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Dynamic Motion Control: Adaptive Bimanual Grasping for a Humanoid Robot

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Abstract. The ability to grasp objects of different size and shape is one of the most important skills of a humanoid robot. There are a lot of different approaches tackling this problem; however, there is no general solution. The complexity and the skill of a possible grasping motion depend hardly on a particular robot. In this paper we analyze the kinematic and sensory grasping abilities of the humanoid robot Nao. Its kinematic constraints and hand's mechanical structure represent an interesting case of study due to lack of actuators for fingers and the limited computation power. After describing the platform and studying its capabilities, we propose some simple controllers and we present a benchmark based on some experimental data.

Keywords: motion generation, robot grasping, humanoid robot

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1. Introduction

One of the features that made humans a very successful living being is their ability to grasp and manipulate objects. Such feature granted humans the possibility to modify and adapt the surrounding environment making it more suitable to their own needs. For such reason, grasping and manipulating objects can be seen as a strategic goal for robotics. A robot equipped with dexterous hands can interact better with the environment performing more complex tasks. Restraining objects is a not trivial task due to each object's geometrical and physical peculiarities.

The robot's grasping capabilities highly depends on the hands' mechanical structure, its sensors and, of course, the available computational power. Moreover, a robot has to be able to perform stable and flexible motions in order to act in a dynamic environment, moving the whole body when necessary. This is especially true if an object has to be grasped with both hands.

In this paper we present an implementation of an adaptive bimanual grasping motion on a humanoid robot. We use visual information to perceive the objects and to estimate their position and size. Additionally, we investigated how different sensors can impact on contact force-driven motion control. In particular we use the motor's internal sensors for estimating the force applied to the object.

In our approach we model the motion in Cartesian space; the joint trajectories are generated by inverse kinematic. We have to ensure the adaptivity and to satisfy some conditions, e.g., stability, at the same time to achieve a general and robust grasp.

1.1. Outline

In the first section of this paper we present and discuss a general overview on the topic in terms of hand's mechanics, sensing capabilities, modeling and control. In the second section we outline the Nao's hardware, its sensing aptitudes, its kinematic constraints and how those bindings may lock-up the motion. In the third part we introduce three regulators and we discuss both their design and control capabilities. In the fourth part we show some experimental data benchmarking the control effectiveness. In the last part we suggest some ideas where to address the further developments.

2. Survey on the Grasping task

The hands are generally used to accomplish three tasks: exploring, grasping and manipulating objects [5]. The first task belongs to the research field of *haptics* that tries to infer perceptions on surrounding environment by touching, like perceiving the shape of a surface. The second task aims to restrain objects, like holding a heavy box without letting it fall or picking up a beer from a table. The third task tries to manipulate a grasped object for carrying out an assignment, like unscrewing a panel, preparing coffee or throwing a soccer ball back in the field. It's easy to understand that grasping and manipulation are strictly related. This paper will mainly focus on the restraining problem in terms of its difficulties and the possible solutions that may be found for them.

Some of the first works focused on restraining were by Asada and Hanafusa [2] and the Mason and Salisbury's three fingered hand [9].

2.1. Mechanics

The hand's mechanical structure has a deep impact on the grasping technique and control strategy. Briefly, hands design may be divided in two categories: anthropomorphic and minimalistic. The first category aims to replicate the human hands' capability of manipulating objects, while the second one is more task oriented [4]. An anthropomorphic hand relies on the wise use of fingertips and phalanges for grasping and manipulating objects. Generally, fingertips are best used for object handling, while phalanxes may be helpful for achieving successful object restraining. Equipping a robotic hand with fingers allows the robot to manipulate and hold objects with arbitrary shapes and ensure a better grip stability and manipulability [3]. However, the more fingers are available the more degree of freedom have to be managed for controlling a single hand. Therefore, grasping an object may be seen as an optimization problem in a high dimensional space, where the target function is the evaluation of grasp quality. Due to the high dimensionality of the search space, it may be useful to simplify the joint space using PCA [6] or other techniques in order to calculate a proper pose in a feasible time. On the other hand, a simple jaw gripper doesn't suffer such problem but its grasping capabilities are much more limited in terms of grip stability and manipulability.

So far, only single handed grasping has been taken into account, but it is possible to grasp objects using two hands. Such technique is generally addressed as bimanual grasping. Bimanual grasping shares all the problems reviewed so far but it adds new complexity nodes due to the mandatory coordination required for grabbing objects using two hands. In fact, the arms workspace may be overlapping introducing the necessity of detecting possible collisions among the arms. Moreover, grasping itself requires a tight coordination among the arms for holding and balancing the object. Bimanual grasping may be useful if the robot has to pick up an object that is too big for one hand, or if an object have to be re-grasped with another arm for some reason, like avoiding an obstacle while manipulating it.

2.2. Sensing

Sensors may be used for force estimation, the most popular are the force/torque sensors, tactile sensors and joint/current data provided by the DC joint's motor [10]. However, sometimes sensor data is not necessary or available for performing a certain task, for instance when the forces applied at the end effector are lower than the sensor's resolution. In such case, uncertainty about the object's position and orientation in the hand may be approached using mechanic constraints and motion strategies, such as squeezing the object a little bit in order to align it along the fingers [7].

Force/torque sensors are the most popular approach. Generally, such sensors are applied on the arm's wrist and they provide a fairly good estimate of the forces applied on the end effector. However, the sensor's measurement may be polluted by dynamic phenomena like inertia; the estimation error can be compensated by a state observer or other types of predictors [8]. Touching sensors can circumvent parts of the shortcomings since forces can be evaluated directly on the contact points. Those devices have to be small and light to be practically applied on a robotic hand and at least a couple should be installed to really improve the control performances. This leads to a higher cost of the robot hand's manufacture and other shortcomings as illustrated in these works [10, 7] .

At last, the motor joint itself can be used as a sensor. A DC motor can exert a torque on a load proportional to the current applied on it. If a force is applied on the rotor, it will be required more current for compensating the disturbance and for maintaining unchanged the motor's configuration. Therefore, joint's current and angle configuration can be used for control and those dimensions can be easily estimated from the motor's internal sensors. This estimation technique is surely the simplest but its effectiveness strictly depends on the distance of the force's contact point from the motor. A force directly applied on the rotor can be estimated much better than a force applied on an end effector placed some centimeters away from the motor, so the estimation may be noisy due to variability in arm's inertia, the load's weight and the joint's friction [10]. Force estimation based on motor's characteristic does not require applying further external sensors on the robot, resulting in lighter and cheaper implementation of a robotic arm at the cost of a less accurate control.

2.3. Modeling

Whenever the hand designing approach is minimalistic or anthropomorphic, a grasping motion is designed and evaluated on the base of contact points. A contact point is a spot on the robotic hand that may touch the target object, i.e., a fingertip. Such points exert a normal force on the object and a tangential force, if the point may provide some friction. If the finger can exert a torsional moment along the common normal, the contact point is called soft point. By handling the kinematic properties of a robotic hand is it possible to derive a grasp motion.

A possible way to formally infer if an object is restrained or not is to verify if two requirements are satisfied: *static equilibrium* and *contact constraints* [4]. An item is in static equilibrium if:

$$Wc + g = 0$$

Where g are the possibly zero external wrenches applied to the end effector, W is the wrench matrix and c is the wrench intensity vector. A wrench matrix is composed by as many vectors as contact points and each vector describes the normal force, the tangential force and the momentum ignoring their magnitude.

The contact constrains impose that the normal forces' magnitude is non-negative and define a proper law for the tangential force and the momentum. Typically, those forces are modeled as tangential friction and momentum friction according to *Coulomb's law* [9].

This definition can be enhanced with the concept of closure. A closure imposes further requirements on the grasping forces in order to derive a possible restraining pose according to two possible configurations: form closure and force closure [4]. Intuitively, a grasp pose achieves force closure if and only if the held object is in equilibrium for any arbitrary wrench, while form closure is achieved if and only if the grasping pose totally constraints the object independently of the forces' magnitude applied on each contact point.

Most of the effort in object grasping relies on force balancing; therefore it is crucial to properly estimate them. In order to safely grasp an object, the forces applied on it, also know as internal forces, have to be evaluated and calculated to achieving object equilibrium and avoid or reduce the slippage risk. This problem is addressed as forced distribution, and can be treated as an optimization problem and solved using linear programming, simulated annealing [6] or other techniques [4, 5]. The force distribution problem can be generalized for bimanual grasping; in this case it is also possible to distribute the object's weight among the two arms by distributing internal forces accordingly.

2.4. Control

Once the hand's mechanical details are defined and the forces can be estimated, it is finally possible to design a grasping controller. Such regulator has to constrain the wrench internal forces to some values in order to stabilize the object in the hand achieving static equilibrium. Of course, to dynamically keep the item in the hand the external forces and noise, like inertia, have to be balanced too. An intuitive way of implementation may be a PID controller. Such controllers are easy to design, to implement and are very effective, but they perform poorly with non-linear systems and are not easily adaptable. Such issues are quite important for the task of grasping, since robot's rotational joints introduce non-linearities and different objects require a hands' control that adapts itself to their shape and weights. For this reason, more advanced control strategies are required.

At first, two classic approaches that may be employed for overcoming such difficulties could be *adaptive control* and *robust control*. The first strategy aims to calibrate dynamically the controller's parameters, while the second one ensures that the plant follows the required behavior in presence of uncertainty, according to some assumptions on system's variables. A further approach that is earning increasing popularity is *intelligent control*. Such technique combines AI with classical control theory to implement a control law suitable for the task. An interesting example may be found in [11]. To circumvent some of the PID's limitations the weights may be adjusted dynamically at runtime and the calibration process may be driven by fuzzy rules.

Since a big variety of control techniques are available for implementation it is not possible to make an exhaustive survey without losing the scope and, therefore, the control strategies possibilities will not be widened any further.

3. Robot Nao: Platform analysis

Nao robot is a humanoid robot produced by the French company Aldebaran and is currently used in *RoboCup* competitions within the *Standard Platform League* [1]. In this section we systematically analyze the available grasping abilities of the robot. At first we present the hardware, then we explore the arm's workspace and its constraints and finally we discuss its sensing capabilities.

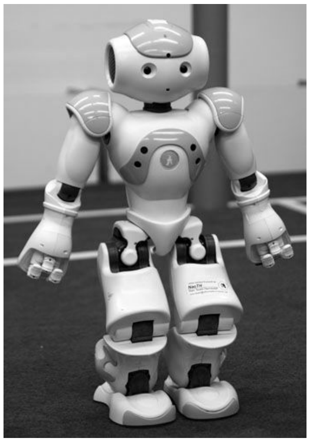
3.1. Nao Robot

Nao robot has a very articulate body. Each arm has 4 degrees of freedom describing a workspace quite similar to the human arm's one. The joints are actuated by DC motors and the platform is equipped with a low power and low consumption processor. Since the CPU processing power is quite limited compared to the robot's physical structure, it is challenging to implement very complex algorithms for motion controlling. Therefore simplicity in design is the preferred approach. The Figure 1 summarize some important hardware specifications.

3.2. Sensors

In order to be able to grasp objects with different properties the robot has to adapt the applied force, receiving a sensor feedback if necessary.

The robot is equipped with four force sensors on each foot, a gyroscope, an accelerometer, two ultrasounds in the chest and two VGA cameras (operating on a single bus) in the head. Each joint is equipped with sensors measuring the actual angular position and the electric current consumed by the motor. The camera images can be received up to 30 times per second, while all other sensor data, like joint's positions and electric current, can be read every 10 ms.



Nao Robot	
Resolution	640×480
Frame rate	30fps
Opening angle	$45° \times 34,5°$
System	Open Embedded
CPU	Geode LX 800
RAM	256MB SDRAM
DoF	21
Height	58cm
Weight	4.8kg

Figure 1. Aldebaran Robotics' *Nao*

The motion system requires a control signal at the same frame rate, i.e., every 10 ms, to ensure the correct execution of the planned movements. Thus, the joint's motor internal sensors are probably the best way for estimating the force applied by the end effector without attaching external sensors. The gyroscope and the accelerometer can be used together with the feet's force sensors for inferring robot body's posture. The camera provides information about the surrounding environment that is very effective for navigation and object recognition. In particular, visual sensing can be used to control the high level parts of the grasping motion, like aligning the hand around the ball, which don't require very high reactivity. The ultrasounds can be used for inferring the position of obstacles in the front of the robot.

3.3. Reachable Space and Dexterity

The *reachable space* of a robot is usually defined as the set of points that can be reached by its end effector, e.g., the hand, with respect to a reference frame of the robot. In general, this space is defined by some basic constraints that a humanoid robot has to satisfy during the motion, including the kinematic constraints, e.g., the limits of joint angles and the collision constraints, and the balance constraints. We represent the *reachable space* by a three dimensional grid, thereby we consider basically the positions of the end effector but not its rotation.

The Figure 2 illustrates the reachability grid for an arm of the Nao robot. The right grid in the figure was generated with a fixed yaw-joint in the elbow, i.e., only three degrees of freedom have been used. Considering the difference between the full and the restricted grid, shown in the centre of the Figure 2, it can be seen that only some positions behind the robot are lost by this restriction. Of course, we lose some possibilities to reach positions with different rotation.

3.4. Morphology of the Grasping

The robot's ability to grasp is highly dependent on its kinematic constraints. An interesting challenge to overcome on the Nao robot is dealing with the hand's structure itself.

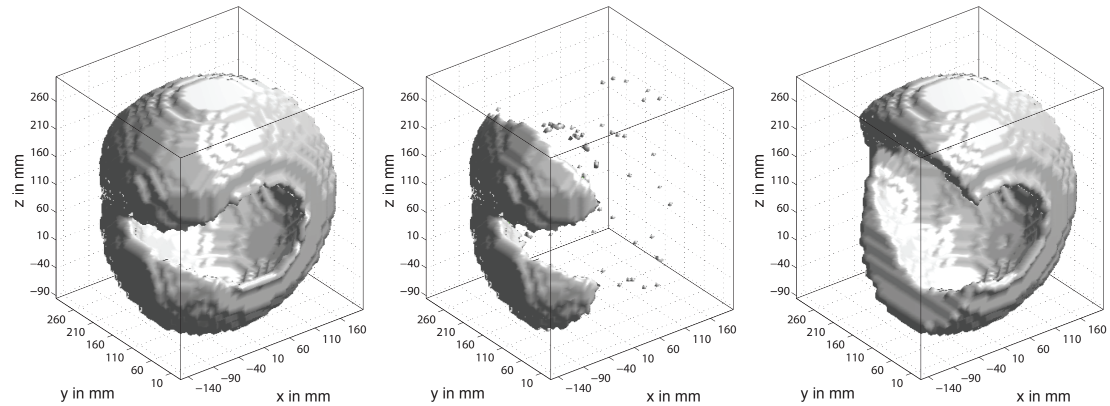


Figure 2. The *reachable space* of the Nao's hand is approximated by a three dimensional grid; (left) the theoretical reachable grid generated in simulation; (right) reachable positions with the fixed yaw-joint in the elbow; (center) difference between both grids;

The end effector, i.e., hand, is equipped with three fingers and has one degree of freedom (open and close) or is passive, depending on the Nao robot's version. Therefore high precision hands' motion control is a harder task because contact points evaluation is not straightforward. Nao's arms are equipped with four joints, two for the shoulder and two for the elbow as shown in the Figure 1 (right). Both links can be controlled along the roll, while the second joint controls the pitch and the jaw for the shoulder and the elbow respectively.

The end effectors can operate in relatively large workspaces that are partially overlapping each other, as discussed in subsection 3.3. However such freedom of movement is a further node of complexity for determining a successful grasping pose, because the same point in the space can be reached in many ways that differs only on the end effector orientation. Moreover, the hand's morphology has some drawbacks. The hand's round surface makes more difficult controlling a grasp motion, especially in its dynamics, however the hand's fingered side has a more convenient structure. Its shape is much closer to a plain surface, but its passive fingers represents still an uneven surface. While it is possible to grasp objects using uneven surfaces, it is not easy to predict and to evaluate exactly how the contact points are going to be displaced on the hands and where the forces will be applied on the object. Moreover, the contact points on this hand configuration are exerting a low friction due to the limited and not predictable contact surface.

Because the hand's mechanics has so many constraints, it is very important to precisely reach a point with a well defined orientation. However, since the Nao arm's kinematic is redundant and the hand's rotation is coupled with the elbow's rotation, many solutions are available for the same point, but not all of them are suitable for approaching an object on the hand's fingered side.

A simple solution that may be tried for circumventing those shortcomings is reducing one degree of freedom. A good trade-off can be obtained by ignoring the elbow's roll, since just a negligible amount of the workspace is lost (cf. Figure 2), but approaching the target on the fingered side it is always ensured. Finally, to improve the grip friction, we taped the robot's hands since the tape has higher attrition and makes the fingered grasping surface more even.

4. Grasping Algorithm

In this section we illustrate some simple controllers used for implementing a grasping motion. At first we show the system's infrastructure and an outline of the control mechanism, on the second part we discuss three possible regulators and finally we provide some experimental data to better analyze the motion control.

4.1. General Design

The whole grasping motion can be divided in two parts: approaching the object and restraining it. The first part of the motion is needed to bring the item in the hands' reachability space and can be further decomposed in the tasks of recognizing the object, reaching it and crouching. Once the target is reachable the core of the grasp motion is executed. At first the hands are aligned to the object and then they are moved in order to squeeze the target. This part of the motion assumes as reference system the robot's chest.

The end effectors are driven by inverse kinematic, so the same point can be reached with different arm configurations. This feature makes the motion more general but introduces an extra degree of complexity due to the freedom of rotation of the arm. In fact, hand's orientation is coupled with elbow's orientation making impossible having a direct influence on hand's rotation without modifying the end effector position, as already pointed out in Section 3.4.

As a consequence, an item may be approached using different arm configurations but not all of them offer a convenient grasping surface. For this reason, the elbow's rotation is fixed for the duration of the entire grabbing motion, forcing the hands to touch an object always on the fingered side. In this way the Nao's arms can be seen as a big two fingered gripper.

Thus, we formulate the geometry of the grasping task as follows: in the first step align the hands around the point $\mu_C \in \mathbb{R}^3$, representing the center of the object, with a certain distance $\rho \in \mathbb{R}_+$. In the second step close the hands reducing the distance ρ between the hands and the point μ_C. Thus, the target positions for the hands can be calculated as points with the distance ρ left and right from μ_C, i.e., $p_L = \mu_C + \rho \cdot e_2$ and $p_R = \mu_C - \rho \cdot e_2$ for the right and left hand respectively (thereby $e_2 = (0, 1, 0)^T$). The point μ_C is controlled by vision and is used for choosing a useful spot where to grasp the object, since the hands will be placed according to it. The distance ρ is driven by joint sensor feedback and a mapping of the end effector force applied to the target: the smaller ρ the bigger the force intensity. The Figure 3 visualizes the geometrical configuration of the grasping.

4.2. Controlling Strategies

In our setup two values have influence on the force applied to the object: the requested distance between the hands and the maximal electrical current applied to the joints. As the first trial, we apply some simple strategies for controlling the distance between the hands. Thereby, we don't change the maximal electrical current.

Now, let $y_D(t)$ be the measured distance between the hands at the time t (this distance can be calculated by forward kinematics from measured angle values of the joints). By $y_C(t)$ we denote the measured electrical current at the joint (this measurement is calculated as the maximum of the current measurements of the roll joint of the both shoulders). Finally, let $u(t)$ be the requested distance between the

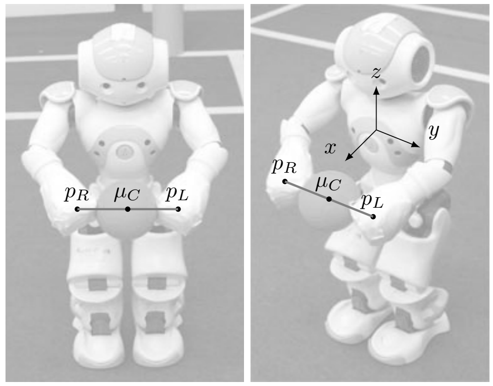


Figure 3. Geometry of the grasping motion: μ_C denote the center of the grasping motion (e.g., estimated center of gravity of the ball), p_L and p_R are the desired points for the hands.

hands (controlled value). The general strategy is to decrease constantly the distance between the hands by δ in each step, depending on the sensor measurements.

With a threshold for the electrical current $\tau_{max} > 0$ and minimal admissible distance d_{min} (the hands are closed) we can define the following simple controlling rules:

(A) No Sensor Feedback: $u(t) = \max\{d_{min}, u(t-1) - \delta\}$

(B) Angle Sensors: $u(t) = \max\{d_{min}, y_D(t-1) - \delta\}$

(C) Current Sensors: $u(t) = \max\{d_{min}, u(t-1) - \chi_{<\tau_{max}}(y_C(t)) \cdot \delta\}$

Where $\chi_{<\tau_{max}}$ is the characteristic function.

Each regulator controls the motion in a different way and, therefore, produces a different result with different characteristics. The three control strategies have been tested and evaluated on the robot and the following section will discuss their peculiarities.

5. Experiments

The primary focus of our experiments is placed on grasping of objects with different properties in terms of weight and material, in particular friction and fragility. Three objects have been chosen as representatives for different types: an elastic ball, a half liter plastic bottle and a paper cup. The ball is made of a deformable material and has a regular geometry, so it doesn't have very specific requirements about the precise position where to grasp it. The cup, instead, is a good example of breakable object. The hardness of the paper guarantees a sensor feedback whenever a force is applied to it, but at the same time, an excessive force will cause a big deformation of the object that may break it or spill out any fluid contained in it. Moreover, its geometry imposes some simple constraints on grasping. The bottle is an interesting test case because of its irregular shape and low friction. Touching such object on different points may lead to very different outcomes, due to its geometry. Moreover, the bottle's weight can be easily adjusted by pouring a liquid inside. For the experiments, the bottle was completely filled with water.

In our first experiment we are aiming to analyze the performance of the different sensors of the robot Nao (cf. Section 3.2) and their suitability in terms of the grasping task. Based on the experiences collected with these experiments we setup another experiment seeking to analyze the abilities of the controlling strategies described in Section 4.2. For evaluation purpose we placed force sensors at the hands of the robot, thus we can directly observe the force applied to the object. In the following we present and discuss the results of both experiments.

5.1. Sensor Benchmark

The aim of the first experiment is to benchmark the electrical current and the joint's angle evolution by grasping different objects and applying increasing power to the motor. Each object was placed at the same reachable position from the robot and grasped five times using the no-feedback control, each time exerting more torque, i.e., more stiffness. In particular, the stiffness values 0.1, 0.3, 0.5, 0.7 and 1 have been used. Thereby we observe the evolution of the electric current at the shoulder roll joints, the force at the end effectors and the difference between the roll angles of the shoulders. The later gives an idea about whether and how much the object has been deformed during the grasping, i.e., we observe whether the hands are getting closer when more stiffness is applied. By successively increasing the torque we can estimate the maximal applicable force for each of the objects. Furthermore, we hope to observe a correlation between the measured electric current and the actual force applied.

The Figure 4 illustrates the data recorded during all experiments in a matrix of plots. The columns of the matrix indicate the different objects, while the rows stand for each of the observed sensors. Each plot contains five graphs visualizing the data of the corresponding sensor for each of the stiffness values used to grasp a particular object. In the following we summarize and discuss the results for each of the objects separately.

Grasping Ball Grasping the ball was always successful, independently of the power applied to the motor. This result was achieved due to the object's simple geometry and its friction. Due to the attrition the tangential force is high enough to compensate the gravity and the spherical geometry offers very convenient contact surfaces. Looking at the middle column in the Figure 4 the ball appears to be a kind of "ideal" benchmark object. The electric current is stable and grows proportional to the stiffness. We can also see a very strong correlation between the electric current and the measured force, it seems we can directly deduce the applied force by only looking at the consumed electric current at the shoulders. Caused by the elastic material of the ball, the deformation looks also proportional to applied stiffness.

Grasping Cup Grabbing the cup, instead, was imposing always some deformation on the object. However, differences in the motor power are translated in higher or lower deformation on the target, which could lead to spill out of its content. Higher torques caused also an asymmetrical grasping and drifting of the object on the picking up surface. The left column in the Figure 4 summarizes the data recorded during these experiments. In particular, in the bottom graph we can see that the cup was strongly deformed when the stiffness was increased, since the difference between the arms is getting much smaller when higher stiffness is used. The electric current and the force are looking more irregular compared to the ball. Caused by the plasticity of the cup, they also don't grow proportionally for higher stiffness values.

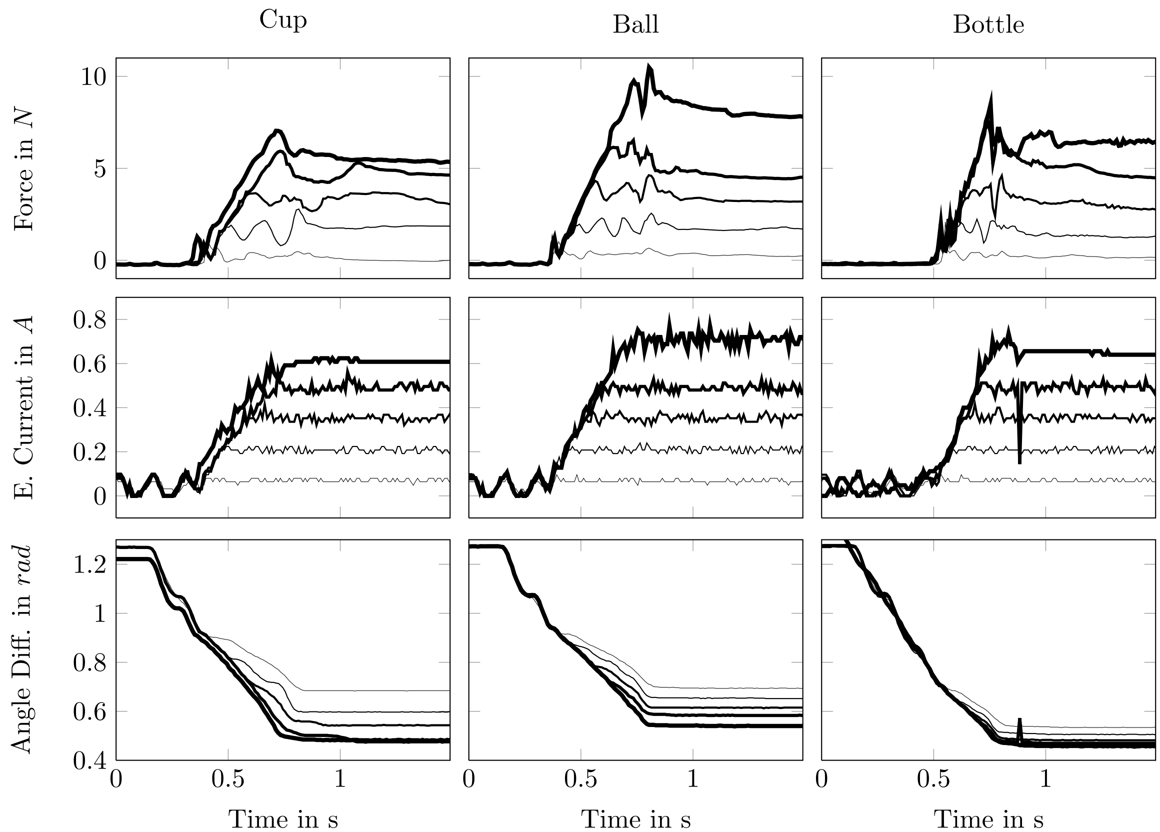


Figure 4. Grasping three different objects without sensor feedback with different stiffness values: 0.1, 0.3, 0.5, 0.7 and 1. Each plot contains the graphs illustrating the data of a particular sensor for each of the stiffness values. Thereby, thicker lines in indicate higher stiffness. Each column lists the different data for each of the used objects. In the top row the force measured at the end effectors is shown and in the middle row the electric current measured at the shoulders. In both cases the maximum of the left and right sensors is plotted. In the bottom row the difference between left and right shoulder roll angle is illustrated, i.e. the smaller the difference, the closer are the hands.

Grasping Bottle The last object is the most challenging. Due to the really low friction of the material, the heavy weight and the irregular geometry, the robot only succeeded to grasp the bottle with the highest possible torque applied (0.9 and 1). The right column of the Figure 4 illustrates the corresponding data. In particular, we can see that the highest stiffness didn't lead to maximal force. The reason for that seems to be the slippage of the hands on the surface. However, the consumed electric current almost reaches its maximum similar to the ball. Compared to the other objects there are only small changes in the angle differences, which can be seen at the bottom plot.

Conclusion To summarize, we have seen, that the electric current at the shoulder roll joint may be directly used to estimate the force applied to the object. Based on collected observations we can estimate the minimal stiffness necessary to grasp for each object. It seems also to be possible to observe the deformation of the objects during the grasping. In particular, the results look promising to be able to distinguish the objects by only looking at the evolution of the electric current and the measured joint angles, which can help to design adaptive controllers.

5.2. Performance of the Different Controllers

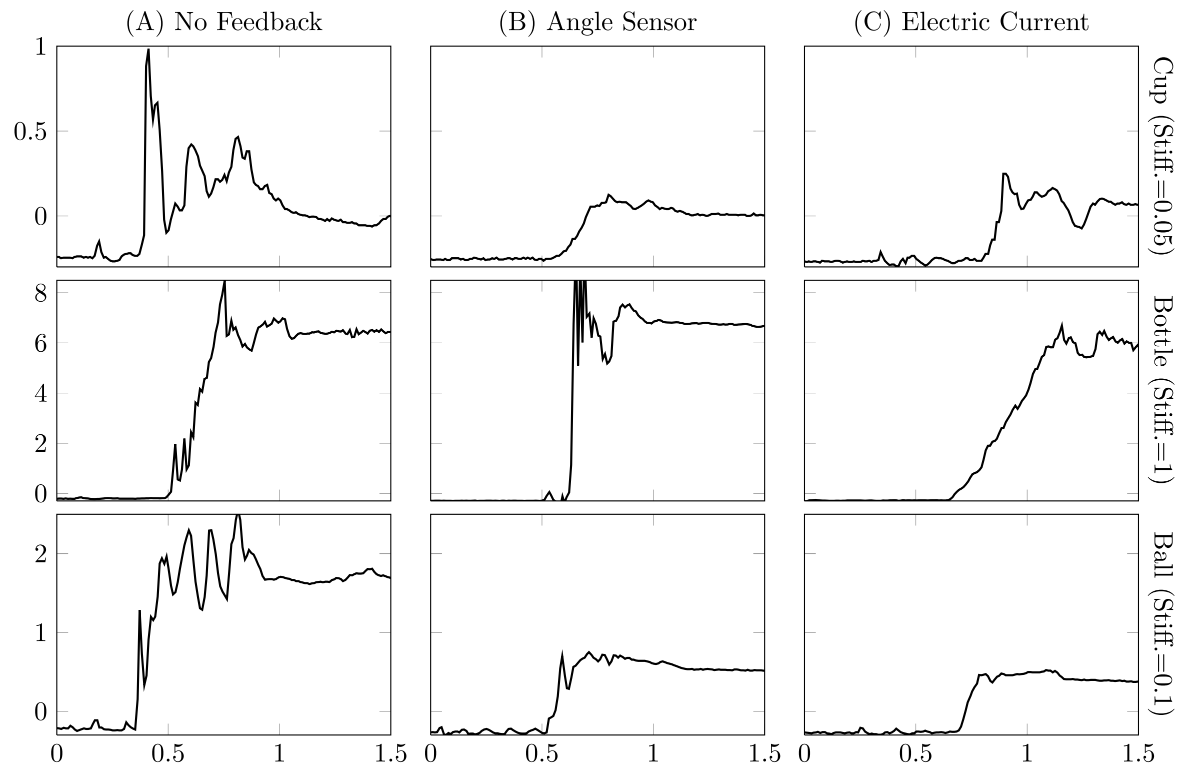


Figure 5. Force measured at the end effectors during the grasping of three different objects using different controllers as described in Section 4.2 with a fixed stiffness for each object.

The aim of the second experiment is to evaluate performance of the controllers described in Section 4.2. In this experiment we have used the same three objects as in the first experiment, i.e., a paper cup, a ball and a plastic bottle. Based on the results of the first experiment we can estimate the minimal stiffness, which is necessary to hold an object. This is 0.05 for the cup, 0.1 for the ball and 1 for the bottle. Now, for each of these objects, we empirically determine the other parameters of the controllers as minimal values where the robot is still able to hold it. Using these minimal parameter sets we perform a grasping trial for each object with each of the controllers. Thereby we observe, in particular, the force measured at the end effectors.

The Figure 5 illustrates the Results of this Experiment. The columns summarize results for each of the controllers; the rows indicate the different objects. The controllers with the sensor feedback seem to be able to control the force much better. In all cases they can achieve and hold the force necessary to grasp the object with low fluctuation. However, in the case of the bottle the high stiffness and step size of the controller leads to a very rapid motion. In general, none of the paradigms seem to be able to solve all three grasping problems at the same time. The parameters have to be adjusted for each of the objects separately. In particular, the parameters suitable for the bottle cause a destruction of the cup. At the same time the parameters adjusted for the cup are not producing enough force to hold the bottle. In conclusion, we need further mechanisms being able to detect, how much force is actually necessary for a particular object to be grasped.

6. Conclusion and Future Work

In this work we analyzed the system and presented some results that may outline some general difficulties of the grasp task and some specific issues arisen on the Nao robotic platform. The three controllers discussed in this paper are able to grab an object, however they are not very general neither robust. Complex geometry and low friction cannot be rejected by the proposed controllers because the underlining model is too simple to capture the complexity nodes. Deriving a better model implies implementing an adaptive controller, which behaves differently according to the targeted object. To make the adaptability more responsive it may be took in consideration the option of adding extra sensors on the Nao's body in order to let the robot estimating the weight by waiving the items.

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