mightability Maps*, which stands for *Might be able to*, and immediately serve as a platform for visuo-spatial reasoning. We have also presented a framework for finding a solution for various tasks in Human-Robot interaction. We have shown that task oriented weights and set operations could be performed on these maps to get a set of candidate solutions. In the current implementation, we have chosen to calculate a set of Mightability Maps based on visibility and reachability of the agents, which in fact could be extended to include and predict various other abilities. The set of visibility and reachability calculation could itself be appended with various other types. Here the motivation was to have an online calculation of Mightability Maps, but one could also choose to have a more rigorous calculation of these maps.

As these maps are independent of the type of manipulation task and are overestimation of different abilities, the feasible solution for a particular task will lie within these maps while greatly reducing the search space for rigorous and expensive feasibility checks. Our presented framework facilitates delaying the introduction of various expensive constraints until the later steps of finding the solution, where the search space has already been reduced significantly. Hence trying to diminish the need of any offline or randomize approaches, which might not provide the solution of highest weight in real time.

Our proposed Mighatibility Maps could not only be used for decision making for the cases requiring common abilities of the agents but also to solve the problems involving what an agent might not be able do. We have shown its use in co-operative as well as competitive scenarios.

Apart from the potential applications discussed in section IV, it would be interesting to extend the calculation of such maps for more agents to facilitate the reasoning on multi-agent task allocation. It would also be interesting to develop methods, which provides the robot with the capability to distinguish autonomously among the types of Mightability Maps, which it should update periodically and which need to be calculated specifically for a particular task.

References

[1] P. Rochat, "Perceived reachability for self and for others by 3- to 5-year-old children and adults," *Journal of Experimental Child Psychology*, vol. 59, Issue 2, April 1995, pp. 317-333.

[2] C. Carello, A. Grosofsky, F. D. Reichel, H. Y. Solomon and M. T. Turvey, "Visually Perceiving What is Reachable," *Ecological Psychology*, Volume 1, Issue 1, March 1989, pp. 27-54.

[3] R. J. Bootsma, F. C. Bakker, F. J. Van Snippenberg, and C. W. Tdlohreg, "The Effects of Anxiety on Perceiving the Reachability of Passing Objects, " *Ecological Psychology*, Vol. 4(1), 1992, pp. 1-16.

[4] P. Rochat, and M. Wraga, "An account of the systematic error in judging what is reachable," *Journal of Experimental Psychology: Human Perception and Performance,* vol.23(1),Feb 1997, pp.199-212.

[5] F. Zacharias, Ch.Borst and G. Hirzinger, "Capturing robot workspace structure: representing robot capabilities," in Proceedings of the IEEE/RSJ IROS, pp. 3229-3236, San Diego, USA, October, 2007.

[6] F. Zacharias, Ch.Borst and G. Hirzinger, "Online Generation of Reachable Grasps for Dexterous Manipulation Using a Representation of the Reachable Workspace," in Proceedings of the International Conference on Advanced Robotics, Germany, 2009.

[7] L. Guilamo, J. Kuffner, K. Nishiwaki and S. Kagami, "Efficient prioritized inverse kinematic solutions for redundant manipulators," in Proceedings of IEEE/RSJ IROS, pp. 1905-1910, 2005.

[8] Y. Guan and K. Yokoi, "Reachable Space Generation of A Humanoid Robot Using The Monte Carlo Method," in Proceedings of IEEE/RSJ IROS, pp. 1984-1989, Oct. 2006.

[9] A. J. Caron, E. J. Kiel, M. Dayton, and S. C. Butler, "Comprehension of the referential intent of looking and pointing between 12 and 15 months," Journal of Cognition and Development, vol. 3(4), 2002, pp. 445–464.

[10] S. Dunphy-Lelii, and H. M. Wellman, (2004) "Infants' understanding of occlusion of others' line-of-sight: Implications for an emerging theory of mind," European Journal of Developmental Psychology, vol 1(1), 2004, pp. 49–66.

[11] G. O. Deak, R. A. Flom, and A. D. Pick, "Effects of gesture and target on 12-and18-month-olds' joint visual attention to objects in front of or behind them," Developmental Psychology,.36(4), 2000, pp. 511–523.

[12] H. Moll, and M. Tomasello, "12-and18-month-old infants follow gaze to spaces behind barriers," *Developmental Science*, vol. 7(1), 2004, pp. F1–F9.

[13] D. L. Gardner, L. S. Mark, J. A. Ward, and H. Edkins, "How do task characteristics affect the transitions between seated and standing reaches?," *Ecological Psychology,* vol. 13, 2001, pp. 245–274.

[14] H. J. Choi, and L. S. Mark, "Scaling affordances for human reach actions," *Human Movement Science*, vol. 23, 2004, pp. 785–806.

[15] L. F. Marin-Urias, E. A. Sisbot, A. K. Pandey, R. Tadakuma, and R. Alami, "Towards shared attention through geometric reasoning for human robot interaction," IEEE-RAS International Conference on Humanoid Robots, pp. 331-336, Paris, France, 2009.

[16] M. Johnson, and Y. Demiris, "Perceptual Perspective Taking And Action Recognition," International Journal of Advanced Robotic Systems,Vol.2(4), Dec. 2005, pp 301-308.

[17] C. Breazeal, M. Berlin, A. Brooks, J. Gray, and A. L. Thomaz, "Using perspective taking to learn from ambiguous demonstrations," Robotics and Autonomous Systems, pp. 385-393, 2006.

[18] J. Gregory Trafton, Nicholas L. Cassimatis, Magdalena D. Bugajska, Derek P. Brock, Farilee Mintz, Alan C. Schultz, "Enabling effective human-robot interaction using perspective-taking in robots", IEEE Transactions on Systems, Man, and Cybernetics, 2005, 460-470.

[19] M. J. Richardson, K. L. Marsh, and R. M. Baron, "Judging and actualizing intrapersonal and interpersonal affordances," *Journal of Experimental Psychology: Human Perception and Performance,* vol. 33(4), Aug 2007, pp. 845-859.

[20] J. J. Gibson, *The Ecological Approach to Visual Perception*. Boston: Houghton Mifflin, 1979.

[21] D. A. Norman, "The Psychology of Everyday Things," New York: Basic Books, 1988.

[22] M. Lopes, F. S. Melo, and L. Montesano, "Affordance-based imitation learning in robots," IEEE/RSJ IROS, San Diego, USA, October 2007.

[23] R. Moratz, and T. Tenbrink, "Affordance-Based Human-Robot Interaction," Affordance-Based Robot Control, LNAI, vol. 4760, 2008, pp. 63–76.

[24] K. Kaneko, F. Kanehiro, S. Kajita, H. Hirukawa, T. Kawasaki, M. Hirata, K. Akachi, and T. Isozumi, "Humanoid robot hrp-2," IEEE ICRA, New Orleans, April 2004.

[25] S. Cambon, R. Alami and F. Gravot, "A hybrid approach to intricate motion, manipulation and task planning." The International Journal of Robotics Research, 28(1):104-126, 2009.