CLAWAR 2012 – Proceedings of the Fifteenth International Conference on
Climbing and Walking Robots and the Support Technologies for Mobile Machines,
Baltimore, MD, USA, 23 – 26 July 2012


# AN IMITATION LEARNING APPROACH FOR TRUCK LOADING OPERATIONS IN BACKHOE MACHINES

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This paper presents a motion planning and control system architecture development for autonomous earthmoving operations in excavating machines such as loading a dump truck. The motion planning system is imitation learning based, which is a general approach for learning motor skills from human demonstration. This scheme of supervised learning is based on a dynamical movement primitives (DMP) as control policies (CP). The DMP is a non-linear differential equation that encode movements, which are used to learn tasks in backhoe machines. A general architecture to achieve autonomous truck loading operations is described. Also, the effectiveness of our approach for truck loading task is demonstrated, where the machine can adapt to different operating scenarios.

*Keywords*: Imitation Learning, Dynamical Movement Primitives, Excavating Robots, Backhoe Machine.

## 1. Introduction

Everyday, earthmoving operations are performed at every time around the world. Moreover, the earthmoving industry is an important economic and productive activity. Furthermore, backhoe machines operations are repetitive and their workspace is complex and non-structured, where they have to interact with humans, trucks and obstacles. Finally, there are a few research works oriented to develop a fully autonomous excavating robot because of the complexity of the problem and their tasks.

On other hand, for service robotics, imitation learning based motion planning systems have been developed to solve objects grasping and manipulation,[1] or biped robot locomotion;[2] for which it has been raised the dynamical movement primitives approach that represent unidimensional discrete and rhythmic movement. In consequence, the autonomous reproduction of movement using learning by demonstration (LbD) could be feasible in any kind of task performed by backhoe machines. Therefore, it is necessary to demonstrate that movement can be generalized in other contexts, i.e. for several positions and orientations of the target in truck loading operations.

In contrast of Autonomous Loading System (ALS),[3] the motion planning system is implemeted through an imitation learning with DMPs based on truck position estimation. This method has the potential advantage to generate motion plans that solve obstacle avoidance problem in the same way as Park.[4]

Finally, Section 2 describes some of the current works for complete autonomy for earthmoving operations, and an overview of our approach. Section 3 expounds the details of imitation learning with DMPs for unidimensional discrete movements. In Section 4, it is shown the implementation of imitation learning with DMPs in a typical backhoe machine for truck loading operations. The inverse kinematics and proposed control system is presented, with the results for truck loading movement generation with our autonomous system. Finally, in Section 5 are shown the comments for the obtained results and futures works.

## 2. Motion Planning Systems for Excavator Robots

Currently, there are few works on complete autonomy for earthmoving operations, because of the environment complexity and the type of tasks for this kind of machines. The backhoe machines usually execute three main operations, which are digging a foundation or leveling a mound of soil and truck loading. In Singh[5 6] the task planning was formulated as constraint optimization in action space, and in Singh and Cannon[7] it was developed a multi-resolution planning systems that performs the digging operations autonomously. In other hand, in Stentz[3] have been raised a hardware and software architecture for autonomous truck loading operations. In this paper, it has been developed an architecture of perception systems similar to,[3] but with some improvements like: the scanning plane is parallel to the ground and the addition of a stereo camera. The perception systems have to determine and estimate the pose of the dump truck, as shown in Fig. 1.

In other hand, humans can execute complex task because of the abilty to learn movement primitives, i.e. dunk the ball to the basket in a basketball game. Therefore, imitation learning methods can be used for motion planning in complex backhoe machine operations. Thus, this approach could allow the execution of complex task.

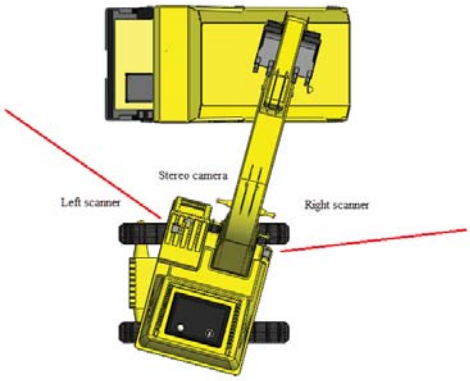


Fig. 1: Perception system architecture.

Finally, it is developed a motion planning system based in imitation learning with Dynamical Movement Primitives. DMPs are used to adequately encode movement primitives; and the learning process becomes a locally weighted regression problem.[8]

## 3. Imitation Learning with DMPs

This section briefly describe the imitation learning approach using dynamical movement primitives framework that is a potential way to simplify learning control policies.

### 3.1. *Dynamical Movement Primitives*

A Dynamical Movement Primitive is a non-linear dynamic equation that code the basic behavioral pattern (i.e. rhythmic or discrete movements),[9] and its formulation is based in attractor theory. Therefore, the purpose of this control policy is to reach the goal state with a particular trajectory shape, independent of its initial state. Besides, DMPs are a compact representation of high-dimensional planning policies and it must have the following properties:

- The convergence to the goal state must be guaranteed.
- The DMP formulation must generate any desired smooth trajectory.
- DMP have to be temporal and spatial invariant.

- The formulation must be robust against perturbations due to the inherent attractor dynamic.

A good DMP formulation for unidimensional discrete movements is developed for grasping and manipulation tasks by Pastor.[1] This representation is a set of differential equations referred to as a transformation system (1), and other as a canonical system(3). Note that the equation (1) can be interpreted as a linear spring-damper system perturbed by an external forcing term $f(s)$.

$$\begin{aligned} \tau\dot{v} &= K(g-x) - Dv - K(g-x_0)s + Kf(s) \\ \tau\dot{x} &= v \end{aligned} \tag{1}$$

where $x$ and $v$ are position and velocity system; $x_0$ and $g$ are the initial and goal position; $\tau$ is a temporal scaling factor; $K$ is a stiffness constant; $D$ the damping constant; and $f(s)$ is a nonlinear function which can be learned for a determine smooth trajectory demonstrated. The $K$ and $D$ gains must be choosen such that the system is critically damped. The non-linear function $f(s)$ is defined as:

$$f(s) = \frac{\sum_i \omega_i \psi_i(s) s}{\sum_i \psi_i(s)} \tag{2}$$

where $\psi_i(s) = \exp(-h_i(s-c_i)^2)$ are Gaussian basis functions, with center $c_i$ and width $h_i$, and $\omega_i$ are the weights that have to be learned.

$$\tau\dot{s} = -\alpha s \tag{3}$$

Note that with this formulation, the spatial and temporal invariance is satisfied, because $f(s)$ depends on a phase variable $s$. The phase variable is monotonically decreasing (from 1 to 0) according to (3).

Thus, the process of learning from demonstration consists in computing the set of weights $\omega_i$ for a given desired trajectory $(x(t), \dot{x}(t), \ddot{x}(t))$, where this requires computing the non-linear function by the equation (4). Therefore, to solve the learning problem it is necessary to minimize the error criterion $J = \sum_s (f_{target}(s) - f(s))^2$; this represent a locally weighted regression problem.[8]

$$f_{target}(s) = \frac{\tau\dot{v} + Dv}{K} - (g-x) + (g-x_0)s \tag{4}$$

## 4. Autonomous Backhoe Machine

To develop autonomous truck loading operations in backhoe machine is important to consider the following three aspects: a perception system that can recognize and estimate the position of the dump truck, a motion planning system that generate appropriate movements to reach the goal, and finally, a control system that adequately command the actuator of the machine. As a result, it was developed an imitation learning with DMP approach for the motion planning in truck loading operations.

### 4.1. *Imitation Learning with DMPs in Backhoe Machine*

Imitation learning using DMPs in backhoe machines is achieved allocating at least one transformation system per Degree Of Freedom (DOF). Thus, each DMP is set up with four transformation systems in order to encode the kinematics variables $(x, y, z, q)$, where $(x, y, z)$ is the cartesian position of end-effector and $q$ is a joint position (pitch angle) of bucket. These state variables represent adequately the characteristics of loading truck operations, and also other kind of tasks performed by backhoe machines, because the orientation of the bucket is a relevant variable in any kind of operation.

The configuration of employed the dynamical movement primitives is illustrated in Fig. 2, where a single DMP generate discrete movements primitives in two coordinates frame concurrently. Moreover, we can see the non-linear target function to be learned (orange signal) and the generation of four states (red signal) in a typical truck loading operation (see Fig. 2).

Thus, the general architecture of the intelligent agent (IA) is illustrated in Fig. 3, which we can see the process of imitation learning, acquisition of environmental information, motion planning and control.

For the generation of autonomous truck loading tasks, the machine operator show a trajectory demonstrated $\left[\mathbf{x_d}(t)\ \dot{\mathbf{x}}_\mathbf{d}(t)\ \ddot{\mathbf{x}}_\mathbf{d}(t)\right]^T$ with the task parameters $\left[\mathbf{x_0}\ \mathbf{g}\right]$ (orange dashed lines) by the operation of the machine. Then, the imitation learning with DMPs system (blue system) find the weights $\omega_i$ based in the information of the tasks. And finally, the perception system send the particular task parameters in order to generate a motion plan and execution of the truck loading operation (red lines and boxes).

### 4.2. *Inverse Kinematics and Control System*

Because DMPs are encoded in cartesian (end-effector position) and joint (bucket orientation) positions, it is necessary to implement an inverse kine-

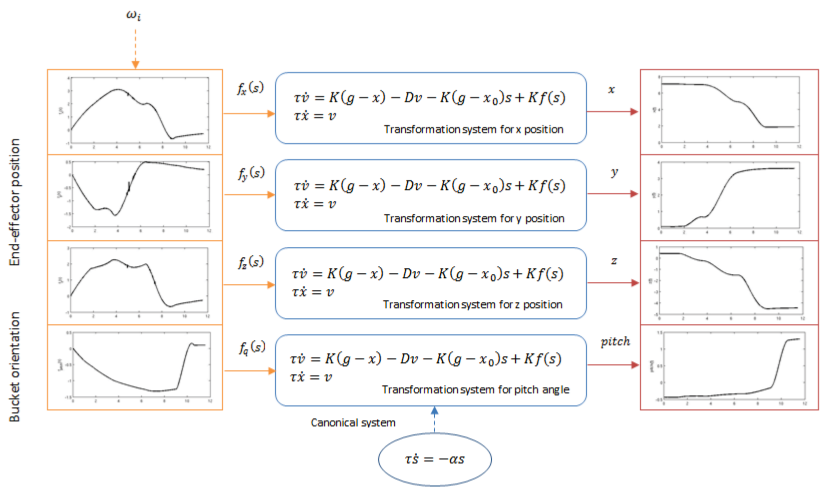


Fig. 2: The DMP implemented with four transformation systems, that is used to generate movements in backhoe machines.

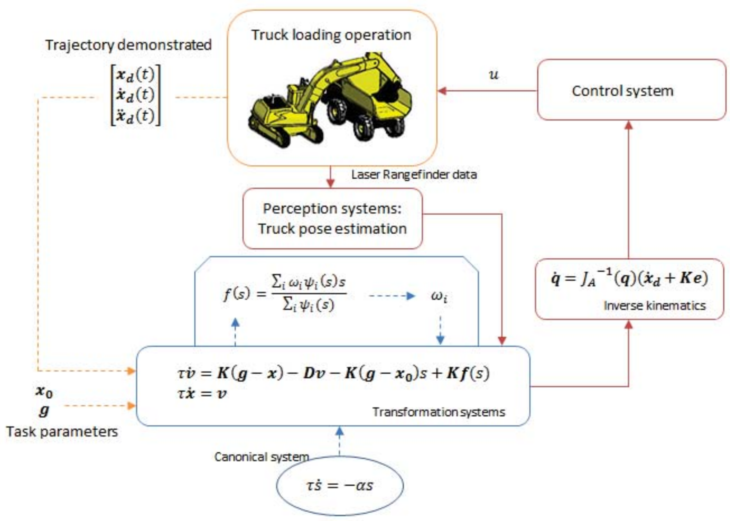


Fig. 3: The general architecture developed for autonomous truck loading operations.

matics algorithm that maps the cartesian coordinates to joint positions. For this purpose, it was formulated an inverse kinematics algorithm with Jacobian inverse as shown in Fig. 3. This computes the positions and velocities of turret, boom and stick joints.

The movement generation is transformed into the position and velocities references for the feedback controller (PID controller). Then, the controller performs appropriate torque commands $\mathbf{u}$ for the actuators.

In Fig. 4, we show the details about the implementation of inverse kinematics and control algorithm, where a feed-forward law control is implemented.

### 4.3. *Truck Loading Movement Generation*

To generate an autonomous truck loading operation, a DMP is selected and adjusted with the task information from perception systems: position to load the truck ($\mathbf{g}$) and the current state backhoe machine arm ($\mathbf{x_0}$) (see Fig. 3). In Fig. 5, it can be seen how the imitation learning with DMPs works in a typical left sided truck loading operation, where eight different cases of movement generation are shown. Thus, the green lines represent the movements generation for four different goal states based in the demonstrated trajectory (black line). The blue lines have the same four goals positions as green but with a new initial position. It can be observed that the motion planning follows the same shape trajectory desired while reaching any goal state.

### 4.4. *Backhoe Machine Simulation*

The simulations were implemented on an Open-Source Multi-Robot Simulator called Gazebo.[10] In the simulation of the autonomous truck loading operation, kinematic and dynamic properties for a typical backhoe machine were employed. Besides, it was implemented a set of range finder lasers with properties similar to those of Hokuyo lasers.

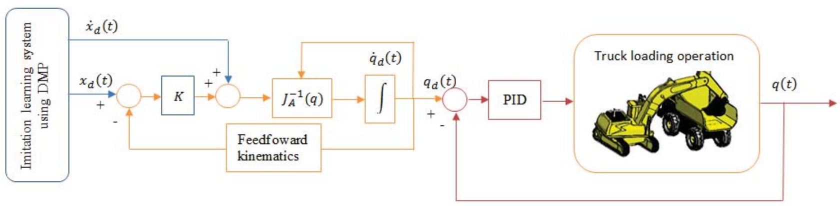


Fig. 4: The inverse kinematics and control algorithm implemented.

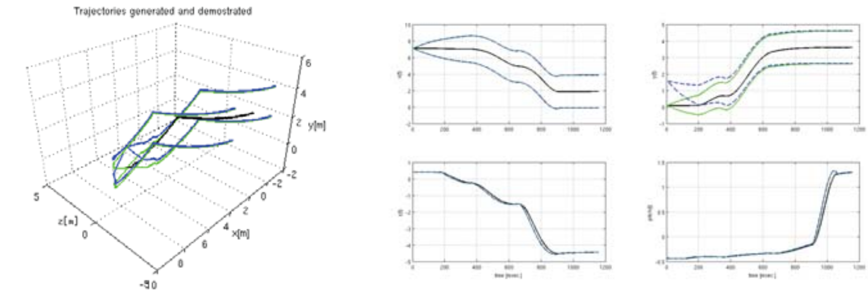


Fig. 5: The truck loading trajectory demonstrated (black whites) and generation movements for new goals (green lines), and news initial states (blue lines).

First, it was teached a movement for making a left truck loading operation. Second, the intelligent agent learned this movement. Third, the perception system recognize and estimate the position of the truck. Fourth, the DMP is selected and adjusted according to the position of truck. Fifth, the machine learning compute step by step the desired movement. Finally, this desired movement is mapped to joint position and velocity references for the generation of the torque commands for the actuators.

In Fig. 6 and 7, it can be seen how imitation learning with DMP approach works for autonomous truck loading operations; where in both cases

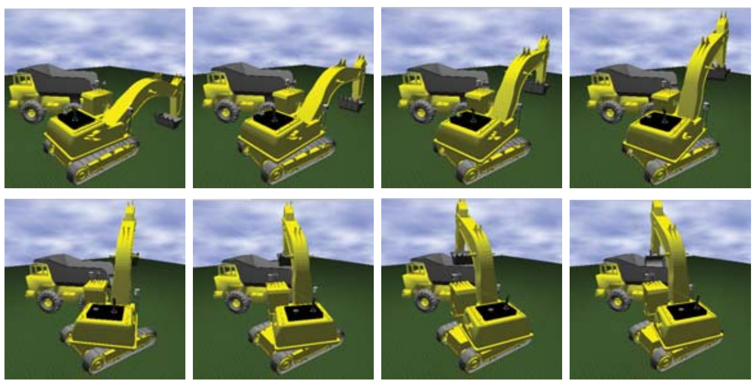

Fig. 6: The autonomous truck loading operation with $g = [1.87\ 3.60\ -4.44\ 1.3]$.

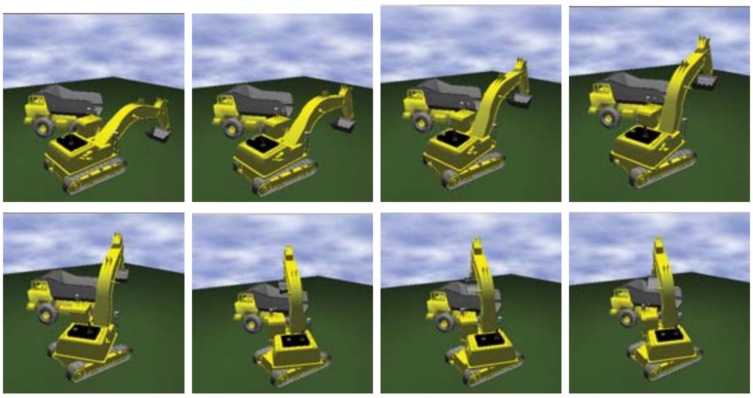

Fig. 7: The autonomous truck loading operation with $g = [2.50\ 4.00\ -4.44\ 1.3]$.

have the same initial state but with different goal states, g=[1.87 3.60 $-$4.44 1.3] and g=[2.50 4.00 $-$4.44 1.3], respectively.

In both cases, an appropiate performance of the truck loading task can be observed. Thus, the bucket position is adequate to avoid solid spilling. Therefore, the utility of the imitation learning with DMPs approach is demonstrated, where the system responded appropriately.

Besides, it is important to highlight that this method codes easily (from human demonstration) a high-dimensional control policy that performs in the same way as an expert operator. It must be noticed that this is not possible with non-learning methods.

## 5. Conclusion and Futures Works

This paper proposed a novel framework of motion planning system for autonomous truck loading operation. It was suggested an imitation learning approach as a motion planning scheme for backhoe machines. Numerical simulations demonstrated the reproduction and effectiveness of this architecture of supervised learning for the generation of motor skills in excavator intelligent agent, which is robust to change in target positions.

The approach could be implemented in other kind of operations as digging a foundation or leveling a mount of soil for the machine here modeled. The autonomous truck loading architecture presented could be extended to complete automation of earthmoving operations in backhoe machines. Also, this technology could be easily extended to other kinds of similar machines (i.e. bulldozers, cranes, etc).

Future works will address the generation of a extended DMP library for most common operations in a backhoe machine. It is important to develop a high-level task planning that make decisions of type of truck loading (i.e. right or left truck loading) based in the perception system; this would choose the most appropriate DMP for the task. In the future, we are interested in developing an efficient algorithm to build a map of occupancy that feeds a potential field generation system for obstacle avoidance. And finally, we want to test the complete architecture in a typical backhoe machine.

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