International Journal of Humanoid Robotics

Synthesizing Unnatural Grasps in Humanoid Robots using Fuzzy Logic

Arun Dayal Udai[§,*], Shiladitya Biswas[†] and Sree Aslesh Penisetty[⊕]

[§] *Department of Mechaninal Engineering,*
[†] *Department of Electronics and Communication Engineering*
[⊕] *Department of Electrical and Electronics Engineering*
Birla Institute of Technology, Mesra
Ranchi, Jharkhand - 835215, India
Email: arun_udai@bitmesra.com

Received Day Month Year
Revised Day Month Year
Accepted Day Month Year

This paper presents a whole body grasping algorithm using fuzzy logic. Firstly, a comprehensive analysis of the human body was performed by decomposing it into a simplistic stick diagram and examining all types of grasps possible. The theory of combinations namely, *Enumerative Combinatorics* was used in order to calculate the total number of grasps possible by the human body. The paper focuses largely upon the grasps which can be physically accomplished by the NAO humanoid robot developed by Aldebaran Robotics. Finally, a fuzzy logic based algorithm was implemented to assign grasping weightage to the body parts, i.e. arms, torso, head, etc. of the robot depending upon the position of the object to be grasped.

Keywords: Prehensile Grasp; Humanoid Robot; Fuzzy Logic.

1. Introduction

Humans perform a wide range of grasping activities using their appendages. These activities include ball picking, shifting an object, tool handling, etc. With the growing demand of social and domestic robots for rehabilitation, space exploration, warehouse maintenance, search and rescue, it is evident that in the future, robots must be developed which can intelligently grasp and manipulate objects. The term 'prehensility' is defined as the quality of an appendage or organ that has been adapted by an organism for grasping or holding. Majority of the prehensile grasps are force/form closure by nature. Humans can perform prehensile grasps both by their primitive grippers, i.e. palm and fingers, and their appendages, i.e. arms, forearms, foot, torso, etc. In this work, the latter type of prehensile grasp[1] was studied to develop an algorithm using Fuzzy Logic. The algorithm was further implemented on a NAO robot. Henceforth, the prehensile grasps done by using appendages are

*Corresponding Author

referred to as *Unnatural Grasps*. Figure 1 illustrates some examples of this type of prehensile grasp.

Figure 1. Unnatural prehensile Grasp Examples

Traditional robots perform grasping operations such as grabbing a standard mug[2] using specially designed grippers and stereo vision. The idea of prehensile grasp i.e. whole arm grasping was first proposed by Salisbury[3] and other works in this domain can be found in Snake robots4 and whole body manipulation[5,6,7]. Advancements in the grasping strategy include full contact grasps[8], bi-manual grasps[9] and adaptive grasp with tactile sensors[10,11,12] instead of traditional fingertip grasps. A geometric approach to grasp manipulation using the robot arms has been implemented in[13,14,15]. However, considering every available appendage of a robot for grasping is not reported so far. Cutkosky, et. al.[16] discusses different human grasp choices giving a detailed analysis of the different types of human hand grasps possible and also describes the problems of robotic grasping. However, these works were limited only to primitive grippers i.e. specially designed for grasping purpose.

An approach to whole body grasping with imitation learning and whole limb manipulation was presented in[17,18]. Mochiyama et. al.[19] presented a mechanical impedance for the whole arm of a serial-chain manipulator, which takes in a curve specifying the virtual target shape of the object to be grasped. An algorithm for precision grasping of bulk objects with two anthropomorphic hands was presented in[20] where objects were modeled as point cloud. Algorithms based on impedance control to grasp bulky and heavy objects were developed in[21].

All the above mentioned research works focused mainly on grasping the object but they do not assign any grasping weightage to the individual body links or appendages. The assignment of grasping weightage can be based on multiple factors such as location, shape, size, surface texture, fragility, etc. In this paper the focus is on location based weightage assignment. Without having weightage, the robot is unable to decide which body part to use in order to perform the grasp in a given situation. For instance, if an object is placed to our left side, we tend to grab it by the left hand. Hence, in this case grasp weightage of left hand is higher than right hand. This is the research gap that was found in the literature survey. A typical grasp planning sequence should be, (a) Obtaining the object location, (b) Decide which body part to use to grasp the object, and (c) Plan a trajectory to grasp the object with the appendages decided in step (b). Mellmann et. al.[22] gives a detailed grasp analysis by NAO humanoid robot.

This paper presents a Fuzzy logic algorithm[23] that assigns grasping weightage to the body parts namely, hands and torso of the NAO robot and then uses position interpolation function, which is a predefined function in NAO Application Programming Interface (API) to grasp the object. Fuzzy Logic controller has many benefits and has been successfully used to perform various robotic tasks like manipulator control and navigation[24]. Fuzzy logic was also reported for robot grasping in[25].

In Sec II a comprehensive grasping analysis of the human body is done. Selection of feasible grasps that a robot can perform is explained in Sec III. In Sec IV an algorithm is developed based on Fuzzy logic to assign grasping weightage to robot body parts, depending upon the location of the object. Step by step implementation of the grasp is presented in Sec V. Finally we discuss the results and possible future works in this field in Sec VI and VII respectively.

2. Comprehensive Analysis

All the possible ways by which a human body can perform unnatural grasp are determined in this section. According to the definition of Unnatural Grasp as defined earlier, the primitive hand-palm grip was ignored. The human body is a hybrid composition of both serial and parallel chain manipulators. Ignoring the palm, the human body has total of 13 links. Figure 2 (a) shows a human body and Fig 2 (b) shows its simplistic link version. The links were labeled alphabetically. Humans possess high level of intelligence to properly coordinate all these links and perform unnatural grasps. Hereafter in this paper a grasp is written as a string of alphabets, where each alphabet represents one of the links participating in achieving the grasp. For example, Right Forearm-Torso grasp is represented as FG.

2.1. *Two point grasp*

Two contact point unnatural grasps are easily achievable.Montana et.al.[26] has worked on the spatial and contact stability of these types of grasps. Some examples of such grasps are EF, DG, FG, JK, HI etc. Theoretically there are total ${}^{13}C_2 = 78$ grasps possible. But taking the kinematic limitations into consideration certain grasps like BC, BD, BG, BH, BI are not feasible. Depending upon the appendages

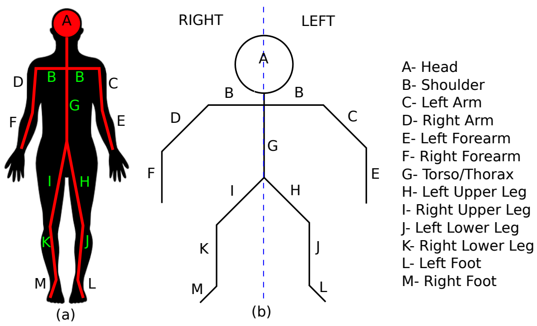

Figure 2. Comprehensive Analysis (a) The human Body. (b)Simplistic Stick Diagram.

used to grasp the object a two point grasp table can be constructed as shown in table 1. Here ✓ and × represent feasible and unfeasible grasp respectively.

Table 1. Two Point Grasp Table

×	A	B	C	D	E	F	G	H	I	J	K	L	M
A	•	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
B		•	×	×	✓	✓	×	✓	✓	✓	✓	×	×
C			•	✓	✓	✓	✓	✓	✓	✓	✓	×	✓
D				•	✓	✓	✓	✓	✓	✓	✓	✓	×
E					•	✓	✓	✓	✓	✓	✓	✓	✓
F						•	✓	✓	✓	✓	✓	✓	✓
G							•	✓	✓	✓	✓	✓	✓
H								•	✓	✓	✓	×	✓
I									•	✓	✓	✓	×
J										•	✓	✓	✓
K											•	✓	✓
L												•	✓
M													•

2.2. *Three point grasp*

Three point grasps are more stabilized as compared to two point grasps. Theoretically, there are a total of ${}^{13}C_3 = 286$ grasp combinations, only a few of them can be achieved practically due to the physical constraints of the human body. These constraints include the consideration of the cases where the stability of the body is not compromised. Some examples of feasible three point grasp are ECB, EGF, EFA, DFG, CEG, CEB, BDF, EGH, FGI etc. Grasps like BGH, BGI and many more are not possible.

2.3. *Multi-point grasp*

Few extreme grasps include four, five, six, seven and eight point contact grasp. These grasps are rarely used or are used in extreme cases by humans. The closest available links in the body are used without compromising the body stability. Hence, there are rare cases where a human uses a leg and a hand or any other link in the upper body to grasp an object. Considering this, the maximum number of nearest links possible are numerically three. The number of such theoretically possible grasps are:

$$\begin{gathered} 4 \text{ point grasps, } {}^{13}C_4 = 715 \\ 5 \text{ point grasps, } {}^{13}C_5 = 1287 \\ 6 \text{ point grasps, } {}^{13}C_6 = 1716 \\ 7 \text{ point grasps, } {}^{13}C_7 = 1716 \\ 8 \text{ point grasps, } {}^{13}C_8 = 1287 \end{gathered}$$

3. Grasping by Nao

In the previous section, the versatile nature of the human body and the wide number of unnatural grasps that it can perform was theoretically explained. All these grasp are possible due to the high flexibility and actuation transparency of the human muscular system. Actuation transparency enables human to propriocept i.e. to have a perception or awareness of the position and movement of the body, very essential to perform unnatural grasp. In contrast, the NAO robot consists of rigid links, joints, offsets etc. Thus it has several kinematic limitations and constraints. Hence, it is evident that NAO cannot perform all the grasps listed in the previous section. For instance, grasps *EFGH, EFGI* (Both Forearms-Torso-Thigh), *EGI, EGH* (Forearm-Torso-Thigh) etc will force the robot to stand on one feet and hence destabilize it. While, other grasps like *AB* (head and shoulder side wise), *LH, IM* (i.e. Thigh-Foot), *BG* (Shoulder-Torso) and other similar grasps are kinematically impossible. Since NAO's head is cylindrical in shape with its axis parallel to the Y axis the chin-torso grasp, although kinematically achievable, it is unable to grasp any object because of the shape of the head, hence this grasp was not considered.

A small subset of all the possible grasps which were achievable by NAO without compromising its stability were selected for the study. These grasps were *FG* (Left Hand-Torso grasp), *EG* (Right Hand-Torso grasp) and *EGH* (Both Hand-Torso grasp).The selection of the subsets was done by careful assessment of the combination of the grasps which could be physically performed by the NAO robot.

4. Weightage assignment algorithm

A Fuzzy Logic Controller (*FLC*) was employed to assign grasping weights to the limbs (*i.e. arms and torso*) of the *NAO* robot. The FLC takes the position of the object as input and uses a Fuzzy Inference system to evaluate the grasp weightage of each limb. Furthermore, an *Occupancy table* was defined which keeps track of the availability of limbs for grasping. In this section, the detailed explanation of the *FLC*, *Occupancy table* and their combined working is discussed.

A Single Input Multi Output (*SIMO*) *Mamdani* Fuzzy Logic Controller was developed. Triangular Membership functions (*TMF*) were used for fuzzification. Evaluating the fuzzified inputs and the areas of TMFs are simple and fast to calculate as compared to other membership functions. Centroid defuzzification was used to get the *crisp values* or the *limb weightage*, as it is a basic and commonly used defuzzification method[27].

Moreover for simplicity, only the Y coordinate as shown in Fig. 3 of the object was considered, keeping the other coordinates fixed. The interest lies in how the limb weights change as the object moves from the robot's left to right keeping its height and distance from the robot constant. Figures 3 and 4 show the robot's Cartesian frame of reference and the block diagram of a SIMO Fuzzy Logic Controller, respectively.

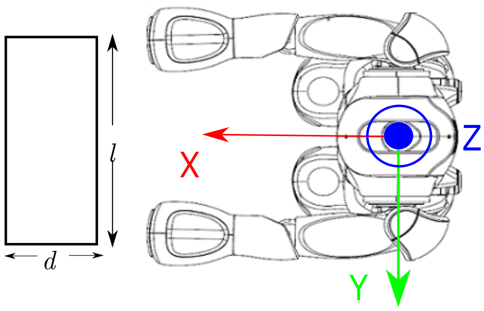

Figure 3. Robot's Cartesian Frame of Reference.

The area in front of the robot where it can perform grasping was divided into three parts i.e. *Robot's Left*, *Robot's Center* and *Robot's Right*; each of these parts were assigned slightly overlapping TMF as shown in Fig. 5.

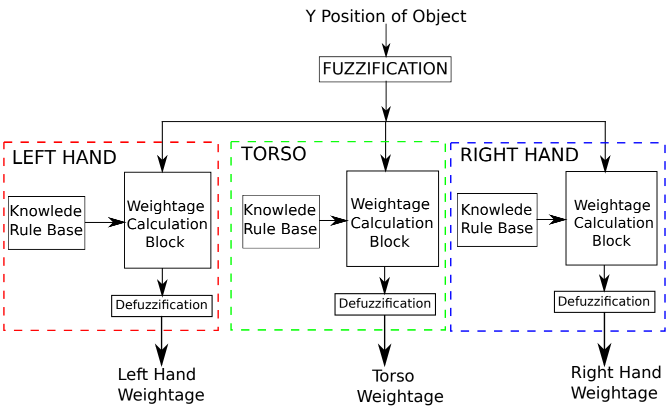

Figure 4. SIMO Fuzzy Inference System.

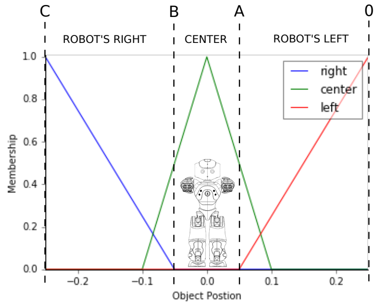

Figure 5. Object Position Membership Function

4.1. *Rule-Base Definition*

Depending upon the position of the object the limbs were assigned weight ranges in percentage to form a linguistic rule base. The algorithm for assignment of TMF is illustrated in 4.1:

Algorithm 4.1: INITIAL $(ObjectPosition)$

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comment: Algorithm for assignment of TMF

START: Get input Object Position
if $0.05m \leq ObjectPosition \leq 0.3m$

$$\textbf{then}\ \begin{cases} \textbf{comment:}\ \text{Object is to Left of NAO} \\ LeftHandWeight \leftarrow (70\% - 90\%) \\ TorsoWeight \leftarrow (50\% - 90\%) \\ RightHandWeight \leftarrow (0\% - 20\%) \end{cases}$$

else if $-0.1m \leq ObjectPosition \leq 0.1m$

$$\textbf{then}\ \begin{cases} \textbf{comment:}\ \text{Object is in Center of NAO} \\ LeftHandWeight \leftarrow (0\% - 20\%) \\ TorsoWeight \leftarrow (80\% - 90\%) \\ RightHandWeight \leftarrow (0\% - 20\%)) \end{cases}$$

else if $-0.3m \leq ObjectPosition \leq -0.05m$

$$\textbf{then}\ \begin{cases} \textbf{comment:}\ \text{Object is to right of NAO} \\ LeftHandWeight \leftarrow (0\% - 20\%) \\ TorsoWeight \leftarrow (50\% - 90\%) \\ RightHandWeight \leftarrow (70\% - 90\%) \end{cases}$$

END: Weightage is assigned accordingly

For example:

IF *Object Position is Left* **THEN** *Left-Hand weight is 70-90 %, Right-Hand weight is 0-20 % and Torso weight is 50-90%.*
In a similar manner, other linguistic rules were also defined. The membership functions are illustrated in Fig. 6.

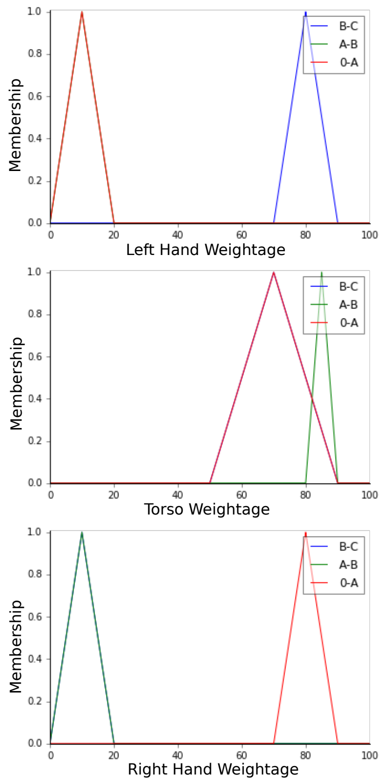


Figure 6. Limb Membership Functions

4.2. *Occupancy Table*

Since the NAO robot does not have any pre-installed tactile sensors on its limbs or appendages, it cannot detect if it has actually grasped an object. Hence, Human feedback was used to verify if the grasp was performed and a limb occupancy table was maintained accordingly. A positive feedback meant that the robot has successfully grasped the object and vice-versa. The Occupancy table was a five bit binary array as shown in Fig. 7 representing the availability of the appendages. If an appendage is being used in a grasp, the bit associated to it in the occupancy table is set to '1' by the algorithm else it is set to '0'. On encountering a negative feedback the robot's limbs went back to the starting/initial position and accordingly the occupancy table was updated. Each grasp was performed after verifying the occupancy table. If the limbs were occupied then it notifies the user that the grasp was not possible.

LEFT HAND	TORSO LEFT	TORSO CENTER	TORSO RIGHT	RIGHT HAND
1	1	0	1	1

Figure 7. Grasp Occupancy Table

4.3. *Complete Working*

The user enters the position and dimension of the object to the program. The program checks the volume of the object. If the volume was small such that the robot can grasp it with its primitive gripper, it grasps the object. If the object's volume was larger than the gripper volume, the program inputs the Y coordinate of the object into the SIMO FLC algorithm to generate the grasp weightage of each body parts. If according to the *occupancy table* the body parts with the highest weights were available, the grasp was performed based on the position of the object. The program then asked for a feedback from the user whether the object was successfully grasped. Depending upon the user's feedback the occupancy table was updated. The complete working can be summarized by the flowchart in Fig. 8.

5. Grasp Implementation

The grasp implementation can be represented mathematically. In view of representation and illustration, (x_l, y_l,z_l) are considered to be coordinates of the end effector position of Left hand in meters, considering ground as reference, (x_r, y_r and z_r) to be the coordinates of the end effector position of right hand in meters considering ground as reference, (x, y and z) to be the coordinates of the object's center position in meters considering ground as reference and $[Length\ (l) \times Depth\ (d) \times Height\ (h)]$ to be the size of the object. The illustration of the co-ordinate axis comparison can be made with the co-ordinate frame of reference shown in Fig. 3.

5.1. *Single Hand Torso grasp*

The Single Hand Torso grasp is the most common prehensile grasp performed by humans. For example, holding a football, or holding a helmet, as shown in Fig. 1. Since the legs of the NAO robot were fixed to the ground, the user had to

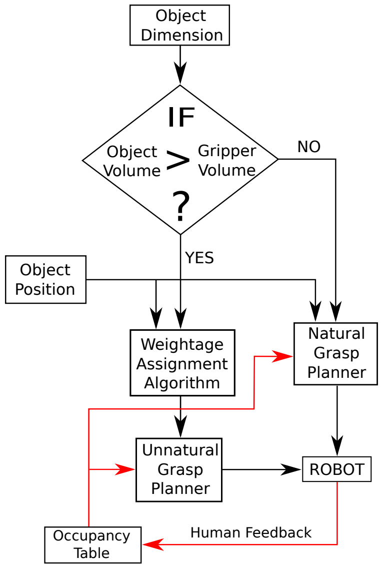


Figure 8. Flow Chart of Complete working

bring the object between NAO's Left/Right hand and the torso for the robot to grasp it. Once the grasp was executed, the program waits for human feedback. The occupancy table was updated according to the feedback given. It was a three step process. The procedure for right hand torso grasp is described below.

(1) The Robot makes sufficient space between its hands and torso to accommodate the object and ensures that the robot's end effector is in its coronal or frontal plane. In order to do so, the gap between the arm and torso was made greater than l as shown in 9. Hence the end effector position should be:
$x_r := 0$ (ensures end effector is in frontal plane)
$y_r := -(y + (l/2))$
$z_r := z$
(2) The user brought the object between the arm and torso such that it's center is in the frontal plane.
(3) Now, in order to tightly grasp the object, the gap g was made less than l as shown in Fig. 9. Thus,
$y_r := -(l - \delta)$, where $\delta > 0$
The tightness of the grasp is directly proportional to the value of δ.
Other coordinates x_r and z_r are left intact.

Similarly, the left hand-torso grasp is also performed, the only difference being, the Y coordinate of the left hand i.e. $y_l = (y + (l/2))$ because the left hand of the robot lies on the positive side of the Y axis. Position interpolation was used

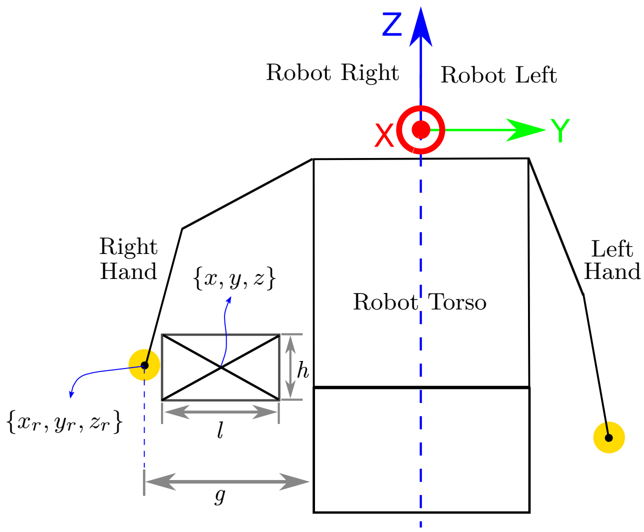


Figure 9. Single Hand- Torso Grasp

to perform this grasp. This feature of the NAO robot takes the position of the end effector and the time stamp associated with each position as input vectors. The software then calculates the transformation matrix accordingly, to reach each predefined position within the given specified time stamps. The entire procedure is shown in Fig. 9.

5.2. *Both Hands Torso grasp*

The object was held with three contact points i.e. one from each hand and the torso. This grasp was performed in four steps:

(1) Reach the object: First, the robot reaches the object. The position of both hands was kept slightly away from the object in order to maintain a grasp offset (δ_1) and avoid displacing the object from its position. The position of the end-effector of both the hands were calculated by the equations below. The value δ_1 was the allowance factor as given in Table. 2 and its value was directly proportional to the allowance/offset.

Left hand	Right Hand
$x_l := x + (d/2)$	$x_r := x + (d/2)$
$y_l := y + (l/2) + \delta_1$	$y_r := y - (l/2) - \delta_1$
$z_l := z$	$z_r := z$

(2) Grab the object: Once the object is reached,it is grasped by subtracting a $\delta_2(> \delta_1)$ term from the current y_l position of the Left Hand and adding the $\delta_2(> \delta_1)$ term to current y_r position of the Right Hand. Here δ_2 is the grasp factor as given in Table. 2, δ_2 is directly proportional to the tightness of the grasp.

Table 2. Delta assignment

δ_1	Offset Factor along Y axis
δ_2	Tightness Factor along Y axis
δ_3	Tightness Offset Factor X axis

Left hand	Right Hand
$x_l := x + (d/2)$ $y_l := y + (l/2) + \delta_1 - \delta_2$ $z_l := z$	$x_r := x + (d/2)$ $y_r := y - (l/2) - \delta_1 + \delta_2$ $z_r := z$

(3) Bring the object to the center: With step (2) completed, the object was needed to be brought to the center (i.e. it was desired that the end effector position of both the hands to be at a distance $(l/2)$ from the X axis, only then the object's center would coincide with the X axis). For an object already at the center, this step was not required.

Left hand	Right Hand
$x_l := x + (d/2)$ $y_l := (l/2) + \delta_1 - \delta_2$ $z_l := z$	$x_r := x + (d/2)$ $y_r := (-(l/2) - \delta_1 + \delta_2)$ $z_r := z$

(4) Bring the object to the torso: After grasping and bringing the object to the center the robot brought the object to the torso. For this, depth d of the object was taken into consideration. Both the hands were made to move at a location that was slightly less than '$d/2$' distance from the torso, keeping other coordinates (i.e., y and z) values fixed. Hence the values of x_l and x_r were changed to $(d/2) - \delta_3$, where δ_3 determines tightness of the grasp with the torso as given in Table. 2. δ_3 is directly proportional to the tightness of the grasp of the object held to the torso.

For this entire grasping process, transform interpolation was used. It is a feature of *NAO* robot which takes in vectors of transform arrays along with there associated time stamps and then make the robot arm move as per the pre-defined transformations at each time stamps. We could have used position interpolation to perform this grasp too. The drawback of position interpolation is, it is a blocking program i.e. we could move only one hand at a time. In this grasp both hands has to move at a time. Hence transform interpolation code being unblocking by nature perfectly suits our purpose here. The complete grasping process is shown in Fig.10.

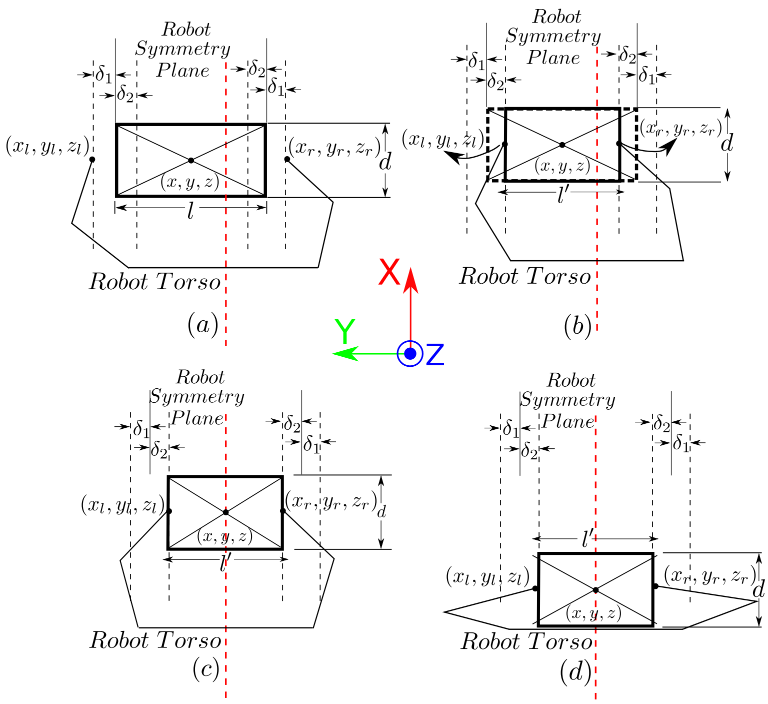


Figure 10. Grasping Steps: a) Reach the object. b) Grab the object. c) Bring the object to the center. d) Bring the object to the torso.

6. Results and Discussions

Several experiments were conducted with object located at different positions to test the algorithm. The robot was able to successfully perform unnatural grasping following the steps discussed in Section 5. The *FIS* was able to assign limb weights according to the position and size of the object. The main aim i.e. to demonstrate the capability of the proposed weightage assignment *FIS* algorithm was successfully tested. The continuous variation of limb weights as the object was moved from left side to right side of the robot, keeping its height fixed is shown in Fig.11. The transition of limbs weights as shown in Fig.11 was abrupt because our *fuzzy Universe of Discourse* had less membership functions. Figures 12, 13, 14 and 15 show the working of the algorithm for the object placed at different location with respect to the robot.

The whole process could not be made online as issues were faced while implementing the grasping steps on the NAO due to its limitations and constraints, as a result it failed to grasp the object at few instances. These issues include:

(1) As the robot's legs were constrained at one place to the ground, it would

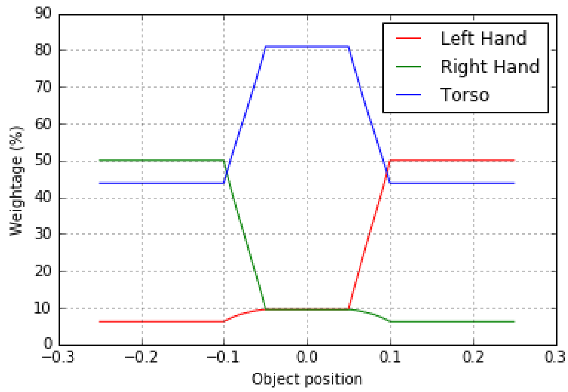


Figure 11. Limb Weight Variation.

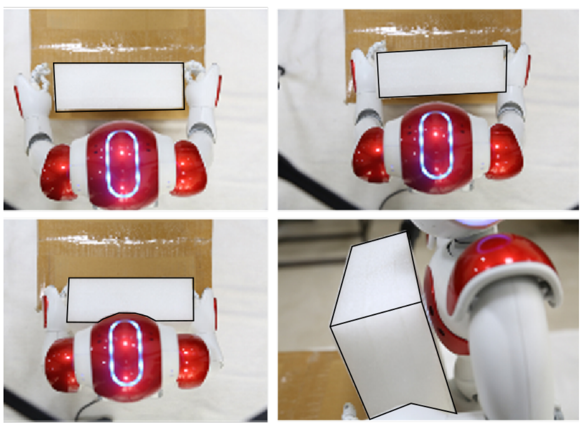


Figure 12. Grasping Object positioned at the center.

often topple while trying to grasp objects located at the periphery of its front workspace along the X axis. It was also observed that the robot would fall while performing the "Both Hands Torso grasp" for objects placed more than $\pm 5cm$ from the sagittal plane or the X axis. Hence, the Center Membership function was assigned accordingly, as shown in Fig. 5.

(2) Since the two vision sensors of the robot are present in a vertical plane they could not be used to instantly determine the position of the object.

(3) The object to be grasped was always placed at a distance less than $15cm$

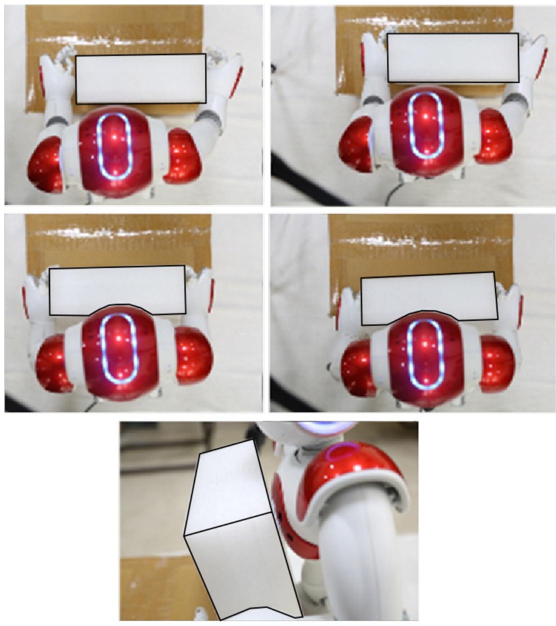


Figure 13. Grasping object positioned slightly towards the right.

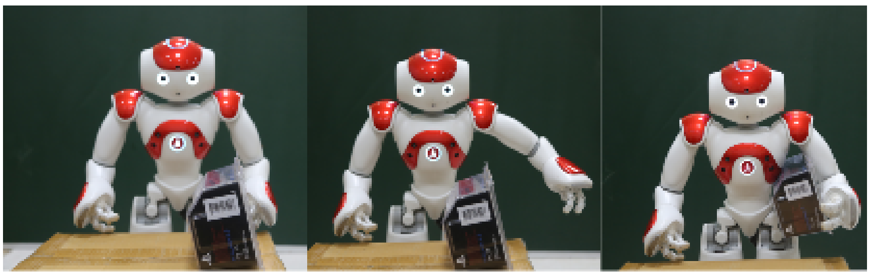


Figure 14. Left Hand- Torso Grasp

away from the robot. The on-board SONAR sensor of NAO has a detection range of $20 - 80cm$ from the robot. Hence the object was always in the SONAR dead-zone. Thus, the sensor data could not be used to automate the proposed algorithm as it was unreliable for determining the position of the object.

7. Future Work

This work opens up a new field of research particularly aiming to increase the grasping and manipulation capabilities of a Humanoid robot using its appendages. The work can be automated by using Microsoft Kinect to determine the position of the object and then build an Artificial Neural Network (ANN) to assign grasping weightage. Embedded artificial skin[28] can be used in combination with force-electric

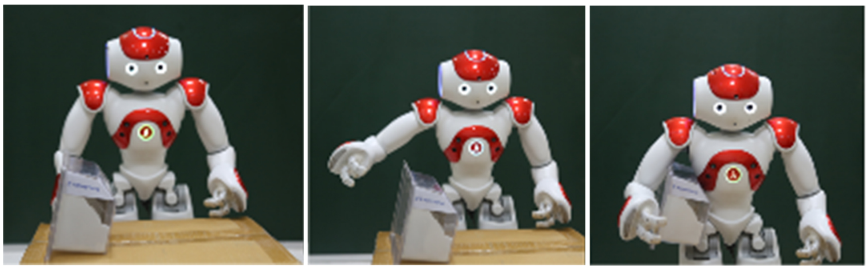


Figure 15. Right Hand- Torso Grasp

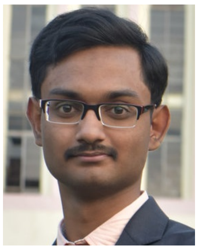
current sensor[11] to perform adaptive grasping by giving live feedback to the system. Finally, the study here deals with stationary objects. In the future, work can be extended to mobile objects as well and limb weightage assignment can be done by considering all the three axes i.e. X,Y and Z.

References

1. Michael Erdmann. An exploration of nonprehensile two-palm manipulation: Planning and execution *Robotics Research*, pages 16–27, London, 1996. Springer London.
2. J. Müller, U. Frese, and T. Röfer. Grab a mug - object detection and grasp motion planning with the nao robot. In *2012 12th IEEE-RAS International Conference on Humanoid Robots (Humanoids 2012)*, pages 349–356, Nov 2012.
3. Brian Eberman and Kenneth Salisbury. Whole-arm manipulation: Kinematics and control. Mar 1995.
4. G. Salvietti, H. X. Zhang, J. Gonzalez-Gòmez, D. Prattichizzo, and J. W. Zhang. Task priority grasping and locomotion control of modular robot. In *Proceedings of the 2009 International Conference on Robotics and Biomimetics*, ROBIO'09, pages 1069–1074, Piscataway, NJ, USA, 2009. IEEE Press.
5. D Braganza, Michael Mcintyre, D.M. Dawson, and I.D. Walker. Whole arm grasping control for redundant robot manipulators. Volume 2006, page 6 pp., July 2006.
6. F. Asano, Zhi-Wei Luo, M. Yamakita, and S. Hosoe. Dynamic modeling and control for whole body manipulation. In *Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453)*, volume 4,pages 3162–3167 vol.3, Oct 2003.
7. Toshiharu Mukai, Shinya Hirano, Morio Yoshida, Hiromichi Nakashima, Shijie Guo, and Yoshikazu Hayakawa. Whole-body contact manipulation using tactile information for the nursing-care assistant robot riba. pages 2445–2451, Sept 2011.
8. Robert Platt Jr, Andrew Fagg, and Roderic Grupen. Extending fingertip grasping to whole body grasping. pages 2677 – 2682 vol.2, Oct 2003.
9. Nikolaus Vahrenkamp, Markus Przybylski, Tamim Asfour, and Rüdiger Dillmann. Bimanual grasp planning. In *2011 11th IEEE-RAS International Conference on Humanoid Robots*, pages 493–499, 2011.
10. Philipp Mittendorfer, Eiichi Yoshida, Thomas Moulard, and Gordon Cheng. A general tactile approach for grasping unknown objects with a humanoid robot. pages 4747–4752, 11 2013.

11. Heinrich Mellmann, Marcus Scheunemann, and Oliver Stadie. Adaptive grasping for a small humanoid robot utilizing force and electric current sensors. In *CS & P*, 2013.
12. Yoshiyuki Ohmura and Yasuo Kuniyoshi. Humanoid robot which can lift a 30kg box by whole body contact and tactile feedback. pages 1136 – 1141, 12 2007.
13. Andrew T. Miller, Steffen Knoop, Henrik I. Christensen, and Peter K. Allen. Automatic grasp planning using shape primitives. In *ICRA*, 2003.
14. Ying Li, Jiaxin L Fu, and Nancy Pollard. Data-driven grasp synthesis using shape matching and task-based pruning. *IEEE transactions on visualization and computer graphics*,13:732–47, 07 2007.
15. J. Bohg and D. Kragic. Grasping familiar objects using shape context. In *Advanced Robotics, 2009. ICAR 2009. International Conference on*, pages 1–6, 2009.
16. Mark R. Cutkosky and Robert D. Howe. *Human Grasp Choice and Robotic Grasp Analysis*, pages 5–31. Springer New York, New York, NY, 1990.
17. Kaijen Hsiao and Tomas Lozano-Perez. Imitation learning of whole-body grasps. In *IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems(IROS)*, 2006.
18. Antonio Bicchi. On the problem of decomposing grasp and manipulation forces in multiple whole-limb manipulation. In *Robotics and Autonomous Systems,* Volume 13, Issue 2, pages 127-147, July 1994.
19. H. Mochiyama. Whole-arm impedance of a serial-chain manipulator. In *Proceedings 2001 ICRA. IEEE International Conference on Robotics and Automation (Cat. No.01CH37164)*, volume 3, pages 2223–2228 vol.3, May 2001.
20. Abiud Rojas de Silva and Raúl Suárez. Grasping bulky objects with two anthropomorphic hands. *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 877–884, 2016.
21. M. Florek-Jasińska, T. Wimböck, and C. Ott. Humanoid compliant whole arm dexterous manipulation: Control design and experiments. In *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 1616–1621, Sep. 2014.
22. Heinrich Mellmann and Giuseppe Cotugno. Dynamic motion control: Adaptive bimanual grasping for a humanoid robot. *Fundam. Inf.*, 112(1):89–101, January 2011.
23. James J. Buckley. Theory of the fuzzy controller: An introduction. *Fuzzy Sets and Systems*, 51:249–258, 11 1992.
24. Yi Tun Wang Ching-Han Chen, Chien-Chun Wang and Po Tung Wang. Fuzzy logic controller design for intelligent robots. *Mathematical Problems in Engineering*, 2017, 2017. Hindawi Publishing Corporation, 12 pages.
25. Matthew J. Sheridan, Stanley C. Ahalt, and David E. Orin. Fuzzy control for robotic power grasp. *Advanced Robotics*, 9(5):535–546, 1994.
26. D. J. Montana. Contact stability for two-fingered grasps. *IEEE Transactions on Robotics and Automation*, 8(4):421–430, Aug 1992.
27. Keshen Wang. Computational Intelligence in Agile Manufacturing Engineering. *, Elsevier Science Ltd*, 2 Sept. 2007.
28. G. Cannata, M. Maggiali, G. Metta, and G. Sandini. An embedded artificial skin for humanoid robots. In *2008 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, pages 434–438, Aug 2008.

Arun Dayal Udai is an Assistant Professor in the Department of Mechanical Engineering, BIT Mesra, Ranchi, India. He completed his Ph.D. from Indian Institute of Technology Delhi, India in the subject area of Force Control of Industrial Robots. He did his Masters in Mechanical Engineering from BIT Mesra, Ranchi in the year 2006. During the tenure of his Masters he co-authored a text book on Computer Graphics, which was published by Tata McGraw Hill, New Delhi in 2008. He completed his B. Tech in Marine Engineering from MERI, Kolkata, India in the year 1999 and worked with Anglo Eastern Ship Management, Hong Kong for four years. He sailed across globe on-board ship to different countries and acquired expertise in various areas of mechanical engineering. His research interests include Robotics, Mechatronics and CAD.



Shiladitya Biswas received his B.E. degree in Electronics and communication Engineering from Birla Institute of Technology, Mesra, India, in the year 2018 and is en route to pursuing his M.S. degree in Electrical and Computer Engineering with specialization in Intelligent systems, Robotics and Control from the University of California, San Diego, USA. His research interests include grasping, manipulation, dynamics, control and simulation.

Sree Aslesh Penisetty received his B.E. degree in Eleectrical and Electronics Engineering from Birla Institute of Technology, Mesra, India, in the year 2019. During his pre-final year he was the captain for his college's robotics team and during his final year, he was the vice-president for his college's machine learning club. His research interests include autonomous vehicles, control, machine learning, dynamics and simulation.