Whole body motion planning – elements for intelligent systems designs

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Humanoid robots become increasingly sophisticated, both in terms of their movement as well as their sensorial capabilities. This allows to target for more complicated problems, eventually leading to robotic systems that can perform useful tasks in every day’s environment. In this paper, we will give an overview on some elements we consider to be important for a movement control and planning architecture. We will first explain the whole body control concept which is the underlying basis for the subsequent elements. We then present a prediction and action selection scheme that evaluates a set of behavioral instances within a parallel prediction architecture. This architecture allows the robot to quickly react to changing environments. We then review a more global movement planning approach which casts the overall robot movement into an integral optimization problem, and leads to smooth and collision-free movements within interaction time.

1 Introduction

While in its beginning, humanoid robotics research focused on individual aspects like walking, current systems become increasingly sophisticated. Many humanoid robots are already equipped with full body control concepts and advanced sensorial capabilities like stereo vision, auditory and tactile sensor systems. This is the prerequisite to tackle complex problems, such as walking and grasping in dynamically changing environments. Motion planning seems to be the most promising way to deal with this class of problems. State of the art planning methods allow to flexibly account for different criteria to be satisfied. Further, many computationally efficient methods have been proposed, so that fast planning and replanning can be achieved in real-world, real-time problems. Many results in the field of planning reaching and manipulation employ sampling-based methods like randomized road maps [1] or rapidly exploring random trees [2]. Model-based approaches are presented for optimal gaits [3] and for full body movements [4]. In general, two problem fields in humanoid robot motion planning have emerged. One recent research focus is centered to solve the foot step planning problem in dynamic environments [5, 6]. This is complemented by efforts to plan collision free arm movements for reaching and grasping [7, 8], and to incorporate the dynamics of the objects to be manipulated [9].

However, there seems to be no approach to address all problem domains within a consistent architecture. In this article, we will present some steps into this direction. We start out with the whole body control concept applied to our humanoid robot Asimo in Section 2. Based on this, we add reactive prediction and action selection with an architecture described in Section 3. It compares a set of different behavior alternatives and selects the most suitable one according to their prediction result. However, this scheme only has a limited time horizon. To generate movements that satisfies criteria throughout the whole trajectory, we present a controller-based optimization scheme in Section 4 in which we determine the attractor points describing the trajectory. The elements share a common basis, the whole body control concept.

The work presented here is part of the efforts towards researching intelligent systems at the Honda Research Institute.

For instance the comprehensive systems presented in [10, 11] are based on the motion generation described in this contribution.

2 Whole body control system

In this section we briefly review the chosen redundant control concept: the general definition of task spaces, inverse kinematics and attractor dynamics to generate whole body motion for high-dimensional humanoid robots. Findings from the field of biology impressively reveal how efficiently movement is represented in living beings. Besides the well-known principle of movement primitives, it is widely recognized that movement is represented in various frames of reference, such as in eye centered, reach and grasp centered or object centered ones [12].

We borrow this principle and represent robot motion in a suitable task representation. For this, the robot control model is described in the form of a tree structure. The individual links are connected by degrees of freedom (joints) or fixed transformations. Further, the tree may also comprise objects from the environment. This allows to derive the inverse kinematics equations not only with respect to a heel or world reference frame, but also to formulate task descriptors accounting for robot-object relations. We define a task as the relative movement of two tree nodes and such can compute the task velocity as .

There are other special cases for tasks, for instance the overall linear and angular momentum, etc.
ables are dependent, in the second case $\varphi$ and $y$ are invariant and can be set to zero. There are many other examples, such as representing a gazing controller as an object in head-centered coordinates which is “pointed” to by the focal axis, or a pointing controller in a similar way. A task can be described in different ways, for instance as linear position, inclination, spherical and Euler angles, etc. A task element may comprise just individual parts of such a description, such as the vertical element of a 3-D position. Based on this, we derive an augmented Jacobian holding all controlled task elements (see also [13, 14]). The underlying redundant whole body motion control is based on the scheme by Liegeois [15, 16]:

$$\dot{q} = J^{\#} \dot{x}_{\text{task}} - \alpha N W^{-1} \left( \frac{\partial H}{\partial q} \right)^T$$  (1)

Matrix $J^{\#}$ is a weighted generalized pseudo-inverse of $J$ with metric $W$. Scalar $H$ is an arbitrary optimization criterion. We employ a joint limit avoidance criterion. Its gradient is mapped into the null space with projection matrix $N$ and scalar $\alpha$ defining the step width.

The trajectories are generated using a dynamical systems approach. This is closely related to the biological findings, and yields further advantages like robustness against perturbations and dynamical environments [17]. We apply a simple attractor system [13, 18] to the task elements to be controlled. The same attractor dynamics are applied to other controllers that are not related to the inverse kinematics, such as “closing the fingers to a power grasp”, etc. Stability and balance is realized by coupling a separate walking and balancing controller (see [19, 20]) with the whole body control scheme. Further, we developed an efficient self-collision avoidance scheme [21]. All task-level functions (Hand and head movement, walking) are accessible via a motion interface.

3 Prediction and action selection

With the presented control concept, Asimo can walk around and safely reach toward objects while maintaining balance and avoiding self collisions. However, the decision of how to reach, for instance what hand to use or how to approach the object, is not tackled. In this section we will present an approach that solves this problem within a prediction and action selection architecture.

First, we will explain the employed visual perception system which is based on a so called proto-object representation. Proto-objects are a concept originating from psychophysical modeling and can be thought of as coherent regions or groups of features in the field of view that are trackable and can be pointed or referred to without identification. Based on these stimuli, a prediction based decision system selects the best movement strategy and executes it in real time. The internal prediction as well as the executed movements incorporate the presented control system.

3.1 Proto-object based perception

To generate proto-objects, the image processing searches entities in the environment that are dynamically stable in position and extent. We extract 3d ellipsoids from the visual input based on a color segmentation and a disparity algorithm. The extracted blobs encode the position, metric size, and orientation of significant visual stimuli. They are stabilized and organized consistently as proto-objects in a short term memory. According to a set of extracted criteria, proto-objects are categorized into found if the object is seen in the visual scene, memorized if it has been found recently but is not seen currently, and inaccurate if it is only partially visible. The 3-d data and the above evaluation result is sent to the behaviors (search, track, reach). Each behavior can then extract the relevant information.

3.2 Tracking and Searching

The output of the sensory memory is used to drive two different head behaviors: 1) searching for objects and 2) gazing at or tracking objects. Separate from these behaviors is a decision instance or arbiter [22] that decides which behavior should be active at any time. The decision of the arbiter is solely based on a scalar fitness value that describes how well a behavior can be executed. In this concrete case, tracking needs at least an inaccurate proto object position to look at. Thus the tracking behavior will output a fitness of 1 if any proto object is present and a 0 otherwise. The search behavior has no prerequisites at all and thus its fitness is fixed to 1.

The search behavior is realized by means of an inhibition of return map with a simple relaxation dynamics. If the search behavior is active and new vision data is available it will increase the value of the current gaze direction in the map and select the lowest value in the map as the new gaze target. The tracking behavior is realized as a multi-tracking of 3-dimensional points. The behavior takes all relevant proto-objects and object hypotheses into account and calculates the pan/tilt angles for centering them in the field of view. The two visual interaction behaviors together with the arbiter switching mechanism show very short reaction times and have proven to be efficient to quickly find and track objects.

3.3 Reaching

Similarly to the search and track behaviors, the reaching behavior is driven by the sensory memory. It is composed of a set of internal predictors and a strategy selection instance. Each predictor includes a whole body motion controller described in Section 2 and a fitness function.
The key idea is to evaluate a set of different behavior alternatives (‘strategies’) that solve the given task in different ways. In the following, we look at the task of reaching toward an object and aligning the robot’s palm with the object’s longitudinal axis. This corresponds to a pre-grasp movement, which brings the hand in a suitable position to grasp an object. In a first step, the visual target is split up into different motion commands, with which the task can be achieved. Four commands are chosen: Reaching toward the target with the left and right hand, both while standing and walking. While the strategies that reach while standing assume the robot model to have a fixed stance position, the strategies involving walking are based on a kinematic “floating base” description of the robot model [13]. This way, the heel position of the control model is permanently updated according to the given target and the null space criteria that are incorporated within the whole body motion controller. This leads to a very interesting property: the control algorithm will automatically find the optimal stance position and orientation with respect to the given target and the chosen null space criteria. If a walking strategy is selected, the floating frame is commanded to a step pattern generator, which generates appropriate steps to reach the desired stance position and orientation.

In each time step, the strategies compute their motion and an associated fitness according to the specific command. The fitness is composed of the following measures:

- **Reachability:** Penalizes if the reaching target cannot be reached with the respective strategy.
- **Postural discomfort:** Penalizes the proximity to the joint limits when reaching toward the target.
- **“Laziness”:** Penalizes the strategies that make steps. This way, the robot prefers standing over walking.
- **Time to target:** Penalizes the approximate number of steps that are required to reach the target. This makes the robot dynamically change the reaching hand also during walking.

The costs are evaluated by the strategy selection, and the strategy with the highest fitness is identified. The corresponding command is given to the physical robot. The robot is controlled with the identical whole body motion controller that is employed for the internal simulations. An interesting characteristic of the system is the temporal decoupling of real robot control and simulation. The strategies are sped up by a factor of 10 with respect to the real-time control, so that each strategy has converged to the target while the physical robot is still moving. Therefore, the strategies can be regarded as predictors, since they look some time ahead of the real robot. From a classical point of view, the predictions could be seen as alternative results of a planning algorithm. A major difference is their incremental character. We use a set of predictors as continuously acting robots that each execute the task in a different way. The most appropriately acting virtual robot is mapped to the physical instance.

### 3.4 Experiments

The system as described above was tested many times with different people interacting with Asimo with a variety of target objects. The scenario was always to have a human interaction partner who has an elongated object that was shown or hidden in various ways to Asimo. The system is not restricted to only one object. If a number of objects are close to each other, the system will try to keep all objects in the field of view. If they are further apart, the objects leaving the field of view will be neglected after a short while and the system will track the remaining object(s).

Objects are quickly found and reliably tracked even when moved quickly. The robot will reach for any elongated object of appropriate size that is presented within a certain distance — from 20cm to about 3m. Asimo switches between reaching with the right and left hand according to the relative object position with some hysteresis. It makes steps only when necessary. Fig. 2 shows a series of snapshots taken from an experiment. From second 1-7, Asimo is reaching for the green bottle with its right hand. At second 8, the object gets out of reach of the right hand, and the strategy selection mechanism selects the left hand reaching strategy, still while the robot is standing. At second 12, the object can neither be reached with the left hand while standing. The strategy selection mechanism now selects to reach for the object with the left hand while walking toward it. The whole body motion control generates smooth motions and is able to handle even extreme postures which gives a very natural and human-like impression even to the casual observer. For more details of this system see [10].
cost function
\[ C = \sum_{i=0}^{T} g(q_i) + \sum_{i=0}^{T-1} h(q_i, q_{i+1}) , \] (A.1)

movement generation
\[ q_{t+1} = q_t + J^\alpha(t) (x_{t+1} - \phi(q_t)) - \alpha (I - J^\alpha(t)) W^{-1} (\partial_q H_t)^T \] (A.2)
\[ x_{t+1} = x_t + \pi(x_t, x_{t-1}, r_{t+1}) \] (A.3)
\[ \pi(x_t, x_{t-1}, r_{t+1}) = \alpha(r_t - x_t) + b(x_t - x_{t-1}) \] (A.4)
\[ r_t = (1-\tau)q_t^{*} + \tau x_t^{*+1}, \quad k = [tK/T] , \quad \tau = \frac{t-kT}{K} \] (A.5)

chain rules following (18)
\[ \frac{dC}{dx_i} = \frac{\partial C}{\partial q_i} + \frac{\partial q_{i+1}}{\partial q_i} \frac{dC}{dq_{i+1}} \] (A.6)
\[ \frac{dC}{dx_i} = \frac{\partial q_i}{\partial q_i} \frac{dC}{dq_i} + \frac{\partial x_{i+1}}{\partial x_i} \frac{dC}{dx_{i+1}} + \frac{\partial x_{i+2}}{\partial x_i} \frac{dC}{dx_{i+2}} \] (A.7)
\[ \frac{dC}{dx_i} = \frac{\partial x_i}{\partial r_i} \frac{dC}{dr_i} \] (A.8)
\[ \frac{dC}{dx_i} = \sum \frac{\partial r_i}{\partial x_i^{*+1}} \frac{dC}{dr_i} \] (A.9)

partial derivatives
\[ \frac{\partial C}{\partial q_i} = g'(q_i) + h^1(q_i, q_{i+1}) + h^2(q_{i-1}, q_i) \] (A.10)
\[ \frac{\partial q_{i+1}}{\partial q_i} = I - J^\alpha(t) J_t + (\partial_q J^\alpha(t)) (x_{t+1} - \phi(q_t)) \] (A.11)
\[ -\alpha (I - J^\alpha(t)) W^{-1} (\partial_q H_t)^T + \alpha \partial_q (J^\alpha(t) W^{-1}) (\partial_q H_t)^T \] (A.12)
\[ \frac{\partial q_i}{\partial x_i} = J^\alpha - 1 \] (A.13)
\[ \frac{\partial x_{i+1}}{\partial x_i} = 1 + \pi'^1 (x_t, x_{t-1}, r_{t+1}) \] (A.14)
\[ \frac{\partial x_{i+2}}{\partial x_i} = \pi'^2 (x_{t+1}, x_t, r_{t+2}) \] (A.15)
\[ \frac{\partial x_i}{\partial r_i} = \pi'^3 (x_{t-1}, x_{t-2}, r_t) \] (A.16)
\[ \frac{\partial r_i}{\partial r_i} = (1-\tau) \delta_{i=k} + \tau \delta_{i=k+1}, \quad \tau \text{ and } k \text{ depend on } t \text{ as above} \] (A.17)

Table 1: Functional network of the control architecture.

4 Movement optimization

The prediction architecture presented in the previous section allows to dynamically act and react in a simple, but dynamically changing environment. However, it does not consider the overall movement throughout the trajectory, which is relevant when it comes to acting in a more difficult environment, with the potential danger to collide with objects, etc. In such cases, it is not sufficient to select simple movement primitives, but more comprehensive planning and optimization schemes are required. In this section, we will review an attractor-based optimization scheme [18]. It incorporates the robots whole body controller into the optimization process, and finds a sequence of task space attractors describing the optimal movement. The key idea is to optimize a scalar cost function by finding an optimal sequence of task space attractor vectors which determines the robots motion. We consider an integral cost function over the movement in the general form of eq. (A.1) of Table 1. It is split into two terms. Function \( g \) subsumes cost criteria that depend on single time steps. It is suited to account for costs that depend on the posture of the robot. We formulate criteria to account for the offset of the final end effector state to a target, collisions and proximities between collidable objects throughout the trajectory, and joint limit proximities. Function \( h \) subsumes costs for transitions in joint space and depends on the current and the previous time steps. It is suited to formulate criteria like the global length of the trajectory in joint space and the end effector velocity at the end of the trajectory.

The movement generation process is summarized by equations (A.2)-(A.5). Since the dependencies between attractor points and the task space trajectories are determined by the attractor dynamics (Eqs. (A.13)-(A.17) ) and the dependencies between task and joint space is determined by the whole body motion control, we can derive analytical gradients to relate the attractor point location to the chosen cost function:

\[ \frac{dC}{dx^*} = \sum_{\text{children } q_i} \frac{\partial q_i}{\partial x^*} \frac{dC}{dq_i} \] (18)

The gradient computation is carried out in a forward and a backward computation step. In the forward propagation step we start with a given set of current attractor points \( x^*_1:K \), then compute the task space trajectory \( x_0:T \), then the \( q_0:T \)-trajectory, and finally the global cost \( C \). In the backward propagation step we propagate the cost function gradients backward through the network using the chain rules. This involves first computing gradients \( dC/dq_i \), then \( dC/dx_i \), and finally \( dC/dx^*_i:K \). Since all computations in the forward and backward propagation are local, the overall complexity is \( O(T) \).

Figure 3 shows a snapshot series of an experiment. The scenario has been chosen such that a purely reactive controller would fail. The robot holds a "bottle" in the left hand and a "box" in the right hand. The target is to place the bottle into the box, which involves moving both, the bottle and the box, in a coordinated way without collision. The solution found by the robot is to move the bottle in an arc upwards and into the box while at the same time moving the box with the right hand downwards below the bottle. The task space in this experiment was defined 10-dimensional, comprising the positions of the left and right hand and the 2D polar orientation of the hand aligned axis for both hands. Figure 4 displays the cost decay during
4.1 Conclusion

We presented elements toward a consistent control, prediction and movement planning architecture for humanoid robots. Movement control is achieved with a classical redundant control concept that has been extended with mechanisms to ensure balance stability and self-collision avoidance. This concept is the common basis of the presented methods that aim toward more movement intelligence. The prediction and action selection architecture predicts the outcome of a set of behavioral alternatives. The novel aspect is to predict control instances in parallel, such being able to quickly reorganize the behavior based on perceptual information. The presented optimization scheme operates on a somewhat slower time scale, but is still suited to be applied in interactive scenarios. As compared to the prediction architecture, it computes movements that satisfies criteria concerning the overall movement throughout a trajectory, such being able to reach toward objects while avoiding collisions and self-limits of the robot. Future work will focus on extending the proposed methods toward grasping and manipulation of objects.

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References


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