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Predictive behavior generation - A sensor-based walking and reaching architecture for humanoid robots

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Abstract. This paper presents a sensor-based walking and reaching architecture for humanoid robots. It enables the robot to interact with its environment using a smooth whole body motion control driven by stabilized visual targets. Interactive selection mechanisms are used to switch between behavior alternatives for searching or tracking objects as well as different whole body motion strategies for reaching. The decision between different motion strategies is made based on internal predictions that are evaluated by parallel running instances of virtual whole-body controllers. The results show robust object tracking and a smooth interaction behavior that includes a large variety of whole-body postures.

1 Introduction

Research on humanoid robots is increasingly focusing on interaction in complex environments, including autonomous decision making and complex coordinated behavior. Several interactive robot systems were already introduced. A complete architecture for a small humanoid (Sony QRIO) that uses a central action selection driven by so called *behavior values* provided by the individual behaviors is described in [1] [2]. Kismet [3] also realizes a variety of interaction abilities and contains both a powerful vision and attention system and behavior selection. The main focus of this system is child-like interaction and developmental learning.

In this paper, we will present a system that enables a humanoid robot to interact with a human. The perception is based on a so called proto-object representation. Proto-objects are a concept originating from psychophysical modeling [4] [5] [6]. They 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. Novel in the context of humanoid robots are the following key points:

- The use of proto objects to form stable hypothesis for behavior generation, e. g. for tracking or reaching for objects.
- Decision mechanisms that evaluate behavioral alternatives based on sensory information and internal prediction.

– A motion control system that can be driven by a wide range of possible target descriptions and that ensures smooth well coordinated whole body movements.

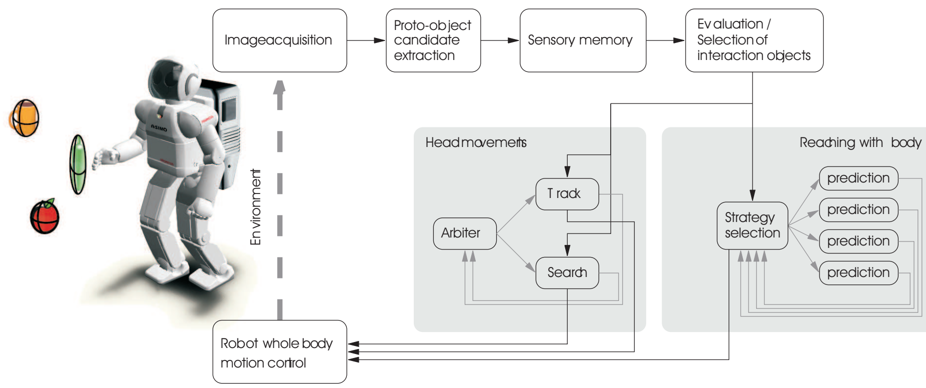

Fig. 1. Overview of the system design.

The general design of the system is depicted in Fig. 1. The perception system uses visual features and stereo based 3d information to detect relevant visual stimuli. It keeps this information as proto-objects in a short-term sensory memory. This sensory memory is then used to derive targets for visual tracking and to form stable object hypotheses from which movement targets for reaching movements can be derived. 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 exploit an integrated control system that uses a flexible target description in task space in addition to cost-functions in null space to achieve well coordinated and smooth whole body movements.

2 Proto-object based perception

In the following, the characteristics of the perception are explained in more detail.

Proto-object Candidate Extraction: To generate proto-objects, the image processing has to find entities in the environment that are dynamically stable in position and extent. Efficient methods to find such entities are color and texture segmentation algorithms, or feature extractors for unique salient points. To obtain 3d information, stereo disparity calculations or other stereo algorithms can be used. 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.

Proto-Objects in Sensory Memory: To form stable object hypotheses, the sensory information is buffered and organized consistently. This is done in form of proto-objects in sensory memory. The incoming blobs are mapped to proto-objects in sensory memory. If the memory is empty, a proto-object is generated from blob data. If the sensory memory already contains one or more proto-objects, a prediction for each proto-object is generated. The prediction is compared to the new measurement. According to the result, either a new proto-object is generated, or the prediction is employed to update an existing proto-object.

Evaluation / Selection of Interaction Objects: The output from the sensory memory is evaluated with respect to the object criteria (in this case distance, size, and minimum elongation). The results are categorized into

- **Found:** The object is found in the visual field.
- **Memorized:** The object is not found in the visual field, but has been found recently.
- **Inaccurate:** The object is found, but close to the image boundary. Since it is only partially visible, the estimation results are likely to be inaccurate.

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 Behavior Generation

3.1 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* [7] that decides which behavior should be active at any time. The decision of the arbiter is solely based on a scalar value that the behaviors provide, which we call a *fitness value*. This fitness value describes how well a behavior can be executed at any time. 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 a very low resolution 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 efficient to quickly find and track objects.

3.2 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 and a cost function evaluation. The underlying whole body motion control is based on the scheme by Liégeois [8][9][10] for redundant systems. The trajectories to reach towards the proto objects are generated interactively using a dynamical systems approach. The trajectories are projected into joint space using a weighted generalized pseudo-inverse of the task Jacobian. Redundancies are resolved by mapping the gradient of an optimization criterion into the null space of the motion. In this work a joint limit avoidance criterion is used. Details on the whole body control algorithm are given in [11][12]. The whole body controller is coupled with a walking and balancing controller, which stabilizes the motion. This scheme allows to perform even fast dynamic whole body motions in a stable way.

Strategy selection

The idea is to evaluate a set of different behavior alternatives ("strategies") that solve the task in different ways. In the following, the task of reaching towards an object and aligning the robot's palm with the objects longitudinal axis will be regarded. 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 towards 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 be fixed, the strategies involving walking are based on on a kinematic "floating base" description of the robot model (Fig. 2 [11]). 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 of the control scheme: the control algorithm will automatically compute the optimal stance position and orientation with respect to a given target and the chosen null space criteria. If a walking strategy is selected, the floating frame is set as the target for a step pattern generator, which generates appropriate steps to reach the computed heel position and orientation. Now each strategy computes the motion and an associated cost according to its specific command. The cost describes the suitability of the strategy in the current context. It is based on the evaluation of a multi-criteria cost function that is composed of the following measures:

- **Reachability:** Penalizes if the target cannot be reached with the respective strategy.
- **Postural discomfort:** Penalizes the proximity to the joint limits when reaching towards the target.
- **"Laziness":** Penalizes the strategies that make steps. This way, the robot prefers standing over walking.

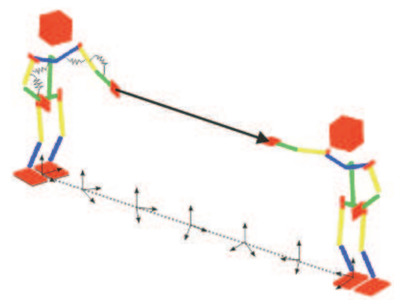

Fig. 2. "Floating" heel frame: The stance position of the feet is the result of the null space motion. It is a local optimum with regard to the given task.

- **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 process, and the strategy with the lowest cost 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 still moves. Therefore, the strategies can be regarded as prediction instances, since they look some time ahead of the real robot. Nevertheless, the control algorithms running within the strategies and on the robot are identical. 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.

4 Results

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.

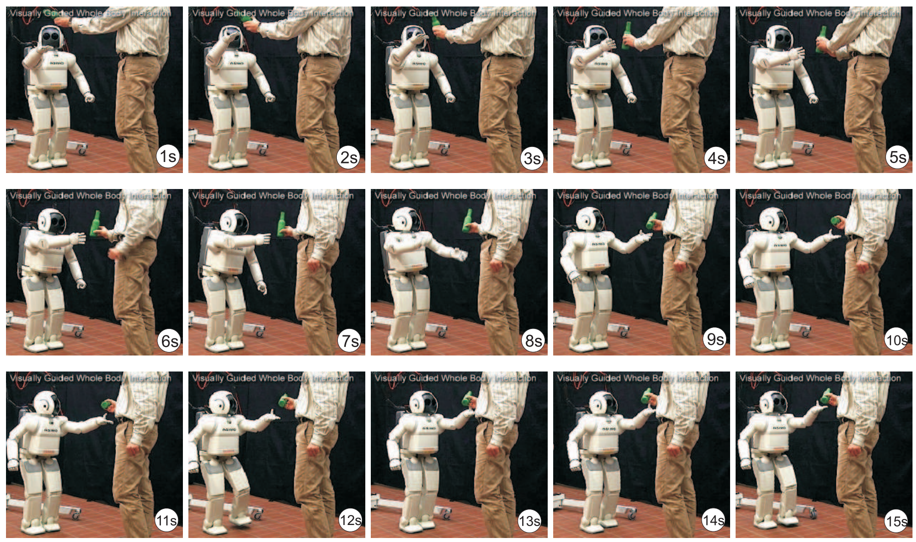

Fig. 3. Snapshot series from an experiment.

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. 3 shows a series of snapshots taken from an experiment. From second 1-7, Asimo is reaching for the green bottle with its right hand. This corresponds to the first phase in Fig. 4. 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 (Second phase in Fig. 4). 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 towards it (Third phase in Fig. 4). 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.

5 Conclusions

We presented an architecture that interactively generates robot behaviors to interact with a human partner. The scheme employs internal predictions of behavioral alternatives in order to select the most suitable behavior in a given situation. The presented methods work in real-time and have successfully been tested on the humanoid robot Asimo. Future work will go in the direction of interactivity, planning and real-time simulation, and providing efficient tools for decision making processes and learning.

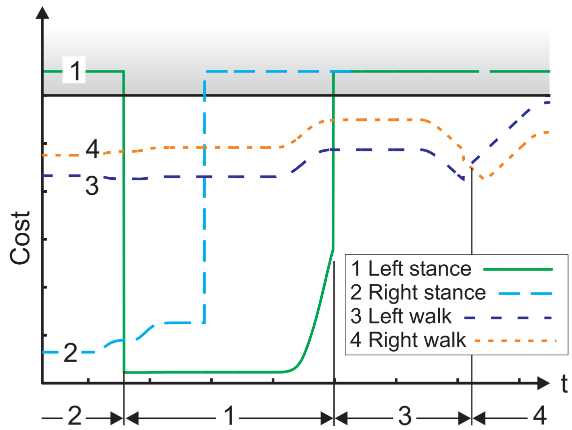

Fig. 4. Progression of fitness values over time.

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