A Proposed Architecture for Autonomous Operations in Backhoe Machines

Carlos Mastalli[1] and Gerardo Fernandez-Lopez[2]

[1] Istituto Italiano di Tecnologia,
Department of Advanced Robotics, Genoa, Italy
carlos.mastalli@iit.it
[2] Simon Bolivar University,
Mechatronic Research Group, Baruta, Venezuela

Abstract. In this work is developed an architecture which consists four main components: perception system, tasks planning, motion planner and control systems that allow autonomous operations in backhoe machines. In the first part is described the architecture of control system. Thereafter, a set of techniques for collision mapping of the scene is described and implemented. Moreover, the development of motion planning system based on Learning from Demonstration using Dynamic Movement Primitives as control policy is proposed, which allows backhoe machines to perform operations in autonomous manner. A statement of reasons is presented, wherein we justified the implementation of such motion system versus planners like A*, Probabilistic RoadMap (PRM), Rapidly-exploring Random Tree (RRT), etc. In addition, we present the results of the architecture. Finally, the tests were performed in a simulation environment called Gazebo.

Keywords: Autonomous Backhoe Machine, Learning from Demonstration, Dynamic Movement Primitives, Perception System.

1 Introduction

Backhoes are machines that execute a set of heavy tasks associated with the waste removal and trench digging operations, nevertheless there is a diversity of tasks such as descending operation using the arm of the machine.

In the operation execution there are constraints associated with the tasks, for example, in the truck-loading tasks must preserve a suitable orientation of the tool *bucket* such that avoids the spilling of material in undesired locations. In addition, in some cases, it is necessary to shake the bucket in order to remove completely the material. This kind of complexities is found in other tasks, for example the proper position of the tool to avoid jamming the mechanism while is descending a hill. For these reasons, planning strategies based on searching of free-spaces such as: A*, *Probabilistic RoadMap* (PRM) or *Rapidly-exploring Random Tree* (RRT) would fail likewise that is shown in [17]. On the other hand, in the autonomous execution of operations, the perception system should

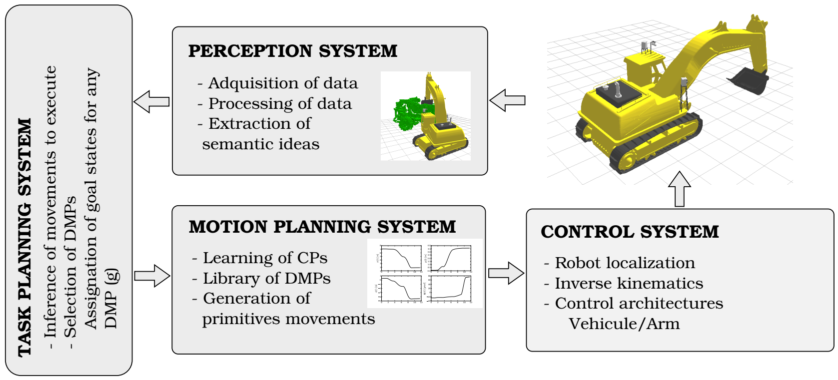

Fig. 1. Systems connexion of backhoe machine.

be capable of extracting semantic ideas quickly, efficiently and reliable. For this purpose, it is required the development and implementation of a set of modules that allow to extract a set of semantic ideas of the workspace. Nowadays, there is little literature about perception systems focused in the autonomous execution of backhoe tasks, nevertheless, among the most outstanding ones, we can mention the works of [10] and [14], which are focused in the development of visual odometry system and integral systems for autonomous truck-loading operations, respectively.

In this paper, we propose an architecture that comprises four subsystems: perception, task planning, motion planning and control systems as is shown in Fig. 1. In section 2, we present an overview of control system developed. In section 3, we propose a set of module for the perception system of the backhoe machine, and also, we present a short overview of the past developments of perception systems for backhoe machines. In section 4, we present an discussion about of motion planning algorithms developed, where we demonstrate the capacities of movements primitives learning techniques for autonomous operations in backhoe machines. Finally, in section 5, we present a discussion and comparison of our approach.

2 Control System

For the purposes of motion planning, it is convenient to encode backhoe tasks in the workspace of the machine. In [6] an imitation learning approach is developed as motion planners, and this motion planning algorithm encodes the backhoe tasks in the workspace of machine. Therefore under these circumstances, we require the implementation of operational space controller that allows the appropriate execution of planned movement.

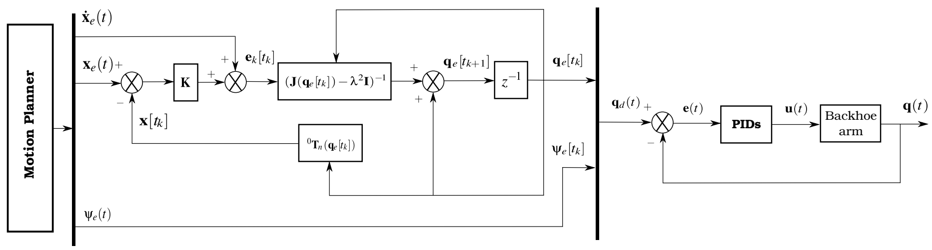

Fig. 2. Backhoe-arm Control System.

Such implementation is based in the use of Proportional-Integral-Derivative (PID) controllers in each rotational joint[3] of the backhoe arm. In Fig. 2 can be seen that the control system implemented has two main components. The first component consists in the implementation of the inverse kinematic algorithm [1][4] that allows mapping the generated movement, in the codification space of imitation learning approach $\left[x_e\ y_e\ z_e\ \psi_e\right]^T$, to joint space. The second component consists in the implementation of control system that is based on PID controllers. We tuned these controller using a asymptotic stability method as is detailed in [7].

3 Perception System

Advances in the accuracy of sensors, new processing techniques and extraction of semantic ideas allow us to develop all capabilities needed for autonomous operations in backhoe machines. In [16] is suggested an acquisition system based on a pair of stereo cameras and range finder lasers for teleoperation tasks in the backhoe. Similarly, [14] implemented an acquisition system based on two range finder lasers located in both sides of the machine, and also, a stereo camera located in the central part of the machine. Therefore, we implemented a pair of range finder lasers in order to sense accurately the element that may be far away, and a stereo camera to capture more information in the vicinity of the machine.

In the following Fig. 3, we show the perception systems developed, which composes two stage; the first stage consists in the acquisition and low-level data processing, and the second stage consists in a high-level data processing.

In the acquisition stage, the stereo vision system makes a 3D reconstruction using Block-Matching algorithm [5], i.e. a extraction of depth maps. Regarding the lasers, it is necessary to implement a shadow filter that removes errors in the measurements, and then transforms both data to a point cloud format. The fusion of point cloud data (stereo camera and lasers) reduces computation times. In the processing stage, we use a voxelgrid filter to reduce the density of point

[3] The dynamic of hydraulic actuators have not been consider in this work.

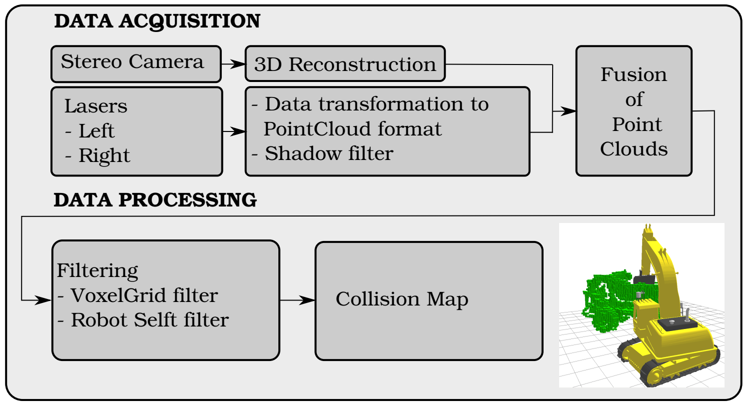

Fig. 3. Perception system developed.

clouds, and then, we eliminate the points that belong to the robot by using CAD position using the forward kinematics of the machine. Finally, we build a collision map using this information.

3.1 3D representation

For the description of the collision map in the backhoe, we have considered the following criteria:

1. **Model of the backhoe's environment:** Modeling process of environment should be capable of representing every element of the workspace. Besides, it is required to model with enough accurately free, unknown and occupied spaces for several tasks such as: autonomous exploration and terrain mapping.
2. **Update capacity:** Update capacity is essential in order to aggregate new information from other agents or robots efficiently, i.e. considering the environment as dynamic, noisy and non-structured.
3. **Flexible:** Collision maps should have multiple resolutions and dynamically extendibles. This characteristic allows us to improve the planning times by using an appropriate resolution of the map.
4. **Compact:** Collision maps should be stored efficiently in order to transmit this data with a limited bandwidth.

For these purposes, we found that only *octrees* representation satisfies all essential requirements to execute autonomous operations in backhoe machines. Therefore, in the Fig. 4 is shown a collision map (green voxels) built using the measurements of the stereo camera and lasers (red data). This map is built using OctoMap library [15].

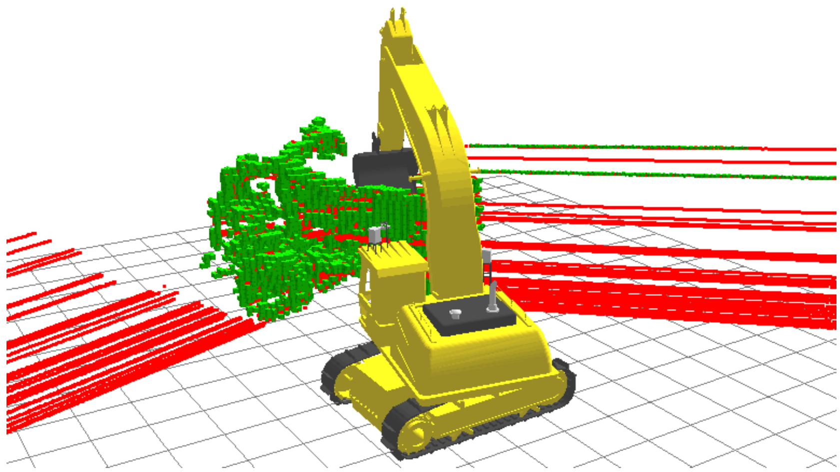

Fig. 4. Collision map of a typical truck-loading operation.

4 Motion Planning System

Today, there is a wide range of approaches that solve the motion planning problem. The first developments are focused in polynomial interpolation techniques of way-points from a certain trajectory, nevertheless, these methods are not adaptable for little changes in the environment, and moreover, objects in the environment are not considered. Researchers later are focused in the development of a set of collision-free path search-based planning methods such as A*, Probabilistic RoadMap (PRM) and Rapidly-exploring Random Tree (RRT). Nevertheless, these methods do not consider the constraints of tasks, despite being better than polynomial interpolation approaches. In view of these circumstances, a new wave of motion planning methods is focused on movements primitives learning techniques. Movements primitives learning techniques allow us to encode relevant characteristic of a movement [3], and could be integrated obstacle avoidance characteristics by using Potential Fields [8].

An example of such necessities is reported in [17], in which they are demonstrated that the search-based methods (RRT) are not enough for generation of complex movements, and also is shown poor results of the RRT planner. Therefore, [17] developed a new motion planning method using learning from demonstration approach called *Demonstration-Guided Motion Planning* (DGMP), which get successful results.

4.1 Control policy for generation of movements

The development of fully autonomous system requires that the machine has the capacity to plan and execute a set of behaviors or basic tasks. This is a high-dimensional and complex problem because the robot needs to consider every

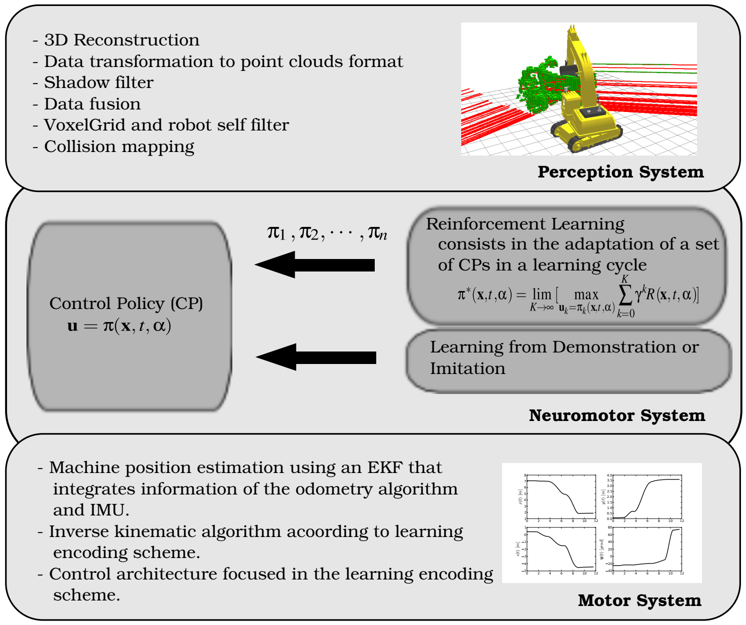

Fig. 5. Control policies.

aspect of the workspace, and also the implicit constraints of the task. Nevertheless, we can encode these behavior in Control Policies (CPs), as is shown in Fig. 5, using the following approaches:

1. Through the use of Reinforcement Learning (RF) algorithms in order to search and find optimal policies.
2. Through the use of Learning from Demonstration (or Imitation) approaches that can capture the important features of a certain motor skill.

In general terms, both approaches attempt to find a control policy:

$$\boldsymbol{u} = \pi(\boldsymbol{x}, t, \boldsymbol{\alpha}) \tag{1}$$

in which consists in mapping the configuration space of the robot (current state vector $\boldsymbol{x}$) to a set of motor commands (control vector $\boldsymbol{u}$), with a possible temporal dependence t. In addition, there is a set of adjustable parameters $\boldsymbol{\alpha}$ in the CP, which describe the conditions of the behavior.

We can posed a CP as Dynamic Movement Primitive (DMP) as is proposed in [3]. A DMP has essentially two systems: transformation and canonical system, where there is a unidirectional connection between the transformation and canonical system.

4.2 Dynamic movement primitive

A Dynamic Movement Primitive (DMP) is a non-linear differential equation that encodes basic behaviors, for example rhythmic and discrete movements. The purpose of this control policy consists in reaching a goal state with a desired shape of the trajectory and independence of initial state. Moreover, the DMPs are compact representations of motion planning policy and must have the following characteristics:

– Guaranteed convergence to the goal state.
– Capable to generate any smooth desired trajectory.
– Time and space invariant.
– Robust against disturbances associated with the attractor dynamic.

There are several formulations of DMPs that depends of the kind of movements (discrete or rhythmic), as is shown in the works [3] [2] [9]. In the case of discrete movements, the proposal of several DMPs have been neurophysiology-inspired, for example in [2] is formulated the DMP using a neurophysiology model of the frog, although this formulation has problems in the adaptation of new goal states. Nevertheless, [9] formulated the DMP as a mass-stiff-damper system disturbances by a non-linear force $f(s)$, which improves the adaptation problem of [2]. This formulation was implemented to encode grasping and manipulation tasks by [9]. We found that this is a good formulation for operations in backhoe machines.

On the other hand, a DMP encodes a motor skills using a set of weights ω_i, that we compute using a learning from demonstration algorithm [6] to capture a demonstration of tasks $(x(t), \dot{x}(t), \ddot{x}(t))$. With the demonstration procedure, the backhoe machine can compute the non-linear function for a certain motor skills $f_{target}(s)$, and then calculates the weights of this function using a locally weighted regression algorithm (LWR).

4.3 Generation of movements using DMPs

Generation of autonomous movements using DMPs requires in every instant to propagate the states of the DMPs. In general terms, the generation of the movements is obtained with the following procedure:

1. **Selection of movement primitives:** the selection of movement primitives consists in the election of a set of weights $\boldsymbol{\omega}$ that describe a certain learned tasks.
2. **Setting the movement primitives:** this procedure adjusts the DMPs parameters in every of the n transformation systems implemented, which depends of the conditions of the operation.
3. **Propagation of movement primitives:** the propagation of dynamic system (DMP) generates the desired positions and velocities in every instant.
4. **Generation of commands:** the generation of appropriate commands require the implementation of inverse kinematics controller because we encode the motor skills in the cartesian space, as is shown below.

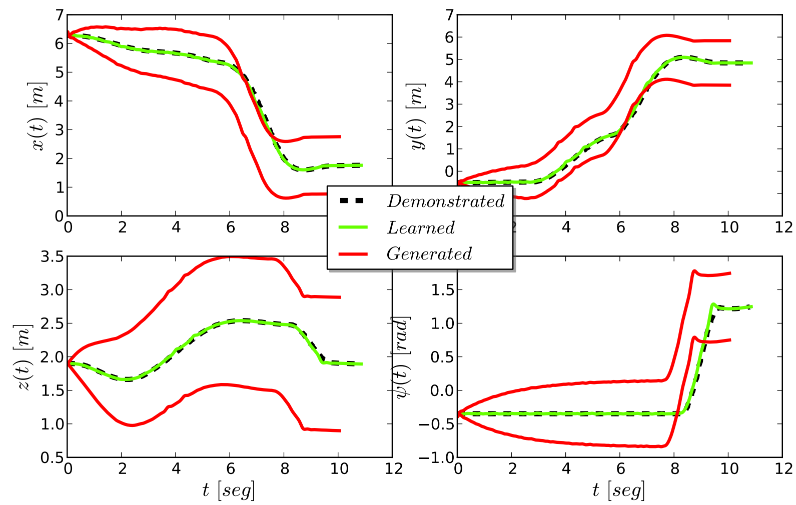

Fig. 6. Learning and generation of DMPs that encode a certain operation in the backhoe machine.

4.4 Autonomous execution of operations

For autonomous operations in backhoe machines is necessary to integrate a set of system: control, perception and planning, in which generate a set of appropriate actions. First of all, it is required to perceive important features in the workspace. Subsequently, the robot need to extract semantic ideas that allow it to build a representation, and then, make decisions about the execution of appropriate motor primitives. Once the backhoe has selected the DMPs, the backhoe generates the desired movements according the specified parameters, which depends of the semantic information of the environment. Finally, the backhoe machine generates the appropriate commands.

We need to design, or configure, a set of DMPs that can encode a fully operation. In this sense, we assign a set of 4 DMPs because the backhoe machine has 4 dof; the first three DMPs are associated to the cartesian positions (x, y, z) of the bucket, and the last one is associated with the joint position ψ of the bucket. For example, in Fig. 6 is shown the results of this learning procedure for a certain operation, where the generation of the movements (red curves) have the same shape of the demonstration trajectory (black curve). Finally, in Fig. 7 is shown a completely sequences of autonomous movements in a typical digging and truck loading operation, where in Fig. 7b is shown the reconstruction of the collision map in every sequence of the movement.

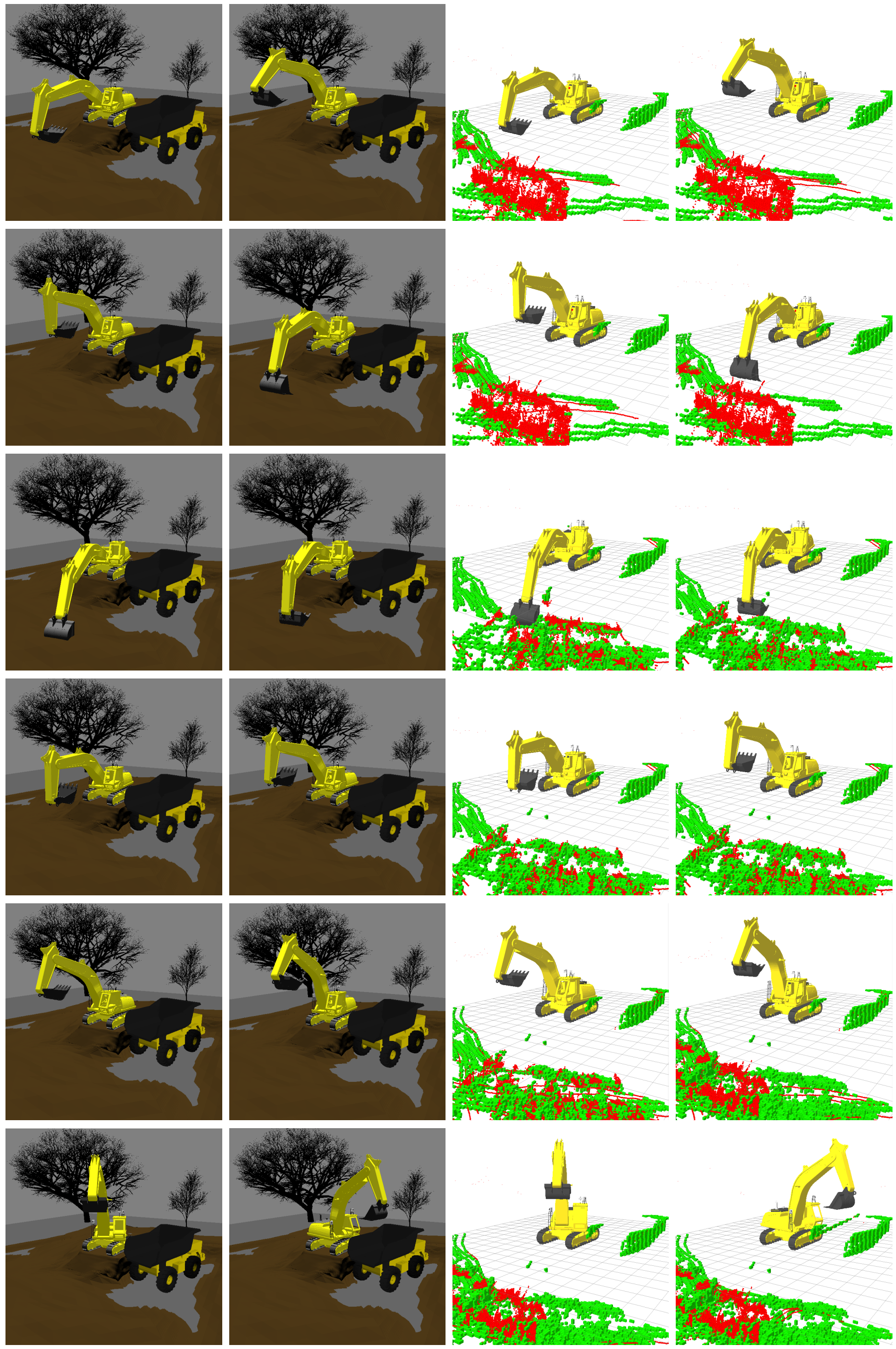

Fig. 7. Autonomous operation in the backhoe machine where in (a) is shown a sequence of movements simulate, and (b) the results of the perception system.

5 Discussion

In this paper we proposed a novel architecture for autonomous operations in backhoe machines. We find that the operations in the backhoe machine are complex and diverse, for example, it is necessary sometimes to climb or descent a hill using the arm of the backhoe machine. For these reasons, we suggest to use learning from demonstration strategies in order to generate complex motor skills, moreover, we can integrate a task planner in order to select a appropriate control policies. This approach allow us to build a library of required motor skills. On the other hand, we propose a basic perception system that allow us to build a collision map, which is important to preserve the security of the operation, where we propose to use voxel representation for any kind of problem: i.e. arm motion planning, navigation, swarm robotics, etc.

Our approach extend the ideas of [14] using a movement primitives learning technique. In addition, we propose a more sophisticated perception system that allow to improve the efficient of the whole-architecture. In contrast to [12] [11] [13], we propose a motion planning system that can be integrate with these tactical planners, where we have considered to implement in a future work as is shown in Fig. 1.

References

1. Buss, S.R.: Introduction to inverse kinematics with jacobian transpose, pseudoinverse and damped least squares methods. Tech. rep., University of California, San Diego (2009)
2. Hoffmann, H., Pastor, P., Schaal, S.: Dynamic movement primitives for movement generation motivated by convergent force fields in frog. In: International Sympsium on Adaptive Motion of Animals and Machines (AMAM). pp. 1–2 (2008), http://www-clmc.usc.edu/publications//H/HeikoHoffmann_AMAM_2008.pdf
3. Ijspeert, A.J., Nakanishi, J., Schaal, S.: Learning attractor landscapes for learning motor primitives. In: in Advances in Neural Information Processing Systems. pp. 1523–1530. MIT Press (2003)
4. Jovanovic, V.T., Sendzimir, T.: On the metrics and coordinate system induced sensitivity in computational kinematics. Tech. rep., Department of Mechanical Engineering. University of Connecticut (1996)
5. Konolige, K.: Small vision systems: Hardware and implementation. In: International Symposium of Robotics Research (1997)
6. Mastalli, C., Cappelletto, J., Acua, R., Terrones, A., Fernndez-Lpez, G.: An Imitation Learning Approach For Truck Loading Operations in Backhoe Machines, chap. 104, pp. 827–830. World Scientific, Baltimore (2012), http://www.worldscientific.com/doi/abs/10.1142/9789814415958_0104
7. Mastalli, C., Ralev, D., Certad, N., Fernndez-Lpez, G.: Asymptotic stability method for pid controller tuning in a backhoe machine. In: ASME Dynamic Systems and Control Conference (2013), https://asme-dscd.papercept.net/conferences/scripts/abstract.pl?ConfID=7&Number=3884
8. Park, D.h., Hoffmann, H., Pastor, P., Schaal, S.: Movement reproduction and obstacle avoidance with dynamic movement primitives and potential fields. Humanoids 2008 - 8th IEEE-RAS International Conference on Humanoid Robots

pp. 91–98 (2008), http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4755937
9. Pastor, P., Hoffmann, H., Asfour, T., Schaal, S.: Learning and generalization of motor skills by learning from demonstration. In: 2009 IEEE International Conference on Robotics and Automation (2009)
10. Saeedi, P., Lawrence, P.D., Lowe, D.G., Jacobsen, P., Kusalovic, D., Ardron, K., Sorensen, P.H.: An autonomous excavator with vision-based track-slippage control. IEEE Transactions on Control Systems Technology 13(1), 67–84 (2005), http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1372547
11. Singh, S., Simmons, R.: Task planning for robotic excavation. In: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems. pp. 1284–1291 (1992)
12. Singh, S.: Developing plans for robotic excavators. In: Proceedings of the ASCE Conference on Robotics for Challenging Environments. pp. 88–96 (1994)
13. Singh, S.: Synthesis of tactical plans for robotic excavation. Ph.D. thesis, Carnie Mellon University (1995)
14. Stentz, A., Bares, J., Singh, S., Rowe, P.: A robotic excavator for autonomous truck loading. In: Proceedings 1998 IEEE/RSJ International Conference on Intelligent Robots and Systems. Innovations in Theory, Practice and Applications. vol. 3, pp. 1885–1893. IEEE (1998)
15. Wurm, K., Hornung, A., Bennewitz, M., Stachniss, C., Burgard, W.: Octomap: A probabilistic, flexible, and compact 3d map representation for robotic systems. In: Proceeding of the ICRA 2010 workshop on best practice in 3D perception and modeling for mobile manipulation (2010)
16. Yamamoto, H., Moteki, M., Shao, H., Ootuki, T.: Basic technology toward autonomous hydraulic excavator. 26th International Symposium on Automation and Robotics in Construction (ISARC 2009) pp. 288–295 (2009), http://www.irbnet.de/daten/iconda/CIB14849.pdf
17. Ye, G., Alterovitz, R.: Demonstration-guided motion planning. In: In Proceedings International Symposium on Robotics Research (ISRR) (2011), http://robotics.cs.unc.edu/publications.html