공학석사학위논문

자동화 굴착기를 위한 숙련자 굴착력 패턴 기반 굴착 작업 궤적 생성

Trajectory Generation for Autonomous Excavators Based on Expert Operator Forcing Pattern

2020 년 8 월

서울대학교 대학원

기계공학부

김 창 묵

자동화 굴착기를 위한 숙련자 굴착력 패턴 기반 굴착 작업 궤적 생성

Trajectory Generation for Autonomous Excavators Based on Expert Operator Forcing Pattern

지도교수 이 동 준

이 논문을 공학석사 학위논문으로 제출함

2020 년 4 월

서울대학교 대학원

기계공학부

김 창 묵

김창묵의 공학석사 학위논문을 인준함

2020 년 6 월

위 원 장 : 이 경 수 (인)

부위원장 : 이 동 준 (인)

위 원 : 조 규 진 (인)

Abstract

Trajectory Generation for Autonomous Excavators Based on Expert Operator Forcing Pattern

Changmuk Kim
Mechanical Engineering
The Graduate School
Seoul National University

In this thesis, we propose an excavation trajectory generation framework for autonomous excavators based on expert operator forcing pattern. The primary focus is to develop autonomous excavator system which is stable and guarantees a certain quantity of excavation in various surroundings. We find the excavation trajectories based on the terrain features and the excavation forcing patterns from the excavation data of expert operators. The expert excavation trajectories are encoded with dynamic movement primitives (DMP) and learn through multi-layer perceptron (MLP). The excavation trajectory is generated according to the terrain feature using the trained model. The excavator is modeled with 3-DoF rigid body system, and the excavation force on the bucket tip is estimated online by using the momentum-based disturbance observer(DOB). The estimated force is added to the DMP as a coupling term to modulate the excavation trajectory in real-time so that the estimated force can follow the expert excavation force pattern. Lastly, we verify the performance of the suggested framework through simulation and actual excavator test.

Keywords: Autonomous excavators, Trajectory generation, Dynamic movement primitives, Multi-layer perceptron, Dynamics, Momentum-based observer.
Student Number: *2018-20186*

Contents

List of Figures

List of Tables

Abbreviations

DMP	**D**ynamic **M**ovement **P**rimitives
MLP	**M**ulti-**L**ayer **P**erceptron
DoF	**D**egree **o**f **F**reedom
SE(2)	**S**pecial **O**rthogonal Group in **2**-Dimensional Space
IMU	**I**nertial **M**easurement **U**nit
LiDAR	**Li**ght **D**etection **A**nd **R**anging
DOB	**D**isturbance **OB**server

Chapter 1

Introduction

1.1 Motivation and Objectives

Today, industries around the world have developed in the direction of unmanned and automated, which has resulted in improved economic efficiency, productivity and product quality, and secured stability against industrial disasters. Nevertheless, the construction industry is far behind the application of unmanned automation technology due to the variable environment and the frequent occurrence of unconfirmed events. The demands for unmanned automation in the construction industry are increasing to solve problems such as profitability deterioration due to rising wages, shortage of skilled workers due to the recognition of dangerous industries, the deterioration of construction technology competitiveness, the aging phenomenon in society, and securing safety at construction sites. In this situation, the automation development of excavators, which are most widely used in construction sites, can be a technical alternative to the above problems. In this thesis, we propose a trajectory generation algorithm for excavation, the most basic and repetitive task of excavators, and generate a safe and productive trajectory for various terrains. The excavation work is highly dependent on the worker's intuition [1], so there are many restrictions on the uniformity of productivity and work quality. Our framework can help to resolve the problems while reducing the duration of work and performing more accurate tasks.

1.2 Related Work

Researches on unmanned and automated excavators have been actively conducted before. In industry, the teleoperation system has been developed and used partially, and machine guidance to assist the work and machine control to assist the operation are already in commercial used. In addition, various studies have been conducted on the generation of trajectory for autonomous excavators in academia.

The teleoperation [2], [3] is remote control of the excavator using the image viewed that watching the workplace directly from the operation site or transmitted from the workplace. This has the advantage that people do not need to be directly put into dangerous sites. However they can not feel the reaction force according to the soil characteristics, and it is difficult to grasp the relative position with the machine due to limited visibility, so the work efficiency is lower than direct operating.

Machine guidance [4], [5] is a technology that generates a map of a work area using target drawings, IMU(inertial measurement unit) sensor and GNSS(global navigation satellite systems). This system reduces the surveying time and facilitates accurate work for the target. Machine control [4], [6] is a technology that provides semi-automation for some of the excavator's tasks, and it has the advantage that even an inexperienced operator can achieve similar performance to a skilled operator for a certain operation. However, these technologies are only an intermediate step towards automated excavators as an aid to the driver.

The previous studies [7], [8] focus on dynamics-based optimization techniques. These studies limit the speed and acceleration of each joint in consideration of the torque applied to the excavator, and generate trajectory to minimize the traveling time of the excavator in limited situations. They do not consider interaction with soil in real-time. In other studies [9], [10], [11] excavation trajectory is generated by adding the soil dynamics in the fixed shape of trajectory. These studies generate the excavation trajectory by the researcher's intuition and do not consider the trajectory used in the actual workplace. For that reason, there are insufficient to ensure productivity and safety in various environments like experts.

1.3 Contribution

In a general construction workplace, the excavator operator recognizes the work area and generates an excavation trajectory considering the surrounding environment. In addition, if there is a hazardous situation for oneself or surroundings due to unrecognized factors such as underground objects, the operator modulates excavation trajectory or stops the excavator to get out of the hazardous situation. However, in the case of an autonomous excavator, the above judgment is impossible because there is no operator in equipment, so the excavation trajectory must be generated and modulated based on the data received by the excavator itself.

The main problem with the excavation trajectory generation is to consider the interaction with complex and unmodelable soil, and create a safe and productive trajectory in various environments. To solve this problem, we aim to generate the excavation trajectories by imitating the work characteristics of expert operators. The excavator learns the DMP(Dynamic Movement Primitives) [12], [13] encoded excavation trajectory by applying the machine learning technique, and generates the excavation trajectory based on the learning model according to the perceived terrain feature. The trajectory is modulated during excavation based on the excavation force pattern of the expert. Simulation is conducted to verify the proposed algorithm, and the robustness of the algorithm is verified through the actual excavator experiments.

The rest of the thesis is organized as follows. Chapter.2 describes the system and algorithm used in the thesis. Chapter.3 explains how to generate excavation trajectories by analyzing excavation data of experts. Chapter.4 shows the simulation and actual excavator test results. Chapter.5, it is written as a conclusion and a future work of the thesis.

Chapter 2

Preliminary

2.1 System Description

The excavator used in this thesis is the commercial model of Doosan DX380LC (Fig. 2.1). The excavator is equipped with IMU (inertial measurement unit) sensors attached to the boom, arm, bucket joint, and swing shaft to measure the angle and angular velocity so the posture of the excavator can be known. Pressure sensors are attached to each cylinder to measure the pressure during operation. In addition, RTK GNSS (real-time kinetic global navigation satellite systems) is attached to the cabin to measure the position and posture of the excavator upper body, and LiDAR (light detection and ranging) is attached to the excavator boom to scan the target terrain to be excavated.

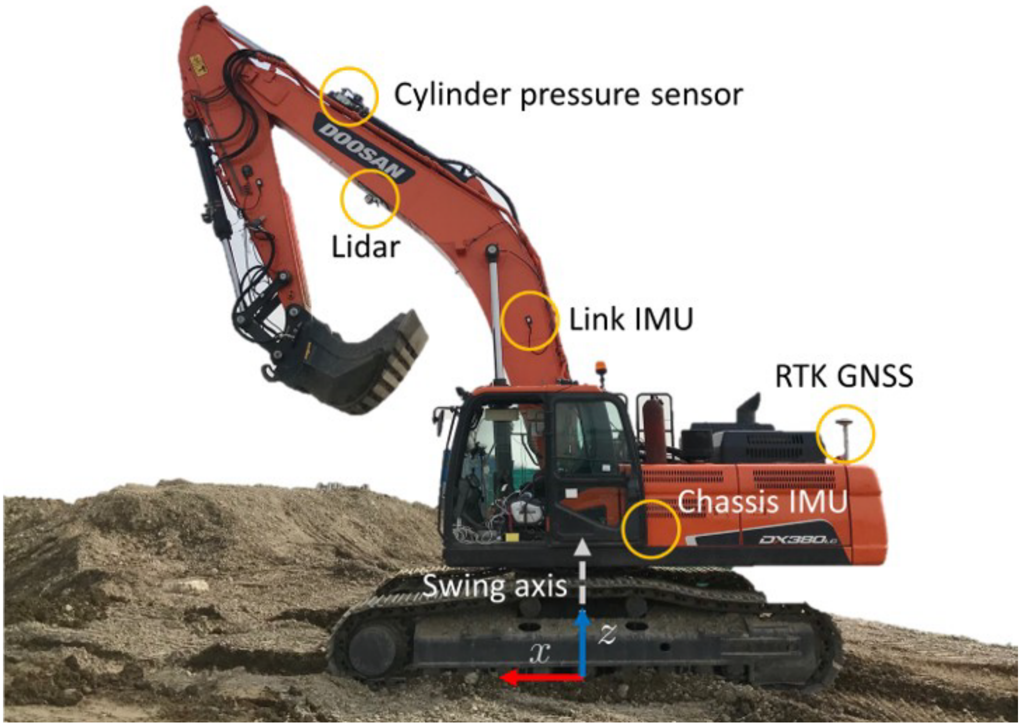

FIGURE 2.1: Doosan excavator DX380LC, with IMUs, LiDAR, cylinder pressure sensors, RTK-GNSS

2.2 Excavator Dynamic Modeling

For the purpose of this study, we model 3-DoF(degree of freedom) rigid body dynamics of the excavator. The rigid body dynamic model can be described as follows:

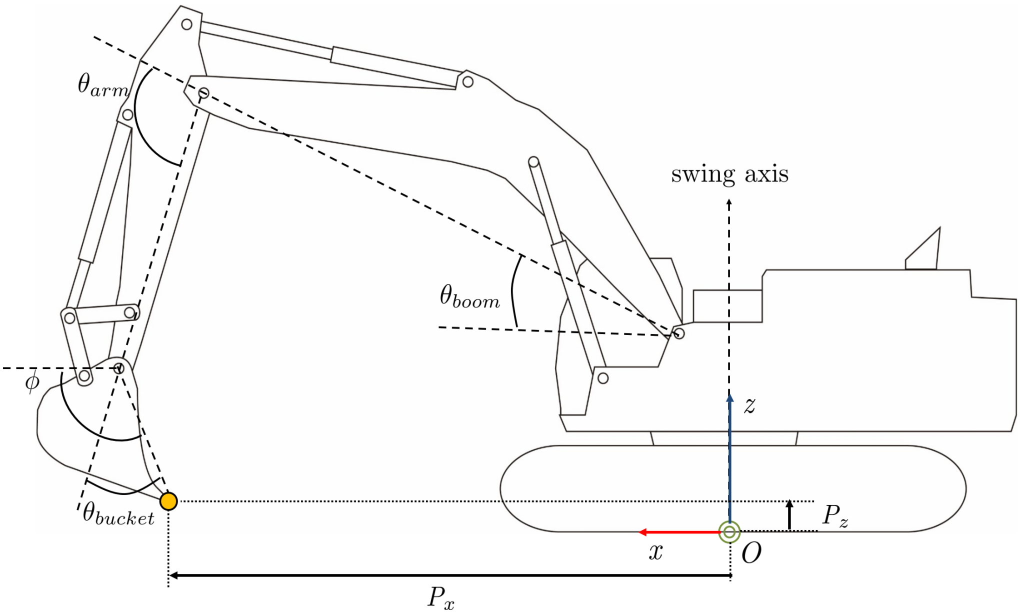

FIGURE 2.2: Configuration of the excavator

$$M(\theta)\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + g(\theta) + F_s\text{sign}(\dot{\theta}) + F_v\dot{\theta} = \tau_u + \tau_{\text{ext}} \tag{2.1}$$

where $\theta = [\theta_{boom}, \theta_{arm}, \theta_{bucket}] \in \mathcal{R}^n$ is the joint angle of excavator, $M(\theta) \in \mathcal{R}^{n\times n}$ is the symmetric and positive-definite inertia matrix, $C(\theta, \dot{\theta}) \in \mathcal{R}^{n\times n}$ is the Coriolis and centripetal vector, $g(\theta) \in \mathcal{R}^n$ is the gravity vector, $F_s, F_v \in \mathcal{R}^{n\times n}$ is the coulomb and viscous friction torques, and $\tau_u, \tau_{ext} \in \mathcal{R}^{n\times n}$ is input torque and estimated external torque. Excavator motion can be represented in another configuration $q = [p_x, p_z, \phi] \in SE(2)$, where p_x, p_z are position, and ϕ means the orientation of the bucket tip. Based on the excavator inertia frame O, the position of the excavator bucket tip can be expressed using q (Fig. 2.2). We use $q \in SE(2)$ for excavation trajectory expression and $\theta \in R^3$ for estimation of real-time excavation force on the bucket tip. In this thesis, we assumed that excavation trajectory is on a two-dimensional plane because swing movement is not generally involved during excavation.

2.3 Force Estimation via Momentum Based Disturbance Observer

Most of the excavator's tasks are done in contact with the external environment. Since the reaction force occurs, it is difficult to control the excavator bucket accurately by the desired trajectory when controlling the excavator bucket simply by position control. For accurate control, it is necessary to generate a trajectory in consideration of reaction force. There is a way to estimat the force using a torque sensor, but the torque sensor that can measure the excavation force is very large and it is impossible in reality. In this thesis, we estimate the excavating force in real-time using the momentum-based disturbance observer [14], [15] and modulate the excavation trajectory based on this. Momentum observer has advantages such as avoiding inversion of the robot inertia matrix, eliminating the need to estimate joint acceleration, and decoupling the estimation result. The momentum based observer is expressed as follows:

$$\begin{aligned}\tau_{ext} &= K_0\Bigg(p(t) - \int_0^t (\tau_u + \tau_\mu - \beta(\theta,\dot{\theta}) + \tau_{ext})ds - p(0)\Bigg)\\ p(t) &= M(\theta)\dot{\theta}\\ \beta &= g(\theta) - C^T(\theta,\dot{\theta})\dot{\theta}\\ \tau_\mu &= F_s sign(\dot{\theta}) + F_v\dot{\theta}\end{aligned} \tag{2.2}$$

where $K_O > 0$ is the diagonal gain matrix of the observer, joint angle θ and joint angular velocity $\dot{\theta}$ can be measured by IMU, and τ_u can be calculated using the cylinder specification and the value of the pressure sensors. Other terms can be found through off-line parameter identification. The excavation force $f_{ext} \in \mathcal{R}^3$ can be calculated by $f_{ext} = J_{ext}^{-T}\tau_{ext}$, where J_{ext} is the Jacobian matrix from the q-space to θ-space.

2.4 Dynamic Movement Primitives

The framework of dynamic movement primitives (DMP) is a method of robotic trajectory planning [12], [13] and it can easily modulate a given trajectory. This method is applicable for periodic movements, and capable of representing optimal behavior in stochastic environments. In this thesis, we encode the bucket tip position in DMP, and DMP is defined by the following system of nonlinear differential equation.

$$\ddot{y} = \alpha_y(\beta_y(g - y) - \dot{y}) + f(s) \tag{2.3}$$

where $y \in \mathcal{R}$ is system state, $g \in \mathcal{R}$ is the goal position, and α_y, β_y are positive gain term. By setting β_y to $\alpha_y/4$, the system can be critically damped to ensure that the system state converges monotonously to the goal position. The shaping force $f(s) \in \mathcal{R}$ is a nonlinear function that defines the desired behavior. We can easily solve and generalize problems with this additional nonlinear system. The shaping force is defined as a function of the canonical system, and canonical system is defined as follows:

$$\tau\dot{s} = -\alpha_s s \tag{2.4}$$

where $s \in [0, 1]$ is monotonically decreasing clock signal, and $\tau > 0, \alpha_s > 0$ are parameters that control the speed of the time constant. The shaping force $f(s) \in \mathcal{R}$ is defined as follows:

$$f(s) = h(s)(g - y_0)s \tag{2.5}$$

where y_0 is initial system state, $h(s) \in \mathcal{R}$ is nonlinear function. We can make the contribution of the $f(s)$ to zero over time by constructing the function with s. This means that it will eventually converge on our goal position regardless of path.

The DMP can modulate the trajectory online through additional coupling terms. In this thesis, coupling terms are used that operate like a PD (proportional derivative) controller by adding to the acceleration and velocity terms of the DMP [16], shown below

$$\begin{aligned} \tau\ddot{y} &= \alpha_y(\beta_y(g-y)-\dot{y}) + f(s) + c_2\dot{C} \\ \tau\dot{y} &= \dot{y} + c_1 C \end{aligned} \tag{2.6}$$

where $c1, c2$ are scaling constant gain, and C is modulation force. Using only the velocity level modulation creates a slight overshoot of forces upon environment contact appears. By adding a derivative of the measured force at the acceleration level, we can minimize this overshoot. We use the modulation force term to modulate the trajectory in real-time using the excavation force.

Chapter 3

Excavation Trajectory Generation

3.1 Analysis of Expert's Excavation Trajectory

Excavation work is the basic and most used task of excavators. However it is highly dependent on the intuition of the workers, so there are many limitations on uniformity of productivity and work quality. It is thought that expert operator manipulate each part of the excavator by sensing the changes in ground conditions, soil properties, reaction forces and relative positions from the excavator and ground. These allow them to work in a direction that reduce fuel consumption and increase productivity. Therefore, we try to find out the factors of high-efficiency work by analyzing the work of the expert operator. Because each expert operator may have different empirical standards, a number of skilled workers were interviewed, and through this, common answers from empirical knowledge are obtained (Table.3.1). However, these are only qualitative answers to what elements are connected for efficient work and not quantitative answers.

Based on the interviews, the important factors in manned excavation are time efficiency(cycle time) and productivity. Cycle time means the amount of time it takes to perform a repetitive work segment of a excavator, typically measured as the time it takes a excavator to return to the same position [17], and productivity means the amount of excavation per unit time. Because these two factors are inversely proportional, it is important to find the appropriate ratio for efficient work, and it depends on equipment, terrain, manned or unmanned, weather, etc. Productivity depends on payload, and according to the interview of expert, the most efficient payload is considered when bucket is filled with 120$\sim$150%. In addition, the experts predict the load on the excavator using engine RPM, pump pressure and speed of the excavator, and they operate excavator under appropriate load to consider the durability of the machine and preventing undetectable danger. Through this, we find that the load should be considered when generate the excavation trajectory. Since the load generated by interaction with unmodellable and complex soil dynamics, we tried to consider the load on the excavator by calculating the excavation force applied to the tip of the bucket.

A result of interview to expert operators
1. What is the criteria for efficiency when excavating?
- Time efficiency(cycle time), productivity
2. Are there standards for excavation length and depth for excavation?
- There is no standard because it is intuition.
3. What is the effective amount of soil in the bucket after the excavation is completed?
- For normal work, 120∼150% is considered the most efficient
4. How do you deal with a shortages of soil or too much soil during excavation?
- Lift or lower the boom to change the excavation trajectory
5. If the size of the excavator changes, does the method of excavating change?
- The method may vary depending on the shape of the bucket, but not the size of the excavator.
6. Are there other important factors when excavating?
- Considers excavator's durability by reducing load.

TABLE 3.1: A result of interview to expert operators

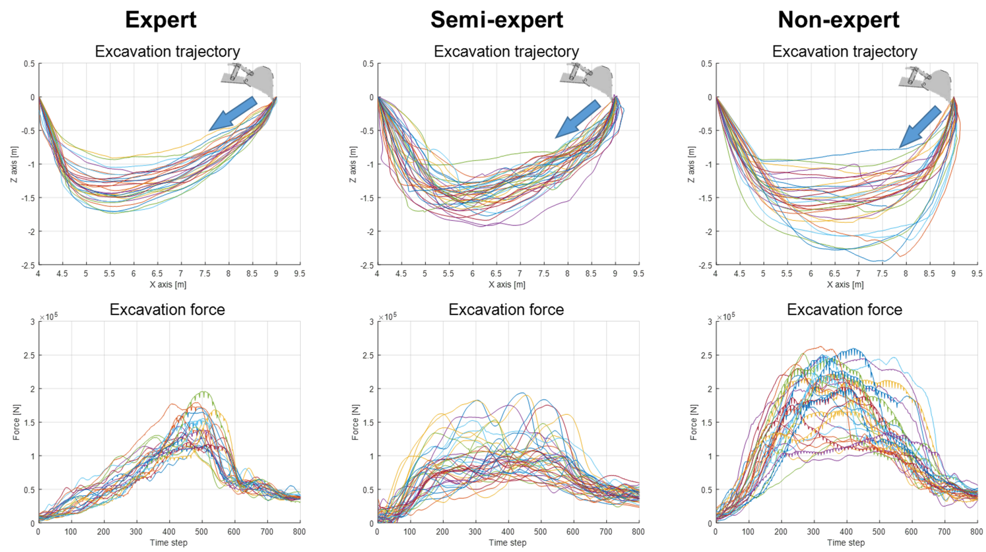

FIGURE 3.1: Excavation trajectories and excavation force patterns

For the analysis of the excavation work, we obtain the data of the various operators using a commercial excavator (Fig. 2.1). The data are obtained through excavation experiments on Doosan Infracore worksite flat terrain and three different angle of slope terrain, and 40∼50 excavation experiment data are obtained for each operator. The expert operator is targeted at person who has been conducting excavator fuel consumption pattern test for more than 20 years. We also obtain excavation work data from the semi-expert operator who has been conducting excavator function test for more than 10 years and the non-expert operator who is function developer in excavator company (Fig. 3.1).

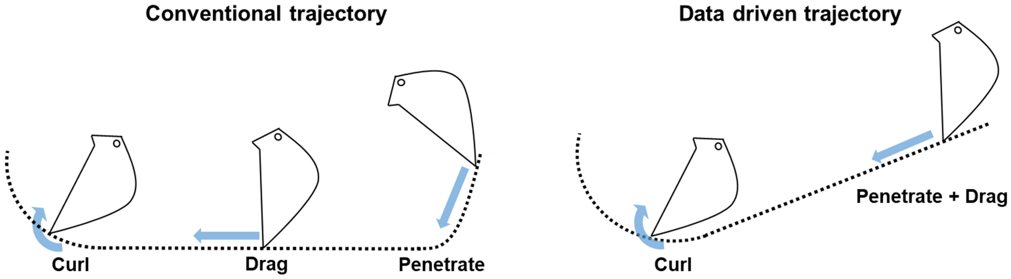

FIGURE 3.2: Excavation process analysis

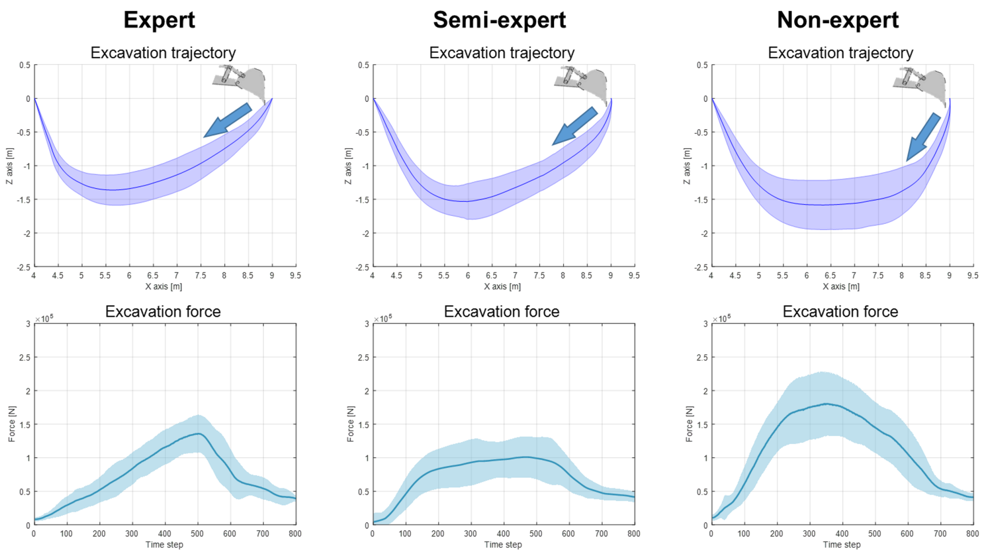

FIGURE 3.3: Mean and variance of excavation trajectories and excavation force patterns

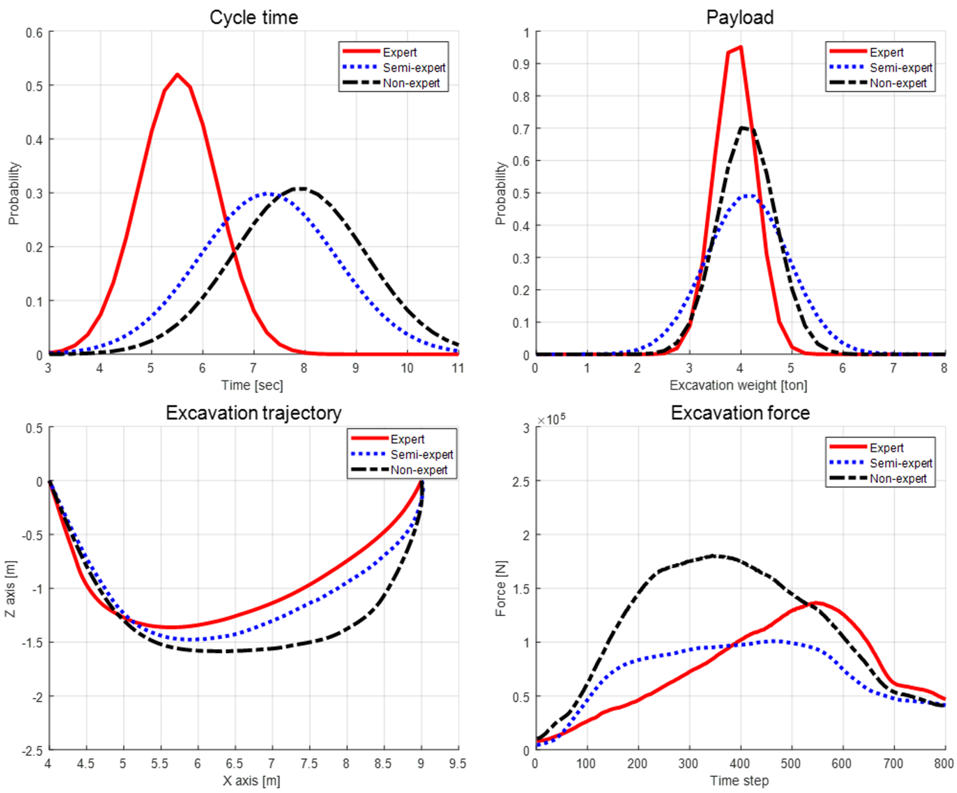

FIGURE 3.4: Excavation data analysis : expert, semi-expert, non-expert

		Expert	Semi-expert	Non-expert
Cycle time (sec)	mu	6.19	7.26	7.89
	sigma	0.77	1.32	1.29
Payload (ton)	mu	3.89	4.13	4.11
	sigma	0.4	0.81	0.55

TABLE 3.2: Excavation data analysis : expert, semi-expert, non-expert

In the case of the excavation trajectory, the existing academic research [8], [11] consider the excavation process divided into three stages: penetrate, drag, and curl. This is a theoretical assumption, so it is different from the actual excavation trajectory of the expert. Analysis of the excavation data appears that the more experienced operators, the less the boundary between the penetrate and drag (Fig. 3.2). Expert shows that the repetitiveness of the work is superior to the non-experts by having constant excavation trajectory and excavation force patterns in various terrain (Fig. 3.3). In addition, we have confirmed that the shorter excavation time and smaller excavation force are shown despite having a similar excavation amount. The amount of excavation is controlled by humans looking at the soil in the bucket, so there is little difference between experts and non-experts (Fig. 3.4), (Table. 3.2).

3.2 Generate Nominal Excavation Trajectory by Imitating Expert Operator

The first thing to be secured in autonomous excavator is safety, and then efficiency (fuel economy and productivity). We want to apply the excavation trajectories and excavation force patterns of the expert for autonomous excavators to create safe and efficient excavation trajectories like expert even in various terrains. To generate excavation trajectory like expert according to the terrain, we use machine learning techniques to train trajectories. The expert excavation

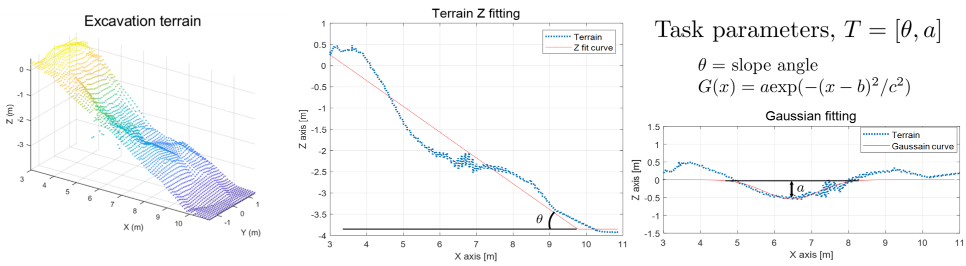

FIGURE 3.5: Terrain feature extraction method

work relies on intuition by experience, so it is difficult to define a handcrafted reward. Based on this characteristic, we decide that imitation learning, which does not require reward, is appropriate algorithm for development. Imitation Learning [18] is a sequential task where the learner tries to mimic the action of an expert in order to achieve the best performance. The used imitation learning algorithm is the behavior cloning [19], where the expert trajectory is optimally assumed, and it learns the policy that the expert observes the terrain and generates the excavation trajectory of excavator.

The learning model is trained to output the joint angle at the next position of the bucket tip when the features of the excavation target terrain and the current boom, arm, bucket joint angle are input [20]. The terrain features are extracted by parameterization using a Gaussian fitting to improve data efficiency by reducing the number of nodes at the input stage. The features of terrain are the slope angle and the maximum depth of the terrain (Fig. 3.5).

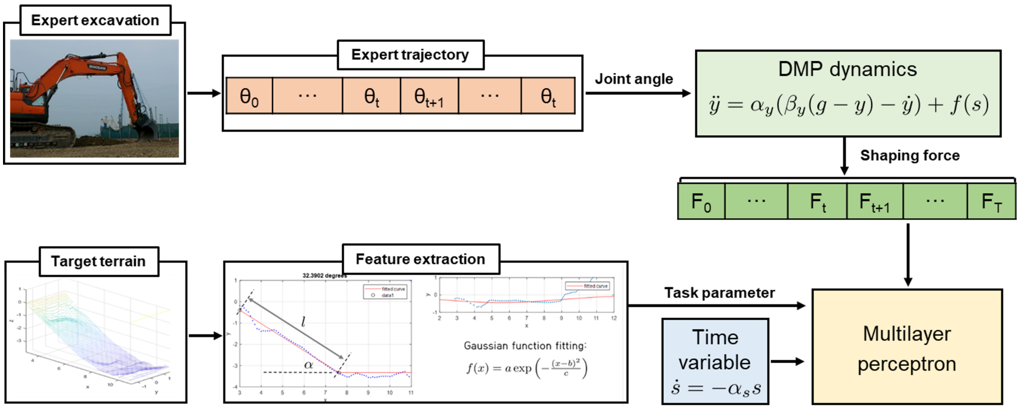

FIGURE 3.6: Expert excavation trajectories learning architecture

The data from expert excavation on flat and three different angles of slope terrain are used for learning. The trajectories used for training are pre-treated to be the starting point when the bucket tip reached the ground, and to be the last point where the bucket tip reached 0.5 m above the ground after excavation. The excavation time of all trajectories used for learning are adjusted to 6.5 seconds considering the average excavation time of expert (Table. 3.2). In addition, the trajectories are encoded in DMP (Eq. 2.3) and used for learning after expressing it as a shaping force $f(s) \in \mathcal{R}$. A goal-directed attraction is guaranteed when generating the trajectory by multiplying a monotonically decreasing clock signal $s \in [0, 1]$. The overall structure of the expert trajectory learning algorithm can be expressed as Fig. 3.6.

3.3 Modulate Excavation Trajectory by Force Pattern of Expert Operator

The nominal trajectory generated by the algorithm only considers geometric information about the terrain, so interaction with the ground is not considered. Therefore, various dynamic properties such as the density and strength of the terrain can cause problems that the bucket of the excavator may not be able to pass through. To solve these problems, we propose the trajectory modulation algorithm by imitating a trajectory modulation technique based on the expert force pattern.

The excavation force data are extracted from the excavation data of experts to modulate the trajectory (Fig. 3.3). First, the excavation force data are cut with the starting point of the moment when the bucket tip hits the ground, and the last point when the bucket tip has reached 0.5 m above the ground after excavation. The cropped data are adjusted to 6.5 seconds considering the average excavation time of expert (Table. 3.2), and the mean value of the data is assumed as the excavation force pattern of expert. The feedback ratio is calculated by comparing the excavation force of the expert with the currently measured excavation force. It can be expressed as follows:

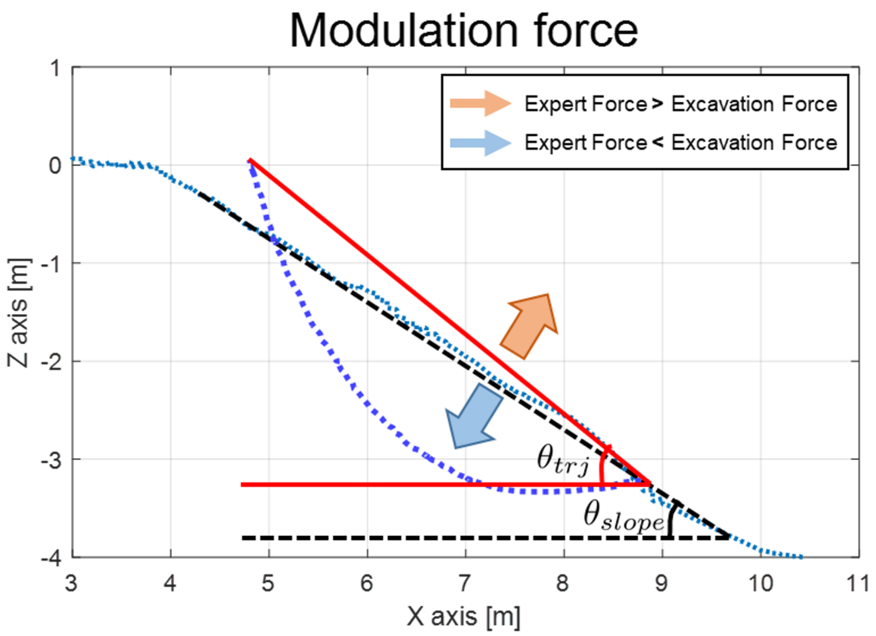

FIGURE 3.7: Modulation force

$$fb = \begin{cases} 1 & f_e > f_{margin} \\ -1 & f_e < f_{margin} \\ f_e/f_{margin} & \text{else} \end{cases} \tag{3.1}$$

where f_e is the difference with measured excavation force and expert force pattern, and f_{margin} is the constant gain that decides whether to feedback. The feedback ratio and modulation force are multiplied and added as coupling term to the DMP for real-time trajectory modulation (Eq. 2.6).

Based on the interviews with experts (Table. 3.1), we assume that the excavation force decreases when the path becomes shallower to the ground during excavation, and the excavation force increases when the path is deeper to the ground (Fig. 3.7). Therefore we define the modulation force as follows:

$$C = \begin{bmatrix} Cx \\ Cz \end{bmatrix} = \begin{bmatrix} -fb \sin(\theta_{trj} - \theta_{slope}) \\ fb \cos(\theta_{trj} - \theta_{slope}) \end{bmatrix} \tag{3.2}$$

The feedback ratio fb is calculated from Eq. 3.1, θ_{trj} is the slope angle of the nominal trajectory created by imitation of the expert excavation trajectory, and θ_{slope} is the slope angle of the terrain to be excavated. The excavation trajectory of the excavator is represented by the two-dimensional plane of x, z. Because this thesis does not consider swing motion when excavating. The trajectory is modulated in real-time by reflecting the coupling term as force feedback in the direction perpendicular to the working surface. The trajectory generation algorithm for autonomous excavator based on expert operator force pattern can be expressed as shown in Fig. 3.8.

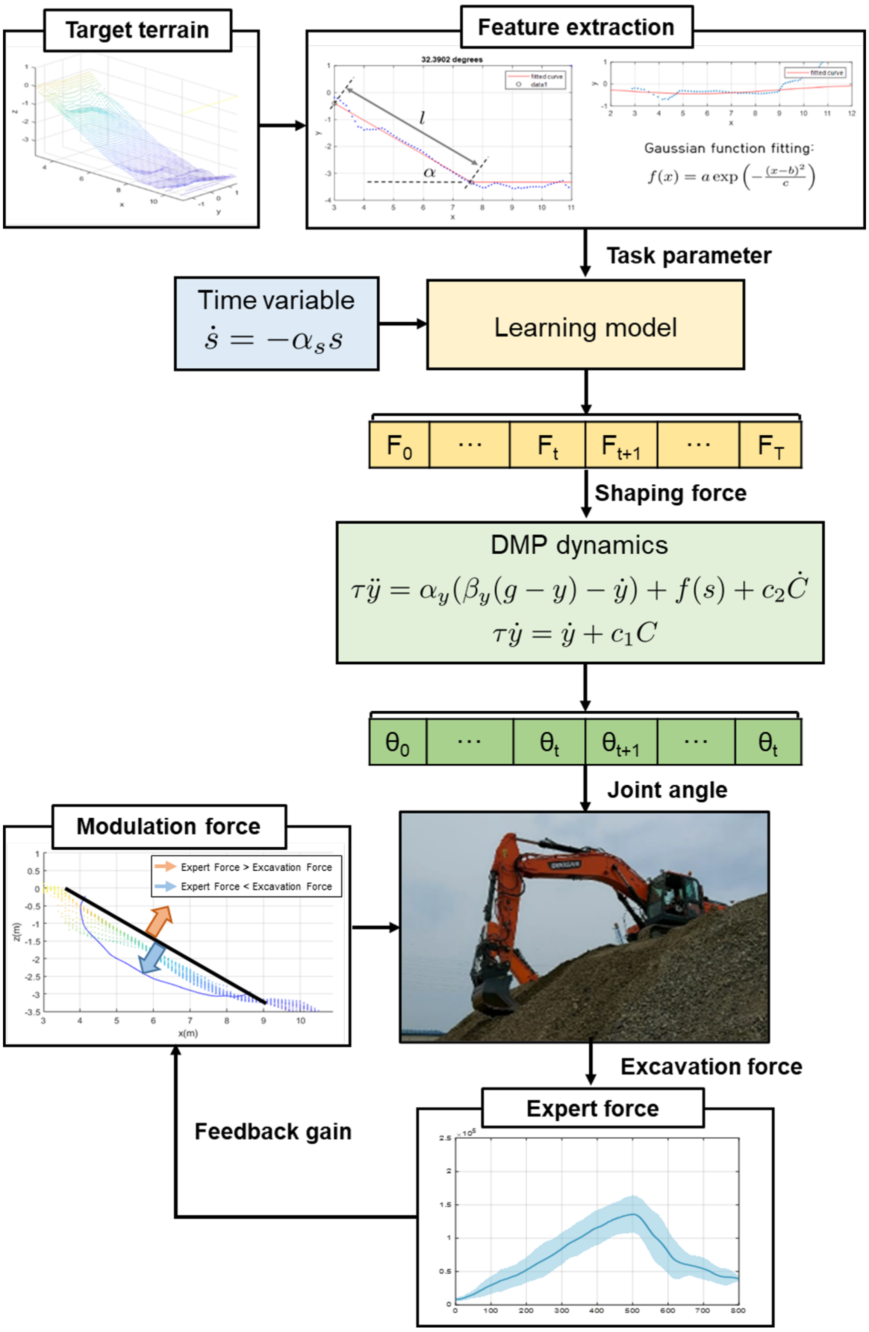

FIGURE 3.8: Excavation trajectory generation architecture

Chapter 4

Experiments

4.1 Excavation Simulation

4.1.1 Excavation on Flat and Slope Terrain

For verification of the proposed algorithm, we perform the simulation using the Vortex simulator of CM Labs. We simulate flat and sloped terrain excavation using the nominal excavation trajectory generated by inputting the features of the terrain into the machine learning model and the modulation excavation trajectory generated by comparing the expert excavation force pattern with real-time excavation force (Fig. 4.1).

Figure 4.1: Excavation simulation experiment environment

Excavation force is most affected by the soil medium and the excavation depth. In the actual vehicle experiment, it is difficult to experiment by changing medium due to the limited environment, so the medium change experiment is conducted in simulation. We assume that even if we change the medium, the pattern of the excavation force would not change, but only the size would change. Thus, experiments are conducted by changing size of the expert excavation force pattern.

First, experiments are conducted on the flat terrain (Fig. 4.2). The flat terrain is tested for two types of media: clay and gravel. The parameters of Eq. 2.6 , Eq. 3.1 are set to $\alpha = 5, \beta = \sqrt{20}$, c1 = 0.05, c2 = 0.3, f_{margin} = 5000N. Because the simulation environment is not the same as the medium in which the excavation force data are obtained, we reduce the expert excavation force by 0.4 times in clay terrain and 0.5 times in gravel terrain and use it for simulation. The reason why we use the smaller excavation force in clay terrain rather than gravel terrain is that the clay medium is so soft and it is impossible to follow the excavation force of expert even when deep excavation. The test results show that the modulation trajectory excavate about 6.1% more soil than the normal trajectory in the clay terrain, and 1.4% more soil excavate in the gravel terrain even though it excavate more shallowly (Table. 4.1). When excavate using the nominal trajectory, the estimate excavation force does not significantly different from the expert excavation force, so there is not much difference in the amount of excavation. On the other hand, we can see that the trajectory modulated to follow the expert excavation force shows more excavation amount during the same time.

Next, clay and gravel media experiments are conducted on the slope terrain using the same parameters as the flat terrain. (Fig. 4.3). The results appear that the modulation trajectory excavate about 14.4% more soil than the normal trajectory in the clay terrain, and 10.7% more soil excavate in the gravel terrain (Table. 4.2). The slope terrain experiments also appear that the modulation trajectory does not overload by following the expert excavation force well, and the amount of excavation is also greater than the nominal trajectory during the same time.

As a result of experiments, we can conclude that the trajectory modulated to follow the expert excavation force shows more productive and stable excavation without overload than the nominal trajectory generated by only learning the trajectory of the expert.

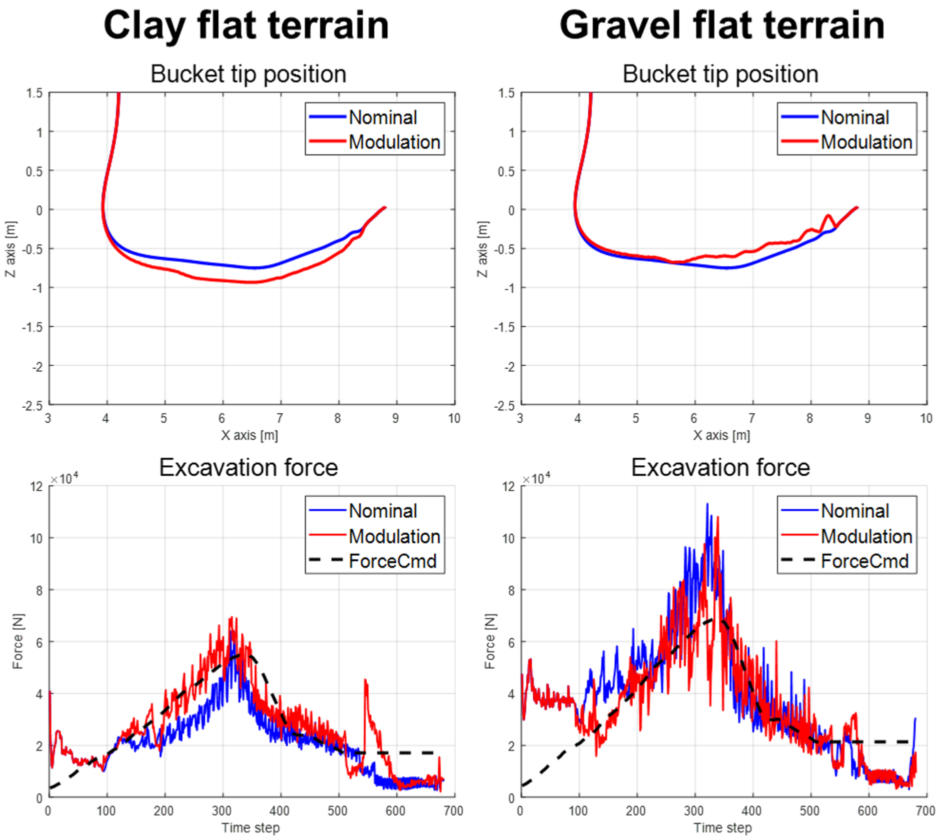

FIGURE 4.2: Flat terrain excavation trajectories and excavation forces

	Payload (ton)	
	Clay flat terrain	Gravel flat terrain
Nominal	1.9369	1.7094
Modulation	2.0578	1.7319

TABLE 4.1: Excavation payload results on flat terrain

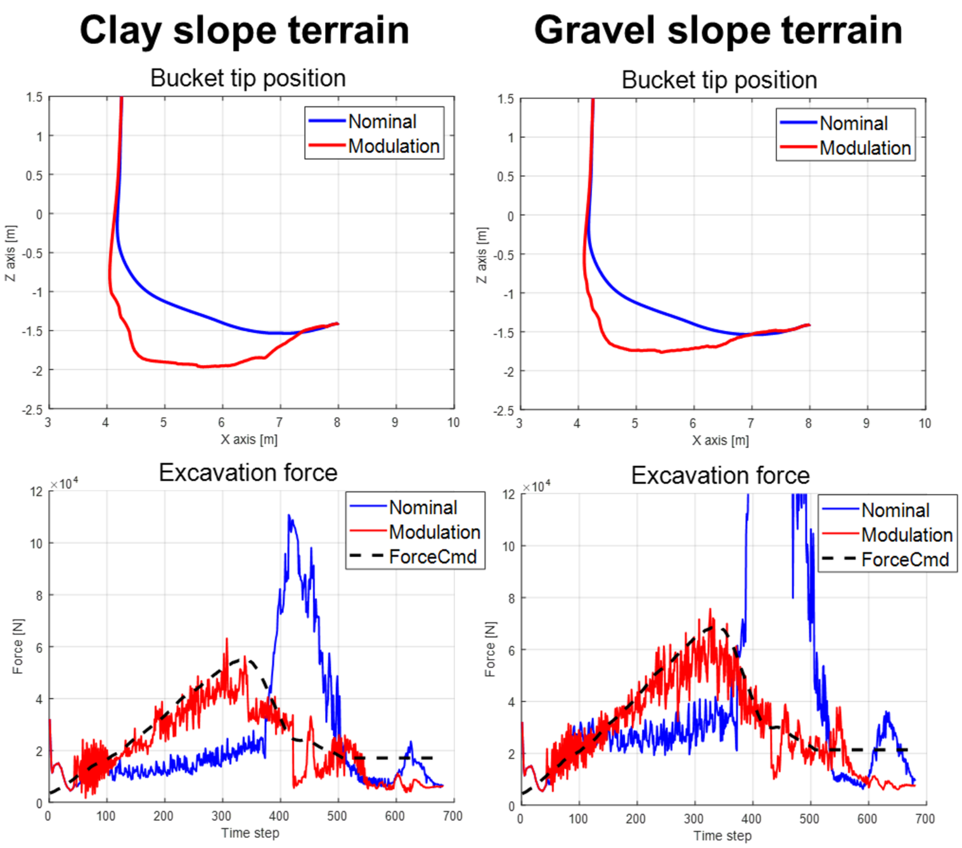

FIGURE 4.3: Slope terrain excavation trajectories and excavation forces

	Payload (ton)	
	Clay slope terrain	Gravel slope terrain
Nominal	1.9518	1.7055
Modulation	2.2332	1.8882

TABLE 4.2: Excavation payload results on slope terrain

4.1.2 Excavation using Trajectory Generated by Incorrect Terrain Recognition

The current algorithm recognizes the terrain using a LiDAR, extracts features of the terrain, and inputs them into the learning model to generate the nominal trajectory. However, if the features of the terrain are incorrectly extracted due to foreign objects during terrain recognition, an excavation trajectory different from the one planned may be generated. The use of abnormal excavation trajectory operations can create hazardous situations for excavators and the surrounding environment, depending on the workplace environment. Since it is difficult to judge whether or not the trajectory is abnormal, and even a general trajectory can cause dangerous situations depending on the environment, we tried to solve this situation through real-time trajectory modulation using excavation force.

In these experiments, the feature parameters of the terrain are adjusted by assuming a situation where the terrain is incorrectly recognized, and a deep excavation nominal trajectory is generated using the adjusted feature parameters. We want to confirm whether stable excavation work is possible even in this abnormal situation through real-time trajectory modulation. Experiments are conducted on a clay flat terrain, and the parameters of Eq. 2.6 , Eq. 3.1 are set to $\alpha = 5, \beta = \sqrt{20}$, c1 $= 0.05$, c2 $= 0.3$, $f_{margin} = 5000$N. The excavation force of experts is multiplied by 0.4 times considering the medium.

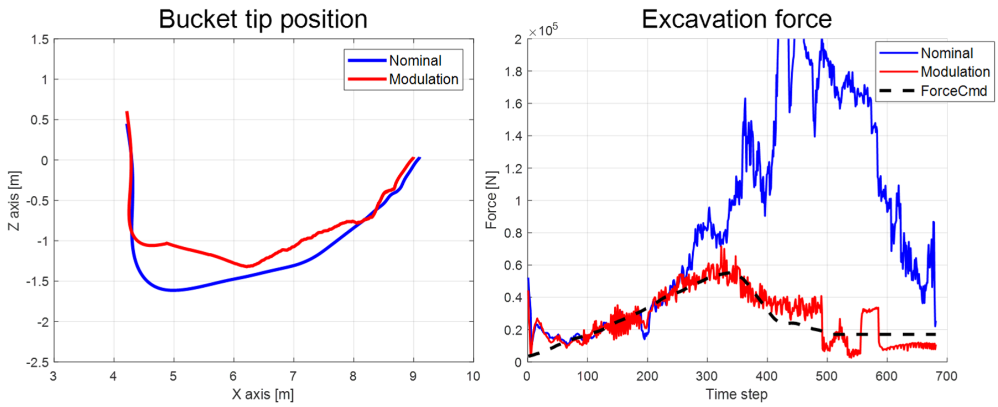

FIGURE 4.4: Excavation test results using trajectory generated by incorrect terrain recognition

	Payload (ton)
Nominal	1.9772
Modulation	2.025

TABLE 4.3: Excavation payload results using trajectory generated by incorrect terrain recognition

In the nominal trajectory, we can see the excavator being dragged away as it is overloaded during excavation. On the other hand, the modulation trajectory follows the expert excavation force with performing stable excavation, and no overload is applied (Fig. 4.4). The amount of excavation shows that the modulated trajectory excavate about 2.4% more than the nominal trajectory even though it is more shallow excavation (Table. 4.3). Through these results, we can confirm that the modulation trajectory ensures productivity and stably excavates even in dangerous situations.

FIGURE 4.5: Excavation test with the obstacle in the ground

4.1.3 Excavation with Obstacle in the Ground

When recognize terrain using LiDAR in the excavator, obstacles in the ground can not be recognized. However, these obstacles can lead to dangerous situations for the excavator and the surrounding environment during excavation. Therefore, we try to confirm whether it is possible to safely excavate through real-time trajectory modulation even in this situations. Experiments are conducted on a clay flat terrain with a pipe buried (Fig. 4.5), and the parameters of Eq. 2.6 , Eq. 3.1 are set to $\alpha = 5, \beta = \sqrt{20}$, c1 = 0.05, c2 = 0.3, f_{margin} = 5000N, and the used excavation force size of experts by 0.5 times.

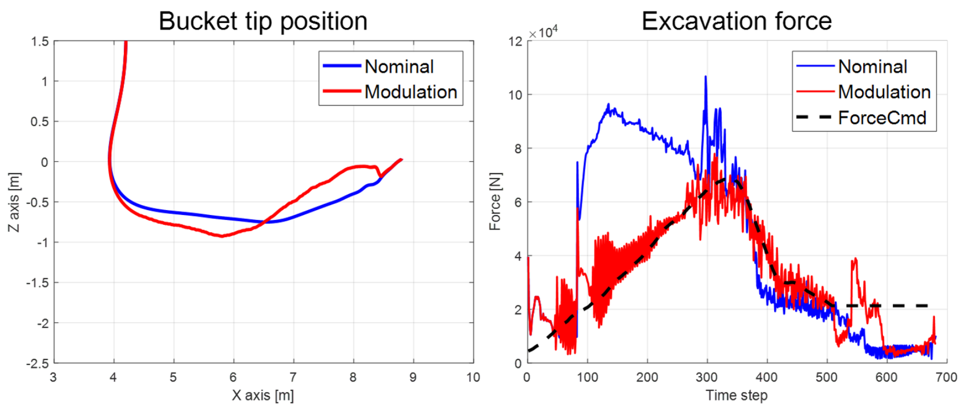

FIGURE 4.6: Excavation test results with the obstacle in the ground

	Payload (ton)
Nominal	1.8687
Modulation	1.9847

TABLE 4.4: Excavation payload results with the obstacle in the ground

In the nominal trajectory simulation, we can see the excavator being lifted while overloaded during excavation. In this case, there is a high possibility of damage to the pipe. On the other hand, the modulation trajectory is able to follow the excavation force pattern of the expert so that it does not overload and produce more payload while excavating away from the pipe (Fig. 4.6). The amount of excavation also shows that the modulation trajectory excavates about 6.2% more than the nominal trajectory (Table. 4.4). Through these experiment results, we can confirm that the modulation trajectory ensures productivity and stably excavates even in dangerous situations.

FIGURE 4.7: Excavation experiment environment using Excavator

4.2 Excavation Test Result using Excavator

We conduct real equipment test using the commercial excavator model of Doosan DX380LC in the Doosan Infracore Incheon test site. These experiments are performed nominal and real-time modulation trajectories by excavating the same terrain twice on flat and slope (Fig. 4.7). The parameters of Eq. 2.6 , Eq. 3.1 are set to $\alpha = 5, \beta = \sqrt{20}$, c1 $= 0.01$, c2 $= 0.3$, $f_{margin} = 5000$N.

As we can see in the result graphs (Fig. 4.8), (Fig. 4.9), the slope terrain excavation, the excavation force follows the expert force pattern through real-time trajectory modulation. In contrast, the flat terrain excavation, we can see that the excavation force follow ability is inferior. This is considered to be a little inconsistent with the overall average of the expert excavation force pattern due to lack of excavation data on flat terrain compare to the slope terrain excavation. We expect to improve if additional flat terrain excavation data is obtained.

When comparing payload (Table. 4.5), it is confirmed that real-time modulation trajectory excavates 53.79% more on the flat terrain and 20.39% more on the slope terrain than nominal trajectory excavation. The bucket of the excavator used for the experiment can excavates about 3 tons of soil when load at 100%, and 120∼150% of the bucket capacity excavation is efficient according to the experts interview (Table. 3.1), so our excavator has the highest efficiency when excavating about 3.6∼4.5 tons of soil. On the flat terrain, we can see that the nominal trajectory excavates about 2.78 tons of soil on average, which is less than the effective excavation. On the other hand, the real-time modulation trajectory excavates about 4.28 tons of soil on average, achieving the efficient excavation amount stated by experts. On the slope terrain, the nominal trajectory excavates about 3.73 tons of soil on average, and the real-time modulation trajectory excavates about 4.49 tons of soil on average, both results are within the range of efficient excavation mentioned by experts. The experiment results show that the payload approaches the more efficient excavation amount during the modulation trajectory excavation. The cycle time are same for all trajectories because when we train the learning model, the excavation time is normalized to 6.5 seconds.

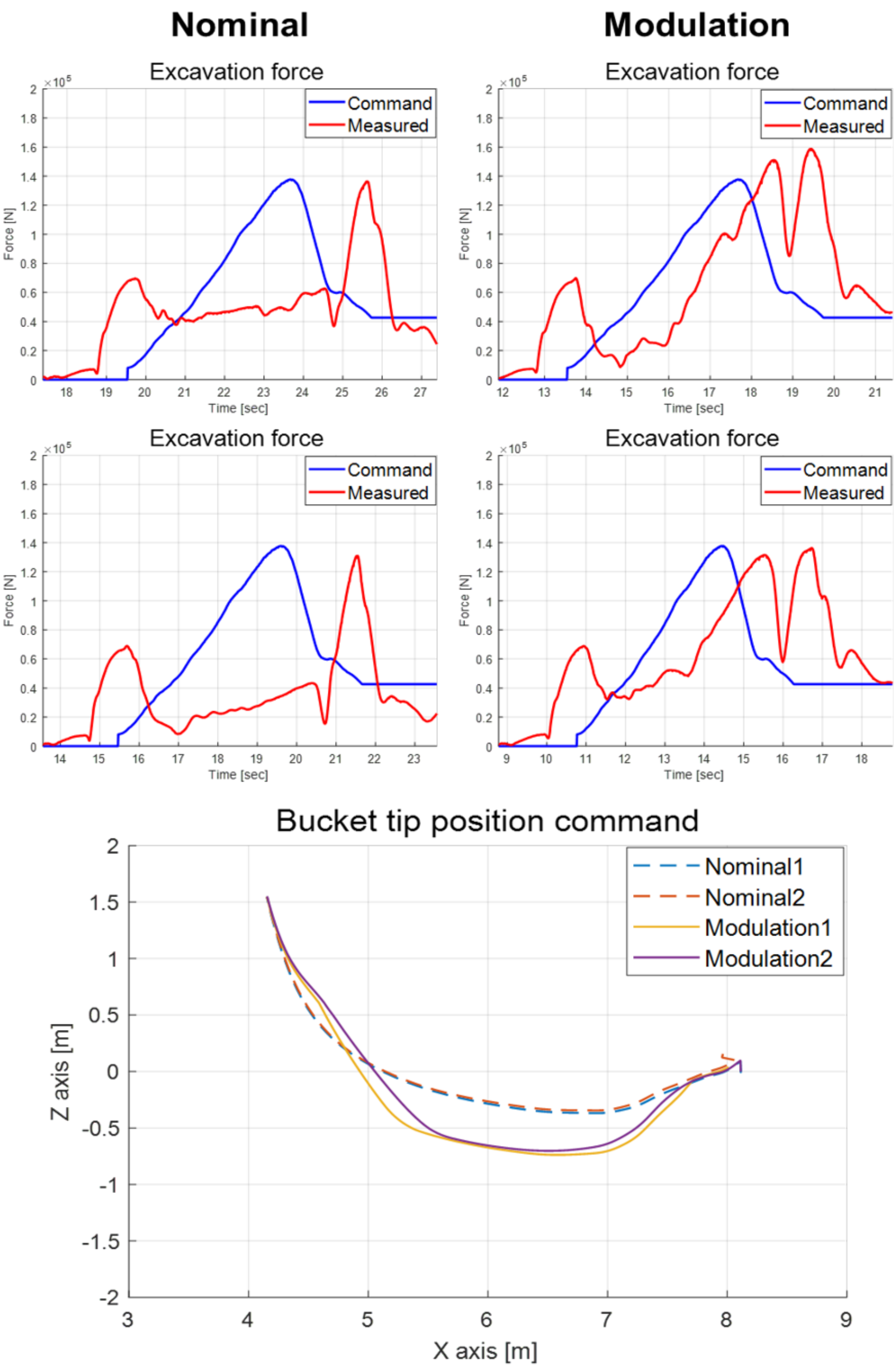

FIGURE 4.8: Excavation test results using excavator on the flat terrain

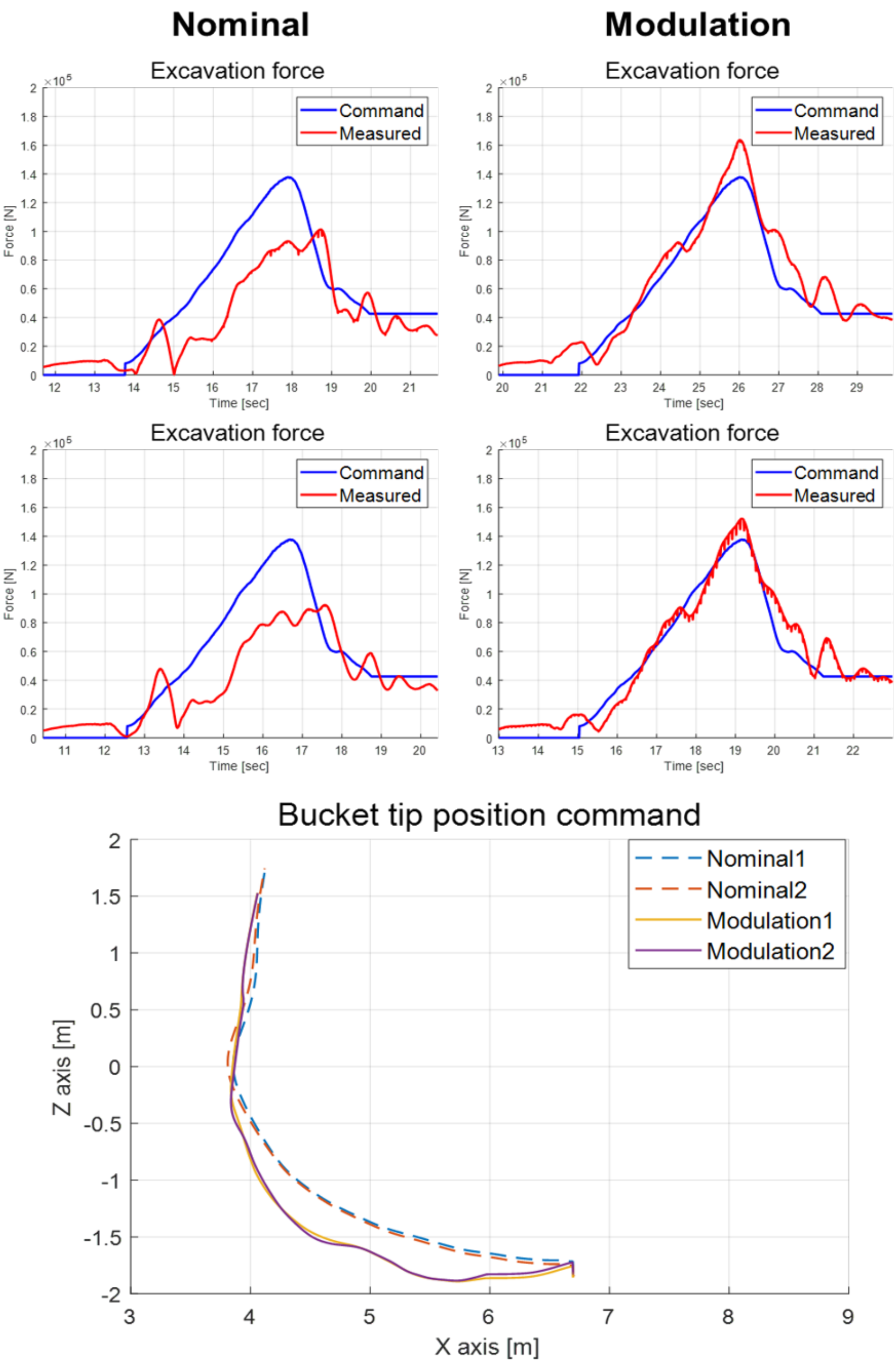

FIGURE 4.9: Excavation test results using excavator on the slope terrain

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Terrain feature</td><td rowspan="2">Excavation payload (ton)</td></tr>
<tr><td>Title angle (deg)</td><td>Max depth (cm)</td></tr>
<tr><td rowspan="5">Flat</td><td>Nominal_1</td><td>0</td><td>-13.74</td><td>3.059</td></tr>
<tr><td>Nominal_2</td><td>0</td><td>-16.92</td><td>2.505</td></tr>
<tr><td>Modulation_1</td><td>0</td><td>-15.7</td><td>4.381</td></tr>
<tr><td>Modulation_2</td><td>0</td><td>-8</td><td>4.176</td></tr>
<tr><td colspan="3">Modulation/Nomianl</td><td>1.5379</td></tr>
<tr><td rowspan="5">Slope</td><td>Nominal_1</td><td>35.27</td><td>-2.688</td><td>3.633</td></tr>
<tr><td>Nominal_2</td><td>33.4</td><td>-2.55</td><td>3.826</td></tr>
<tr><td>Modulation_1</td><td>30.74</td><td>-5.34</td><td>4.457</td></tr>
<tr><td>Modulation_2</td><td>30.64</td><td>-6.12</td><td>4.523</td></tr>
<tr><td colspan="3">Modulation/Nominal</td><td>1.2039</td></tr>
</table>

TABLE 4.5: Excavation test terrain features and payload results

Chapter 5

Conclusion and Future Work

5.1 Conclusion

Excavator is the most widely used equipment in construction sites, and automated development of excavator can reconsider the stability of the worksite and improve quality and productivity. Therefore, we try to generate an excavation trajectory that ensures excavation volume by performing stable excavation work similar to an expert operator in various working environments of automated excavator.

In this thesis, we generate the excavation trajectory for autonomous excavators based on the excavation data from expert operators and modulate the excavation trajectory to have a similar excavation force pattern to the expert based on the measured excavation force. Through this, we solve the problem of the interaction with unmodellable, complex soil dynamics, which is the most difficult point in excavation trajectory generation. Our algorithm is verified by excavation simulation with various terrains, and it is confirmed through the actual excavator experiments that an efficient excavation trajectory is generated in the autonomous excavator.

5.2 Future Work

There may be several factors that affect the excavation force, but the important factors are the medium and depth. Due to the limitations of the test environment, we are not able to experiment in various type of soils, so our force pattern is about the excavation depth. The assumption that changing the terrain medium does not affect the excavation force pattern but only affects the size, should be verified through actual experimentation. Therefore, we will conduct excavation experiments on terrain of various media. By adding the soil information in various environments, we plan to upgrade the algorithm to generate more stable excavation trajectories.

Bibliography

[1] S. Dadhich, U. Bodin, and U. Andersson. Key challenges in automation of earth-moving machines. *Automation in Construction*, 68:212–222, 2016.

[2] S. Salcudean, S. Tafazoli, K. Hashtrudi-Zaad, P. Lawrence, and C. Reboulet. Evaluation of impedance and teleoperation control of a hydraulic mini-excavator. *In Experimental Robotics V*, pages 227–240, 1998.

[3] Y. Hiramatsu, T. Aono, and M. Nishio. Disaster restoration work for the eruption of mt usuzan using an unmanned construction system. *Advanced Robotics*, 16(6):505–508, 2002.

[4] F. Schreiber, P. Rausch, and M. Diegelmann. Use of a machine control and guidance system, determination of excavator performance, cost calculation and protection against damaging of pipes and cables. *In 1st International Conference on Machine Control and Guidance*, pages 1–10, 2008.

[5] W. Tanoli, J. Seo, A. Sharafat, and S. Lee. 3D Design modeling application in machine guidance system for earthwork operations. *KSCE Journal of Civil Engineering*, 22(12):4779–4790, 2018.

[6] Y. Shimano, Y. Kami, and K. Shimokaze. Development of PC210LCi-10/PC200i-10 machine control hydraulic excavator. *Komatsu technical report*, 2014.

[7] S. Sing. Synthesis of tactical plans for robotic excavation. *PhD Thesis. Carnegie Mellon University*, 1995.

[8] Y. Yang, L. Zhang, X. Cheng, J. Pan, and R. Yang. Compact reachability map for excavator motion planning. *In 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 2308–2313, 2019.

[9] S. Lee, D. Hong, H. Park, and J. Bae. Optimal path generation for excavator with neural networks based soil models. *In 2008 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, pages 632–637, 2008.

[10] F. E. Sotiropoulos and H. H. Asada. A model-free extremum-seeking approach to autonomous excavator control based on output power maximization. *IEEE Robotics and Automation Letters*, 4(2):1005–1012, 2019.

[11] D. Jud, G. Hottiger, P. Leemann, and M. Hutter. Planning and control for autonomous excavation. *IEEE Robotics and Automation Letters*, 2(4): 2151–2158, 2017.

[12] A. Ijspeert, J. Nakanishi, and S. Schaal. Movement imitation with nonlinear dynamical systems in humanoid robots. *In Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat. No. 02CH37292)*, 2: 1398–1403, 2002.

[13] A. Ijspeert, J. Nakanishi, H. Hoffmann P. Pastor, and S. Schaal. Dynamical movement primitives: Learning attractor models for motor behaviors. *Neural Computation*, 25(2):328–373, 2013.

[14] S. Haddadin, A. De Luca, and A. Albu-Sch. Robot collisions: A survey on detection, isolation, and identification. *IEEE Transactions on Robotics*, 33 (6):1292–1312, 2017.

[15] J. Back and W. Ha. Robust tracking of robot manipulators via momentum-based disturbance observer and passivity-based controller. *International Journal of Control, Automation and Systems*, 17(4):976–985, 2019.

[16] A. Gams, B. Nemec, A. Ijspeert, and A. Ude. Coupling movement primitives: Interaction with the environment and bimanual tasks. *IEEE Transactions on Robotics*, 30(4):816–830, 2014.

[17] F. Ng, J. A. Harding, and J. Glass. An eco-approach to optimise effciency and productivity of a hydraulic excavator. *Journal of cleaner production*, 112:3966–3976, 2016.

[18] S. Schaal. Is imitation learning the route to humanoid robots? *Trends in cognitive sciences*, 3(6):233–242, 1999.

[19] D. Michie, M. Bain, and J. Hayes-Miches. Cognitive models from subcognitive skills. *IEE control engineering series*, 44:71–99, 1990.

[20] B. Son, C. Kim, C. Kim, and D. Lee. Expert-emulating excavation trajectory planning for autonomous robotic industrial excavator. *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2020. Accepted.

요약

본 논문에서는 자동화 굴착기를 위한 숙련자 굴착력 패턴 기반 굴착 작업 궤적 계획 프레임워크를 제시한다. 본 프레임워크는 자동화 굴착기의 다양한 작업 환경에서 숙련자와 유사하게 안정된 굴착 작업을 수행하며, 굴착량이 보장되는 작업을 하는 것이 목표이다. 우선 숙련된 굴착기 작업자들의 굴착 작업 데이터로부터 지형 특징에 기반한 작업 궤적과 굴착력 패턴을 찾아내었다. 숙련자의 굴착 궤적은 dynamic movement primitives(DMP)으로 encoding하여 neural network의 한 기법인 multi-layer perceptron(MLP)을 통해 학습하고, 학습된 모델을 기반으로 지형에 따른 굴착 궤적을 생성하였다. 굴착기를 다자유도 강체 시스템으로 모델링 하고, 실시간으로 버켓 끝단에 걸리는 굴착력을 momentum-based disturbance observer를 이용하여 추정하였다. 추정된 굴착력은 실시간으로 굴착 궤적을 재생성 하기위해 DMP에 coupling term으로 추가하였고, 이를 통해 추정되는 굴착력이 숙련자의 굴착 패턴을 따라갈 수 있도록 제어하였다. 마지막으로 제안한 프레임워크에 대해서는 시뮬레이션 실험과 실제 굴착기를 이용한 실험을 통해 정합성 검증을 진행하였다.

주요어: Autonomous excavators, Trajectory generation, Dynamic movement primitives, Multi-layer perceptron, Dynamics, Momentum-based observer.
학번: *2018-20186*