Assisted Tele-Remote Control of Wheel Loaders in Underground Mining

Siddharth Dadhich

Industrial Electronics
Assisted Tele-remote Control Of Wheel Loaders In Underground Mining

Siddharth Dadhich

Dept. of Computer Science and Electrical Engineering
Luleå University of Technology
Luleå, Sweden
December 2016

Supervisors:
Ulf Bodin, Ulf Andersson, Fredrik Sandin and Jerker Delsing
Abstract

Tele-remote operation of mobile earth-moving machines in underground mines supported by operator assistance functions is attractive for safety and productivity reasons. This way, operators can avoid hazardous underground environments with poor air quality and the productivity can, in principle, be improved by saving the time required to commute drivers to and from the operational areas. The infrastructure needed to do tele-remote control in the form of high-capacity wireless IP networks is nowadays being deployed in underground mines. In mines with sufficiently high ceilings, wheel loaders are used in short loading cycles to load blasted rock onto dump trucks. Bucket filling on remote control is less efficient than manual operation due to the loss of sensory perception resulting from not being in the actual environment. Automatic bucket filling algorithms have been developed earlier but, due to the complexity of bucket-environment interactions, such algorithms have not produced satisfactory results and are not commercially available. If tele-remote operation is enabled, it can also be used to rescue future autonomous machines, when they malfunction. This thesis presents the key challenges in automation and tele-remote operation of earth-moving machines, surveys the literature and available technologies to address these challenges. The key contributions of this thesis are highlighting important knowledge gaps based on a survey in the field of automation of earth-moving machines and proposing a machine learning based framework for automatic bucket filling for front-end loaders. The proposed machine learning based approach to automatic bucket filling uses linear regression and classification models of lift and tilt actions, which are fitted to the behavior of an expert driver filling the bucket with gravel pile. The models of operator behavior from the recorded data reveals relationships between sensor data and operator actions and shows that a learning based approach is feasible. A case study has been done on the use of wheel-loaders in underground mining presenting the use case of assisted tele-remote control based on audio-video and sensor feedback. A good communication setup, that considers requirements of real-time video transmission, is important for tele-remote control. Furthermore, a simulation study evaluates two transport layer protocols with respect to video quality for tele-remote control over wireless IEEE 802.11 networks. It has been identified that adding operator assistance functions to tele-remote control is a good approach towards autonomous operation of earth moving equipment.
# Contents

## I Thesis Introduction

1 Introduction
   1.1 Motivation of research .......................................................... 3
   1.2 Application use case ........................................................................ 5
   1.3 Assisted tele-operation ...................................................................... 5
   1.4 Scope and limitations of the work ..................................................... 5
   1.5 Research questions and methodology ............................................... 6

2 Background
   2.1 Wheel loader .................................................................................... 7
   2.2 Basics of tele-remote operation ......................................................... 7
   2.3 Challenges in tele-remote operation ................................................... 10
   2.4 Bucket filling .................................................................................... 10

3 Automatic bucket fill
   3.1 Learning based approach ..................................................................... 13
   3.2 Wheel slip ......................................................................................... 14

4 Research contributions
   4.1 Paper A ............................................................................................ 17
   4.2 Paper B ............................................................................................ 17
   4.3 Paper C ............................................................................................ 18
   4.4 Paper D ............................................................................................ 18

5 Conclusion and future work .................................................................... 21

Bibliography ............................................................................................. 23

## II Appended Papers

Paper A .................................................................................................... 29
Paper B .................................................................................................... 43
Paper C .................................................................................................... 71
Paper D .................................................................................................... 85
Acknowledgement

First, I want to thank my parents to be supportive of me always in my life. I also thank my supervisor Ulf Bodin for his guidance in my PhD studies so far. He has encouraged me to explore the area as much as possible and define the research questions quite independently. I would also like to thank Wolfgang Birk who supervised me in a summer project during my master studies and later recommended me in my PhD applications.

I thank my assistant supervisors Ulf Andersson, Fredrik Sandin and Jerker Delsing. Ulf has been in the field of mine automation for more than two decades and his expert opinions have shaped the course of my work. He has also helped me in conducting experiments and during visits to underground mines at Boliden. Fredrik has provided an excellent support to me for data analysis. He is an expert in learning systems and his guidance has been very important. Jerker has provided the role of the principal supervisor in the start of the PhD studies and great thanks goes to him to for his efforts.

I would like to thank Sergio, Sandeep, Dennis and other colleagues at LTU for providing the social environment necessary to main a healthy work-life balance. I also thank my girlfriend to share the life together and to have supported me at all times.

Currently I have been working from Volvo CE in Eskilstuna. This transition from university to industry during PhD has been difficult and I thank Erik Uhlin who has done the best he could to make it comfortable for me in Eskilstuna. I also thank Jimmy, Calle and Törbjörn for support with discussions, logistics and sharing know-how. I also thank Ted, Albin and Marcus and other colleagues at Volvo for their companionship.
Part I

Thesis Introduction
Chapter 1

Introduction

Earth-moving machines are used in mining, construction and quarries to move materials such as soil, gravel and rock between loading and dumping points. The most common types of earth-moving machines are excavators and front-end wheel loaders. Wheel loaders are used in underground mines with sufficiently high ceilings and narrow corridors for their cost effectiveness. They are also preferred for their better maneuverability compared to Load-Haul-Dump (LHD) machines which are preferred when underground mines have low ceilings. Wheel-loaders are versatile machines [1] and used for multiple tasks including loading blasted rock onto the trucks in short loading cycle and filling the excavated areas with waste-rock.

LHD machines are most commonly used in load and carry cycles where the loading point and dumping point are at-least a few hundred meters apart. On the other hand, wheel loaders are used in short loading cycle (Fig. 1.1) where the loader dumps the material on a near by standing dump truck.

The harsh environment in underground mines with bad air quality has motivated the research for mine automation since many decades. The bottleneck problem in mine automation is the excavation task itself which has proved to be difficult to automate. Initial work in autonomous excavation by Mikhirev [2] and Hemami [3] has guided several others to work on their ideas. However, even three decades of research in autonomous excavation has not produced any commercial available fully autonomous system as claimed by Maeda in his doctoral thesis [4].

This thesis concerns with the operation of wheel loaders in underground mining environment. Tele-remote operation is considered as an intermediate step towards full automation of earth-moving process. In this work, the knowledge gaps between tele-remote control and autonomous operation are discussed and the ongoing work has been reported. The first part of the thesis presents a summary of this field and the ongoing work but a more detailed introduction and background of this work is presented in the paper B, appended to the thesis.

1.1 Motivation of research

Underground mines in Sweden have strong commitment towards mine automation. The working environment in underground mines here, is relatively better than some other countries but still far from ideal. The dark environment in underground with poor visibility and bad air quality are few factors that makes work uncomfortable. The noise from the machines and motion and vibration of the machine makes sitting in machine’s cabin for long hours very uncomfortable. Tele-remote operation of mining equipment can improve the working conditions for drivers by
The steps performed by a wheel loader in one operation cycle are as follows: 1: Approach to the pile, 2: Loading, 3: Retract from the pile 4: Approach the dumper, 5: Dumping, 6: Retract from the dumper having the drivers operate the machines from remote control stations located above the ground.

Tele-remote operation and automation of earth-moving machines can also result in increased productivity for mining industry. In manual operation, a substantial amount of time is spent to drive operators back and forth to the excavation site during shift changes and breaks, both in underground mines and open-pit mines. In underground mines, production has to stop immediately after a blast before toxic gases are ventilated and conditions become better for manual operation. With automation and tele-operation, some of these productivity losses can be reduced and the mining process can be streamlined.

Although there exists some semi-autonomous solutions which combine tele-remote control with autonomous navigation, they are not efficient enough to substitute the driver in the manual operation. According to Andersson’s doctoral thesis [5], bucket filling with earth moving machines (LHD in this case) on tele-remote control is less efficient than manual bucket filling. This is because, on tele-remote, operators lose first hand sensory perception of the environment and have to take their actions based on slightly delayed audio and video. With only 2D videos streams from cameras, depth perception is also lost and very importantly remote-operators also lack direct motion feedback which helps humans to detect balance via feedback from ear pressures.

Some commercially available systems for tele-remote control are available, also for mining equipments, for example, Sandvik’s Automine [6], and Caterpillar Minestar [7]. These solutions do not yet provide any support to perform short loading cycle which poses additional requirements due to narrowness of space in underground mines. Also, no autonomous bucket filling algorithms are available with these commercially available solutions.
1.2 Application use case

The short loading cycle (shown in Fig. 1.1) operation of wheel-loaders is underground mines is quite challenging. In a short loading cycle, the wheel-loader typically makes a V-Y curve between the pile to be excavated and the dump truck.

Tele-remote operation should be efficient and meet the minimum requirements of the production in terms of productivity and fuel efficiency. The productivity is measured in terms of the weight of loaded material per unit time (ton/hr) and fuel efficiency is measured in terms of the amount of fuel spend per unit loaded material (cost/ton). Tele-remote operation should also be safe in terms of no potential threat to humans, and wear and tear to the machine should be as minimum as possible. The tele-operated machine should not hit any walls or other machines and possibility of wheel-slip, which is detrimental to tyres, should be reduced as much as possible.

In an underground environment, the work space of wheel loaders operating in short loading cycle is often narrow and hence the margin of error during navigation is small. Also, the fragmentation size of the blasted rock varies from blast to blast which makes efficient bucket fill non trivial. To develop safe and efficient tele-remote solution for this use case, carefully selection of technologies and new and robust methods for automatic bucket filling are desired.

1.3 Assisted tele-operation

A simple tele-remote control can be extended via operator-assistance functions which is named as assisted tele-operation in this thesis. Operator-assistance functions can be fairly simple, for example, warning the operator before collision or alert them about inefficient and unsafe use of the tele-operated machine or rather complex, for example, overriding remote-operator's judgment and executing a bucket filling algorithm based on machine vision and other sensors. Assisted tele-remote operation features components that enhance the operability of the tele-operated machines. Examples of operator assistance functions include bucket filling function, localization and navigation functions.

1.4 Scope and limitations of the work

Tele-remote operation is a part of the broad scope of automation of earth-moving operations. In this thesis, the focus is specifically on wheel-loaders operating in a short loading cycle. Here, following aspects related to tele-remote operation are discussed in the form of literature study, experiments, results or discussions.

- Automatic bucket filling without considering wheel slip
- Wheel loader’s operator experience and strategies
- Transport layer protocols for video transmission

Enabling tele-remote control can cover important milestones needed to close the gap between manual operation and autonomous operation. But, this work is by no means holistic and there are several inherit limitations.

In this work, localization in the underground environment is not discussed but it is assumed that this problem can be solved by using simultaneous localization and mapping (SLAM) using LIDARs. To automate bucket filling a data driven machine learning approach is proposed. A
limitation in this regard is that the experiments are performed on gravel but it is assumed that, with some modifications, the proposed theory will also extended to blasted rock due to the presence of fundamental operator behaviors during bucket filling. For bucket filling, wheel slip is briefly discussed in sec 3.2 but has not been included in the approach so far.

For the communication channel between the machine and remote control station, transport layer protocols which are more tolerant to occasional congestion are discussed but more on a theoretical level. However, it is assumed that a sufficiently good IEEE 802.11 radio link is available from the machine to the nearest access point.

1.5 Research questions and methodology

There are, primarily, two research questions addressed in this work. These research questions will be called RQ1 and RQ2 in the thesis.

RQ1: How to overcome the lack of perception and awareness of machine, and loss and delay in feedback data to enable safe and efficient tele-remote operation of earth-moving machines in mining industry?

RQ2: How to implement a machine learning based operator assistance function for bucket filling of medium course gravel that can load a truck as fast as drivers?

The methodology used to answer RQ1 has been literature study, simulation study of transport layer protocols and discussions including interviews of wheel loader’s operators. The simulation study compares two transport layer protocols: UDP and SCTP and aims to address if SCTP is more suitable than UDP to prevent losses during periods of network congestion. The network simulator used in the simulation work is ns-3, which is an open source networking simulator widely used in research and teaching. Simulation studies have an advantage that such experiments can be done in a repeatable way where one has full control of all variables in the environment. However, results with network simulation studies do not always extrapolate to real networks due to the presence of unpredictable variables across the protocol stack in computer networks.

The methodology used to answer RQ2 has been literature study, performing experiments to collect data and subsequent data analysis. It has been concluded in [8] that experimental research and data driven methods can be good ways to answer RQ2. The aim of these experiments is to study the driver’s behavior during bucket filling and if there exists fundamental relationships between measurable sensor data (lift/tilt angles, velocities, forces and speed of vehicle) with driver’s actions. The data was collected from one driver only and thus it possess a bias corresponding to this driver’s style of filling the bucket. However, it can be said that, data from multiple drivers in slightly varying pile conditions could be better for robustness of the bucket filling algorithm. Medium-course gravel is chosen for the bucket filling data analysis because it is neither a simple medium as soil, which can be modeled fairly well [9, 10], nor a difficult medium as blasted rock where driver actions can be complex and their behavior can be hard to interpret. In real scenario of blasted rock, considerable amount of time is spent to prepare the material before the actual filling of the bucket. Even further, the driver actions while filling blasted rock may also involve use of steering along with lift and tilt to break apart rocks locked into each other.
Chapter 2

Background

In this chapter, some basic concepts regarding the wheel-loader, tele-remote operation and related challenges are discussed.

2.1 Wheel loader

Front end wheel loaders are used for very different purposes by using different attachments. The attachments possible for a wheel loader include buckets, forks, grapple and raker. The kinematics and dynamics of wheel-loaders are already well studied and presented in literature in earlier studies [5, 11, 12, 13].

The basic construction of a wheel loader is shown in Fig. 2.1. The rear part of the vehicle is the body which has the cabin, the engine and drive-train components. The front part is like a robotic structure consisting of lift (also called as boom) and tilt arms which are used to lift and curl the attachment respectively via hydraulically driven lift and tilt piston cylinders. Mathematical models for the lift/tilt robotic mechanism similar to as in wheel loader are also well understood and presented in [12]. Long Wu [13], in his doctoral thesis, discussed drive train, power distribution and also presented an empirical model of torque converter.

Power transfer scheme

Most commonly, a wheel loader has a diesel engine which powers the hydraulic system and the drive train. A close loop diagram of power transfer scheme of a wheel loader is shown in Fig. 2.2. The power generated by the engine is used to propel the machine and actuate the lift and tilt arms. A key aspect of the this depiction is that, in the manual operation, the human operator is indeed the main controller. The operator issues commands to the engine via the throttle pedal, to the hydraulic system via the lift/tilt actuator joysticks and to the transmission via gear selection. The operator behavior is specially interesting during bucket filling which is both hard to model and automate.

2.2 Basics of tele-remote operation

Tele-remote operation has three components: 1. Machine 2. Remote control station and 3. Communication link. Tele-remote operation of construction equipment has been carried out
Figure 2.1: Wheel-loader components

Figure 2.2: Power transfer scheme of wheel-loaders [14]
earlier as well, and reported in [5, 15]. The performance of the tele-operation depends on all aspects of the mentioned components. The control interface in the machine needs to be fast but safe and secure. The remote control station should represent the site environment in a realistic way without introducing too much latency. The communication link bears the responsibility of relaying the information with minimal loss and delays.

Remote control station

Remote control station can be as simple as joystick interface for gas, brake, steering, lift, tilt and gear control with display screens for live video feedback. On the other hand, it can be a complete machine’s cabin with exact design of a specific machine along with motion simulators to provide the operators with the same experience when they switch between manual operation and tele-remote operation. Head mount displays have also been proposed in HMI research for remote controlled excavators [16]. Presentation of the information is very crucial for obtaining effective results. A localization view of the machine in underground mining is important to navigate in the low light underground environment since camera images does not capture the depth information normally available to us with our binocular vision.

Video quality and latency

High bandwidth IEEE 802.11 (WiFi technology) has penetrated in underground mines [17]. In order to transport video over an IP network, the data from the cameras should be available in or converted to digital signals. The raw data from cameras is also encoded before transmission to save bandwidth and then decoded at the remote control station. The encoding and decoding of the captured video stream is the main source of latency. H.264 and MJPEG are two options for encoding with standard industrial IP cameras. If needed, H.264 can be configured to save bandwidth several times (approximately 10 times) compared to MJPEG encoding. Both encoding comes with several parameters which can be tuned to find appropriate trade-off between frame-rate, resolution, bandwidth and latency. For tele-remote control, a glass of glass latency of more than 100ms has been found detrimental in several research works [18]. Table 2.1 lists the desired properties for a low latency video stream from an IP camera over a network. In some papers, video jitter has shown to cause even more damage to remote control performance than latency [18]. This is because the human brain can adapt better, to the constant delay than variable delay [19]. RTP and RTSP video transmission protocols, which can be used on top of UDP and TCP, provide protection against the variability in delay (also called jitter) in the video frames. On the other hand, sources of latency can be quite many and should be reduced and tackled more carefully.

The main source of latency in digital IP cameras is the encoding and decoding of H.264 or MPEG codec [20]. A second source of latency in the video stream is the camera itself which needs time for exposure of the sensor and processing. The remaining sources of latency in the video stream are then in the display and in communication link.

The communication link can also be an unpredictable source of latency especially when parts of the communication link are wireless. For real time video, User Datagram Protocol (UDP) is the standard choice of transmission protocol while SCTP has been proposed and investigated in [21].
2.3 Challenges in tele-remote operation

In manual operation, drivers use their 3D-visual, auditory, tactile (vibration and motion) capabilities to operate the machine. The main challenge for tele-remote operators is therefore to overcome limited perception and awareness.

In short loading cycle, driving backwards is one of critical steps where chances of collision are higher. Slamming the bucket into an obstacle while driving backwards is not uncommon during tele-remote operation of LHD machines [22].

In manual operation, the short loading cycle in underground mines often requires sign language communication between the dump-truck drivers and the wheel-loader drivers. Absence of such a non-verbal interaction combined with limited perception makes it difficult to load the truck safely. Signal degradation and data loss results in glitches of video frames and must be handled appropriately by triggering safety functions, for example, by safely stopping the machine.

A challenge with tele-operated machines is their integration with other machines working in the same area. In some cases, pockets in underground mines are located in a corridor where other trucks can also pass. It is important that the tele-operated wheel-loader avoids blocking the traffic.

Assisted tele-remote operation will increase demand for network bandwidth on a system level. This can result from an increase in the number of cameras and other network devices on machines, or an increase in the total number of tele-operated machines. Low latency and minimal loss in the video feedback is a key for efficient tele-operation. Therefore, it is important to select transport layer protocols suited for real-time data, but which can provide congestion control mechanism to prevent the network from self-jamming.

2.4 Bucket filling

Wheel loaders come in different sizes and may have different types of linkage for the boom and the bucket depending on the intended use. Also, earth-moving operations across mining and construction industries deal with piles of different size and properties. In [23], an autonomous function for scooping rock with an LHD machine has been shown to work using only the curl action (tilt). The differences in hydraulics and bucket design between wheel loaders and LHD machines makes this solution unusable for wheel loaders.

A challenge in developing a bucket filling function for tele-remote operation is to find methods which can adapt to other types of machines and materials. Therefore, machine learning methods have been advocated on the basis that they can adapt to a different situation if trained on data from the corresponding situation.

In underground excavation, the quality of blast depends on several factors and this can
occasionally result in a bad blast with big boulders in the pile. This makes the excavation of blasted-rock the most difficult among other earth-moving operations. Drivers, after they hit such a boulder in the pile, may have to change their strategy several times until they can either avoid the boulder or scoop it.

Wheel slip, which can damage the tires, is common during bucket filling and it contributes to 20-25% of the machine’s total maintenance cost [5]. Wheel slip can occur during scooping when an excessive torque is applied to the wheels, for example, when the tool hits a boulder. This practice is common with novice drivers and wheel slips becomes a bigger risk with them [24]. The challenge for the scooping function is to refrain from this behavior, identify any irregular experience and handle it in a safe way without damaging the tires.
Chapter 3

Automatic bucket fill

It had been identified in [8] that autonomous bucket filling is an essential operator assistance function for tele-operation since bucket filling on tele-remote is less efficient. The requirement for an autonomous scooping function is to fill the bucket with maximum (or demanded) weight of material in the least possible time with minimum fuel consumption. This requirement is difficult to translate in a conventional control problem as it is difficult to decide what should be the control variable during the bucket filling process [25]. Alternatively, machine learning appears more suitable for this problem as humans are much better at this task than autonomous bucket filling functions developed so far. Hence, in this work, machine learning based autonomous bucket filling is investigated.

3.1 Learning based approach

Machine learning is a subfield in artificial intelligence with growing potential resulting from sharply increasing computing capacity of hardware. This is enabling machine learning algorithms to learn from vast amount of data and produce groundbreaking results in classical AI problems [26, 27].

The learning based approach for automatic bucket filling requires data from sensors, which is used to train a model. If this data is collected while drivers operate the machine manually, the model learns to mimic the actions of drivers. In [25], Hemani advocates for more experimental research in this field. The approach in this work is essentially a data driven method which requires experiments for development and validation. But, a disadvantage with this approach is that it is resource intensive to perform experiments with heavy machines.

The three branches of machine learning are supervised learning, unsupervised learning and reinforcement learning. In this work, supervised learning is used as a tool to investigate if an algorithm can learn to fill a bucket.

3.1.1 Supervised learning

Supervised learning is class of methods in which algorithms are trained on data, identified to belong a group (marked data) or have known common characteristics. In bucket filling problem, the training data can come from good examples of bucket filling from expert drivers or bad examples that include wheel slip, for example.
There are two subcategories in supervised learning also: (1) classical regression, which aims to predict some outcome which is continuous in nature, and (2) logistic regression (classification), which aims to predict a binary outcome.

In this work, both regression and classification are used based on the idea that drivers use both continuous and discrete decisions during bucket filling. Classification models are trained to predict: should the action (for example, tilt/tilt) be used and regression models are trained to predict the intensity applied to that action (lift/tilt joystick value).

3.1.2 Drivers’ behavior model

In order to develop an automatic bucket filling function, the approach proposed in this thesis is presented in [21, 28]. These two papers present the theory used to develop behavior models of drivers. The models presented in these appended papers is based on data from an expert operator filling the bucket of medium-course gravel.

Bucket filling in blasted rock is more difficult than in gravel pile for the following reasons. The fragmentation size of blasted rock (also called muck in mining terminology) in underground mine varies greatly between days even in a same mine. An visual observation of bucket filling of blasted rock with a wheel loader shows that sometimes even expert drivers fails to fill the bucket to its full capacity. The actions and behavior of drivers are difficult to transcribe in words and are a reaction of their sensory input (vision, auditory and vibrational) combined with their experience. Automation of bucket filling for blasted rock is hard but [23, 29] has recently shown some success with LHD machines.

3.2 Wheel slip

Wheel slip results in wear and tear of tires and must be prevented [30]. Tires contribute to around 20-25% of the total maintenance cost of earth-moving machines in mines [5] and hence avoidance of wheel slip is important. Wheel slip is fairly common when scooping low-density material and becomes difficult to avoid with heavy-density materials (e.g. blasted rock). Wet conditions make wheel slip even more likely. In our learning based behavior model, wheel slip is not included and it remains part of the future work. Below, the basic concept of wheel slip is discussed in brief.

In Fig 3.1, a free-body-diagram of one of the tires is shown to discuss the traction force and wheel slip. In ideal condition, when the machine moves forward, the tires rolls on the surface and $F_A$ (propulsion forced applied on the ground by the wheel) equates $F_T$ (traction or friction force). The traction force has a maximum bound which is equal to the maximum available static friction force between the ground and the tire. The maximum value of static friction force is $F_{T_{\text{Max}}} = \mu_S F_N$. Assuming no wheel slip, $F_N$ (Normal reaction) is equal to $F_D$ (total downward force). Wheel slip becomes more probable in following ways

1. When $\mu_S$ is low (wet and damp conditions on surface).
2. $F_N$ is decreasing and, $F_A$ is high and increasing.

In order to combat wheel slip via surface conditions, the drivers attempts to make the surface level before bucket filling. While scooping, the drivers also try to use the lift action to maximum, making the lift force value, $F_{L_{\text{max}}}$, large. High value of $F_{L_{\text{max}}}$ increase $F_D$ and thus increases $F_X$. This way, the operator can throttle more, increasing $F_A$, which is necessary to enter into the pile while reducing the chances of wheel slip.
Detection of a wheel slip is not difficult if measurements of speed from all four wheels are available. But no commercial wheel-loader comes with this possibility. In theory, a downward looking vision or radar system can also detect individual wheel speeds but such a solution is not considered robust enough. Wang [31], proposed to predict wheel slip by tracking variables $F_{\text{lift}}$, engine RPM (a measure of $F_A$) and comparing it with theoretical speed measured by transmission axle’s rotation.

An effective wheel slip detection or prediction system is important for an automatic bucket filling function to work. Wheel slip in a learning based framework can be considered as punishment (negative reward) to a possible reinforcement learning based algorithm making it difficult for the algorithm to repeat the behavior which led to wheel slip.
Chapter 4

Research contributions

4.1 Paper A

Title: Remote controlled short-cycle loading of bulk material in mining applications

Authors: Ulf Bodin, Ulf Andersson, Siddharth Dadhich, Erik Uhlin, Ulf Marklund and Derny Häggström

Published: In 4th IFAC Workshop on Mining, Mineral and Metal Processing MMM 2015 – Oulu, Finland, 25–27 August 2015.

Summary: This paper introduces the idea of remote control of wheel loaders for short loading cycle. It highlights and discusses different aspects of remote control via wireless IP networks. It presents challenges in remote control and monitoring of earth-moving machines via high-capacity wireless IP networks in mining environments. It presents a generic communication solution for an operator assistance concept capable of adapting to varying communication properties.

Contribution: The author participated in the discussions and contributed in writing of the section called “Adaptive remote control”.

4.2 Paper B

Title: Key Challenges in Automation of Earth-moving Machines

Authors: Siddharth Dadhich, Ulf Bodin and Ulf Andersson

Published: In Automation in Construction, vol. 68, August 2016, Pages 212–222.

Summary: This paper, originally submitted in October 2015, is a literature study in the field of automation of earth-moving machines. It highlights main research areas in this field and highlights key challenges and knowledge gaps in the development of autonomous machines for earth-moving operations. It provides a survey of different areas of research within the scope of the earth-moving operation. The survey of publications presented in this paper is conducted with an aim to highlight the previous and ongoing research work in this field with an effort to strike a balance between recent and older publications. Another goal of
the survey is to identify the research areas in which knowledge, essential to automate the earth moving process, is lagging behind. The paper concludes by identifying the knowledge gaps to give direction to future research in this field.

**Contribution:** The author conducted a literature survey, wrote the first manuscript and contributed in iterative improvement of the manuscript.

### 4.3 Paper C

**Title:** Machine Learning approach to Automatic Bucket Loading  
**Authors:** Siddharth Dadhich, Ulf Bodin, Fredrik Sandin and Ulf Andersson  
**Published:** In 24th Mediterranean Conference on Control and Automation - Athens, Greece, 21-24 June 2016  
**Summary:** This paper presents the work on data-analysis of scooping of medium-course gravel by a Volvo 110G machine. The aim of the paper is to form the basis of an operator assistance function for bucket filling. A general solution should provide good performance in terms of average bucket weight, cycle time of loading and fuel efficiency for different types of material and pile geometries. Machine learning approach is applied to automatic bucket filling problem. Linear regression models for lift and tilt action are presented that explain the variance in the recorded data and outline a learning approach for solving the automatic bucket loading problem. It is concluded that linear regression helps to understand driver’s behavior during scooping but it is not sufficient to develop an automatic bucket filling function and should be extended further.

**Contribution:** The author participated in the discussions, conducted experiments and analysis of the collected data. The author wrote the first version of the manuscript and contributed in iterative improvement of the manuscript.

### 4.4 Paper D

**Title:** Assisted tele-remote operation of mobile earth moving machines in underground mines  
**Authors:** Siddharth Dadhich, Ulf Bodin, Fredrik Sandin, Denis Kleyko, Ulf Andersson and Erik Uhlin  
**To be Submitted:** In 3rd International Conference on Vehicle Technology and Intelligent Transport Systems  
**Summary:** This paper presents the continued work from Paper C on learning based operator assistance function for scooping. The use of wheel loaders in underground mines is discussed in the form of a case study based on interviews with expert drives at one of Boliden’s mines in Sweden. The paper also presents a simulation study on evaluation of SCTP protocol as an alternative to UDP for video quality (using H.264 video codec) in terms of packet loss. Further study of data from manual scooping experiments with medium-coarse gravel is presented along with a modified approach of learning model to develop an operator-assistance function for scooping.
Contribution: The author participated in the analysis of scooping data provided by Volvo CE. The author also contributed in the ns3 simulations reported in discussions around the use of SCTP protocol as an alternative to UDP. The author wrote the first draft of the sections II, III and V and contributed in iterative improvement of the manuscript.
Chapter 5

Conclusion and future work

This thesis discusses some important aspects to make tele-remote control of construction equipment viable in underground mining environment. Working conditions in underground mines are far from ideal for humans, and mining industry can also benefit from efficiency improvements if the operation can be done from above the ground via tele-remote control. Short loading cycle is a repetitive task in some underground mines and constitutes as the application use case of this work. Tele-remote control can benefit from operator assistance function to fill the bucket, navigate and dump the material onto the truck.

The wheel loader has complex but well studied hydraulic system and structure. The kinematic and dynamic models of wheel-loader are known but they also not so central in a learning based approach to automatic bucket filling. In this work, wheel slip problem had been introduced briefly but not tackled in the scope.

The key contributions of this thesis are highlighting important knowledge gaps based on a survey in the field of automation of earth-moving machines and proposing a machine learning based framework for automatic bucket filling for front-end loaders.

The scope of the thesis work includes identification of the main challenges and evaluating technologies to enable safe and efficient remote-control of wheel loaders in underground mine, and to develop a framework for automatic bucket filling algorithm. Paper A, B and D partly address RQ1 with literature survey, discussions and simulations. The simulation results reveal that use of SCTP is not so advantageous compared to UDP without delving into interlayer modifications to the protocol itself. The case study with drivers reveal interesting aspects around wheel loader’s usage, for example, the strategies to handle boulders in the rock pile. These special cases must be taken into account in the solution, in future.

The automatic bucket filling problem is a bottleneck issue in automation of earth-moving machine and machine learning methods can provide a viable solution. A major limitation of work presented in this thesis is that the research is aimed at operation in underground mining while the experiments done to develop the presented theory is done with gravel pile. With machine learning approach, there is a need for more experiments and validation tests to address the research question RQ2 in more detail. Paper C and paper D presents the core idea of bucket filling algorithm and partly address RQ2. There is enough scope of improvement in the theory, for example by including more classification levels and variables, but it is rather important to implement the theory in practice to gain insight with experiments.

The research work will be continued in the direction of the two research questions: RQ1 and RQ2. Safe and efficient tele-remote control in underground environment requires work in
several areas including low latency video solution and a positioning system to increase situation awareness while navigating. Another problem not mentioned earlier is that the wheel-loaders used in underground mines are equipped with very strong lights which forces even wide-dynamic-range image sensors of IP-cameras into saturation. The video solution under development will define the lightning and camera specifications along with their placements on the machine. A simple ultra-sonic sensor based safety stop system will be tested in the highly reflective underground environment.

The ongoing work on automatic bucket filling will be implemented on a Volvo L180H wheel loader. The experiments to be conducted in future will challenge the theory proposed in this thesis. Under the assumption of satisfactory results, reinforcement learning may be used to learn the bucket filling in new environments. Reinforcement learning can, in theory, improve the performance of bucket filling beyond drivers by using reward functions. Positive rewards can be given to the bucket filling algorithm for loading close to targeted amount of material in less time with less fuel consumption while negative rewards (punishments) can be given for undesirable consequences such as stalling in the pile and wheel slip. Accumulated reward and sensor data can update the parameters of the underlining models in the algorithm to improve its performance, overtime.
Bibliography


Part II

Appended Papers
Remote controlled short-cycle loading of bulk material in mining applications

Reformatted version of paper originally published in:
4th IFAC Workshop on Mining, Mineral and Metal Processing MMM 2015 – Oulu, Finland,
25–27 August 2015.
Remote controlled short-cycle loading of bulk material in mining applications

Ulf Bodin*, Ulf Andersson*, Siddharth Dadich*, Erik Uhlin**, Ulf Marklund †, Denny Häggeström‡

*Luleå University of Technology, 97187 Luleå, Sweden (Tel: +46-920-19 40 90; e-mail: {ulf.bodin,ulf.andersson,siddharth.dadich}@ltu.se).
** Volvo CE AB, Jolindervägen 100, 83185 Eskilstuna, Sweden (Tel: +46-16-51 19 40; e-mail: erik.uhlin@volvo.com) † Bolden Mineral AB, Kontorvägen 1, 93881 Bolden, Sweden (Tel: +46-816-77 40 90; e-mail: ulf.n.marklund@bolden.com) ‡ Orgu Prototyping AB, Twistäva 18, 90738 Umed, Sweden (Tel: +46-90-348 19 40; e-mail: denny.haggestrom@orgu.se)

Abstract
High-capacity wireless IP networks with limited delays are nowadays being deployed in both underground and open-pit mines. This allows for advanced remote control of mining machinery with improved feedback to operators and extensive monitoring of machine status, wear and fatigue. Wireless connectivity varies however depending on channel impairments caused by obstacles, multi-path fading and other radio issues. Therefore remote control and monitoring should be capable of adapting their sending rates to handle variations in communications quality. This paper presents key challenges in advanced remote control and monitoring of working machines via high-capacity wireless IP networks in mining environments. We reason about these challenges in context of underground short-cycle load, haul and dump operation with large-volume built wheel-loaders and present a generic communication solution for an operator assistance concept capable of adapting to varying communication properties.

1. INTRODUCTION

The mining industry has since the early 2000’s tried to exploit recent advances in ultra-high-frequency (UHF) technology, especially cellular phones, wireless local area network (WLAN), UWB and radio frequency identification (RFID) [1]. This trend is driven by needs for improved safety and efficiency. For example, in the United States with a total of 14,885 mines in operation, the Mine Improvement and New Emergency Response Act of 2006 (MINER Act) stipulates that by July 2009 underground mine operators must install wireless two-way communications and tracking systems that will link surface rescuers with underground workers [2].

In Sweden, Boliden Group has in their underground and open-pit mines deployed IEEE 802.11ac wireless networks for communications as well as real-time localization of both workers and
machinery [3]. In addition to better safety these networks facilitate effective voice communications as well as remote controlled and monitored machinery. This paper presents key challenges in advanced remote control and monitoring of such machinery, and presents a generic communications solution for industrial working machines. We reason about these challenges and communications solution in context of underground short-cycle load, haul and dump operation with large-volume built wheel-loaders in Boliden underground mines.

Remote controlled mobile machinery such as Load Haul and Dump machines (LHDs) has been used in industrial applications for more than ten years [4]. Such machines have early on been remote controlled and partly autonomous because of the harsh working environment in mines and to enable excavation at times when personnel cannot be present in the machine, e.g. directly after blasting and during ventilation. The productivity of remotely operated LHDs is however not in parity with on-board operation. One specific weakness is lower average payload of remote excavated buckets [5].

The variation in the fragmentation of blasted material to be excavated in underground hard rock mines is significant higher compared to material is of granular type. The challenges for efficient remote controlled or autonomous excavation are therefore higher in underground hard rock mines [6,7].

Autonomous loading of bulk material is considered to demand further work and research [8]. We consider operator assistance functions for remote control with skilled operators as a more viable approach than fully autonomous loading in the short to mid-term, as well as an important step to collect experience to refine fully autonomous loading for improved productivity.

Shortcomings of remote operated LHDs are relevant also for high-volume produced wheel-loaders such as construction machines, which in many cases are to perform similar work as for ore excavation in mines. In some cases, such wheel-loaders are even used for underground ore excavation when specialized machines are avoided for reasons such as extensive need for mobility and flexible maneuvering.

Efficient remote operation depends on reliable and predictable wireless communications. Remote monitoring is further essential to assure that machine issues are properly tracked although personnel are not on-board machines. It is then important to stress that remote control and monitoring systems can adapt their sending rates and handle temporary communications capacity reductions or even complete loss of connectivity as well as delay variations.

Adequate remote operator stations with support for testing during development and operator training are essential for efficiency reasons and to avoid machine damage due to misuse. Such station need to support evaluations and training related to adaptive operator assistance, which needs to be designed for intuitive usage to avoid operator mistakes.

The rest of the paper is organized as follows. Section 2 present and reason about challenges related to underground short-cycle loading. Section 3 discusses means of adapting remote operation in context of the different sequences conducted in such loading operation. Section 4 presents a generic communications solution supporting adaptive remote operation, while Section 5 describes our system implementation and testing. Section 6 concludes the paper.
2. KEY CHALLENGES

An overall challenge in operating remote controlled working machines is how to perform the work safely and fuel efficiently with high productivity without causing unnecessary wear and fatigue on the machine. This is because the remote operator typically lacks motion feedback and is limited to rely mainly on video to operate of the machine, which leads to an information gap compared to the on-board operator in the cabin of the machine. Hence, the remote operator has to base the control of the machine on information with less content and inferior quality.

System design, encompassing wheel-loader, operator and application, has a large impact on energy efficiency and productivity \[\text{[6]}\]. This is due to the complex nature of the construction equipment operations and interactions between machine and operator. Tests show performance differences between operators in the magnitude of several hundred percent. These differences mainly depend on the operator's ability to plan the operations. The work-cycle of a skilled operator is typically performed smoothly with a minimum of (unnecessary) machine movements. Skilled operators also ensure that bucket filling is performed energy efficient while achieving large bucket loads.

To minimize issues with low fuel efficiency and poor system performance, several approaches are possible. One is training of operators which has by general experience from operator training shown to be an effective tool to improve fuel efficiency and productivity. Another approach is on-board systems that measures and informs the operator of in-cycle performance and even suggests corrective actions.

The operator impact on system performance is highly relevant when controlling operations remotely. Challenges on system performance in terms of for instance delays in control and feedback will need to be overcome, especially at locations where wireless connectivity is unreliable. The remote operation under such circumstances further motivates targeted training of operators, involving practicing with remote operated machines, through simulations, or a combination of both. With remote operations increasing the complexity of operations, higher demands will also be put on operator performance feedback and functions for assistance and guidance.

Consequently, an important challenge related to safe and energy efficient operation while avoiding misuse is how to select the best combination of different feedbacks. Visual, sound, tactile and possibly motion feedback should be combined to make the best of a remote operator's abilities. Also, the best combination of decentralized control loops to be closed locally at the machine and loops to be closed by the remote operator need to be determined. For example, local control loops can assist in achieving large bucket loads at low energy cost. Selecting where to approach the pile of material to be loaded may on the other hand involve a control loop closed by the remote operator taking decisions based on video feedback.

Two challenges in operator assisted and autonomous underground loading of fragmented rock in comparison with a skilled manual driver are (1) obtaining high average bucket weight at low average cycle time and (2) avoiding collisions with the walls in narrow tunnels and nearby working machines (e.g. trucks)
With blasted rock, the size distribution of the material varies a lot, implying that the optimal control strategy for an automatic loading function might vary from one scooped bucket to another. Figure 1 (left part) shows a pile of blasted rock with varying rock sizes, and a snuffbox with diameter 7.5 cm. According to experience at Bolden the rock size can vary between a few mm to almost 30 cm.

![Figure 1 Blasted rock and draw point in cut-and-fill mine](image)

The un-loading of the bucket on a truck in case of short-cycle loading is challenging in several respects. For example, the truck might be at different positions from one bucket to another, the truck might need to be moved during un-loading, and the height of the tunnels can impose constraints on bucket maneuvering.

3. ADAPTIVE REMOTE OPERATION

For the adaptive assisted operator approach, we consider the specific case of underground short-cycle load, haul and dump operation with bigger-sized and large-volume built wheel loaders to be important. This is because it comprises of the challenging task of bulk material loading in a unit operation, which has been well explored with LHD-machines [4]. The type of unit operation commonly performed by LHD-machines involves hauling the loaded media to a remote dumping location. Such longer hauling exercise is not a part of the short-cycle load operation. Instead, a dumper truck is typically present in the vicinity of the machine, and the complete load cycle takes place in a small time frame of 25-30 seconds [9].
Figure 2 The short loading cycle

In short-cycle loading the steps performed by the wheel loader in one operation cycle are as follows: 1: Approach the pile, 2: Loading, 3: Retract from the pile 4: Approach the dumper, 5: Dumping, 6: Retract from the dumper.

When approaching the pile, a good loading spot needs to be located where the machine navigates to while placing the bucket in the right position. Although different machine vision approaches to automatically identify the best loading position have been studied [10, 11], we believe that this step should be performed by the remote operator specifically in this case of loading of blasted rock in the underground mines. This is because of great variation in the size distribution of blasted rock and the narrow space for maneuvering, which complicates the selection of loading spots. One should also keep in mind that the narrow tunnels limits the options regarding the best loading position. It might even be so that the loading has to be done with a significant articulation angle of the loader if the blasted rock is located in a curved part of the tunnel.

Even though short delay and high-resolution video feedback possibly with some depth perception are highly desirable, the remote operator may, in cases of limited wireless capacity, need to cope up with lower resolution video and longer delays. Operator assistance functions that can aid the remote operator to select the best possible loading spot could potentially help in such cases, while also constituting a step towards fully automatic operation.

Although the loading sequence is clearly challenging due to the variation in size distribution of the material to be loaded, we envision the full automation of this step while achieving high average bucket weights. Possible automatic control methods for the loading step include compliance control [12], feed-forward control [13], and artificial intelligence approaches like rule based fuzzy logic [14].

Since a strict position control can only be realized in free air and not while traversing through a pile, compliance control argue for modifying the trajectory of the bucket on the fly in compliance with the resisting forces on the bucket. The idea behind the feed-forward control is to model the complex and stochastic interactions of the bucket with the pile as a disturbance to the loading...
Iterative learning methods combined with artificial intelligence based control is one of the candidates to perform the loading operation autonomously. A common idea behind these artificial intelligence based methods is to code the intelligence of an expert operator into a computer algorithm [15].

An autonomous function for loading may depend on remote supervision acting as an outer control loop for adjusting and selecting from different alternative solutions. For example, settings for a solution based on an adaptive fuzzy control may require continuous inputs from the remote operator to perform loading with high bucket weights. High-resolution video, audio and other feedback data (vibration and tactile) would also be desired for such a remote operator task. Hence, limited wireless capacity may impact on the performance of the remote supervision of automated loading.

As noted in Section 2, blasted rock characteristics might vary from one scooped bucket to another, which requires different control strategies for the bucket filling. Selecting the optimal control strategy for a particular rock profile and use it for all loading cycles is hence likely to give lower bucket weights than adapting this strategy based on available inputs. We argue for that the adaptation of the control strategy for automatic loading is a key function for remote loading to achieve high average bucket weights. Such adaptation could be based on the visual and tactile feedback to the remote operator, the measurements on the machine for the local control, or a combination of these inputs.

The sequences, 3, 4, 5 and 6 (Figure 2) which are, retracting from the pile, approaching the truck, dumping and retracting from the truck can be automated by using the already advanced research in the field of localization, navigation and path planning [6, 17]. Mines in which the cut-and-fill caving method is used are however often very tight and narrow at draw points, making these sequences hard to automate. Examples of such mines are the Boliden Kristineberg and Kankberg mines [38].

Figure 1 (right part) shows a draw point in the Boliden Kankberg underground mine. At this draw point for every loading cycle, the truck needs to move forward to leave space for the wheelloader to load where after the truck reverses to take position for dumping. These interactions between the wheelloader and the truck in the tight and narrow environment illustrate the maneuvering difficulties in making short-cycle loading fully autonomous.

These difficulties in maneuvering at tight and narrow draw points motivate the need of assisted remote operation aiming at semi-autonomous solutions in the longer term. Desired operator assistance functions aiding the remote operator in maneuvering include collision detect systems and relative localization solutions, for example needed to position the wheelloader correctly towards the truck for dumping.

As discussed, wireless capacity and delay can have impact on the remote operation of wheelloaders performing short-cycle loading in mines. Degraded communication properties will result in limited remote controllability, feedback or a combination of both and in such cases, the machine
control should move towards a safer operation. This means that to avoid the risks of accidents as well as unnecessary wear and fatigue on the machine some pre-defined functional restrictions can be forced on the machine depending on the operation mode. Possible restrictions can be on the parameters such as maximum speed and limited power defined by the maximum RPM of the engine.

Restrictions targeting the safe operation should aim for a good balance between energy efficiency, productivity and safety without risking the wear and fatigue on the machine. For example, all the steps in the short loading cycle involving navigation may benefit from different restrictions put under varying communication properties depending on how the operator assistance functions are designed. A trustworthy collision detect function build to avoid collisions with the tunnel walls may motivate higher speed in retracting sequences, while the sequence 4 (Figure 2), i.e. approaching the truck needs to be performed at a much slower speed due to the complexity and the risk of damaging the truck if a collision occurs.

By measuring the available wireless capacity and the delay in the uplink and the downlink to the machine, constraints in the communication that affects the type and the quality of available feedback to the operator as well as the remote controllability can be detected. Such information can be used to impose pre-defined functional restrictions and adapting the control strategy for the loading. Therefore, the communication solution needs to be capable of measuring the data forwarding quality, adjusting the transmissions accounting for detected variations, and reporting to the operator assistance functions on the machine.

4. A GENERIC COMMUNICATIONSOLUTION

The generic communications solution that we propose for adaptive operator assistance is based on the SCTP protocol [19], active measurements of communications properties inspired by PPM [20], and machine localization obtained from WLAN positioning. The IEEE 802.11ac wireless networks deployed in Boliden mines supports real-time localization of both workers and machinery [3].

Tracking personnel is important for security reasons, e.g. to make sure that everyone presently in an underground mine are inside a rescue chamber in case of an accident. For this application the present positioning resolution of around 50 meters is sufficient. The accuracy can be further improved e.g. using path loss modeling and RFID tags with known exact positions [21]. Thereby, applications of the system requiring better positioning accuracy become possible.

With positioning resolutions in the order of a few meters, measurement results for wireless capacity at different locations can be compiled into statistics for discrete locations. That is, measurements for positions in the same area of say 10 square meters in a tunnel can be used to predict the wireless capacity at that particular place. This predicted capacity could then be used to adapt beforehand in a controlled manner the control and feedback data rates, and if necessary because of previously experienced wireless capacity limits, force functional restrictions on a remote operated machine.

The continuous measurements of wireless capacity can capture throughput, delay and delay variation (a.k.a. jitter). This information can be used to adapt control and feedback data rates
in case not adapted beforehand, e.g. because of not previously seen degradations in wireless capacity, or in absence of a wireless capacity prediction solution. In this context, it is important to notice that several big machines operating in the narrow tunnels might have a disturbing influence of the communications capacity.

In case of degraded wireless uplink capacity from a machine, video feedback need then move to lower resolution or reduced number of frames per second, or a combination of both. Should downlink capacity become degraded, the rate of control signals needs to be reduced. As noted in Section 3, such reductions in feedback and control may need to be accompanied by functional restrictions forced on the machine to ensure the safe operation.

Although measurements and predictions can be used to force restrictions on remote operated machines, they still face increased risks of being damaged from collisions and become subject to more wear and tear than manually operated machines. Therefore, we argue that extensive remote monitoring should be seen as a vital part of the communications solution.

Wireless communications in mining, industrial and construction environments may constitute more than one wireless infrastructure. 802.11 networks may for example be complemented with cellular data systems such as the 3GPP LTE [22] and CDMA at the 450 MHz frequency bands [23], offering coverage also at distant and sparsely populated locations. This means that the communications solution needs to support switching between different networks. We further advocate applying TCP-friendly congestion control and avoidance to all transmissions. This is to avoid saturating the wireless networks causing throughput degradations and longer delays.

Our communications solution can be seen as a middleware providing generic functions for machine automation. Figure 3 shows the block diagram for its components and their interconnection when instantiated in machines. The instantiation at control sites is basically the same, except that the machine restrictions application does not force restrictions to the machine. Instead it may inform remote operators of that restrictions currently are in effect.

The communications solution is based on two SCTP socket associations (i.e. connections between machine computer and computer at control site), one for feedback and control and another for monitoring data. Both these SCTP associations can be multi-homed in case several networks are available. The multi-homing feature allows a single association be associated with more than one IP address. This allows for switching between networks using the SCTP built-in functions for multi-homing [24].

The lifetime of an SCTP message determines how persistent the transport service should be in attempting to send the message to the receiver [25]. The lifetimes of feedback and control messages are preferably set short to avoid retransmissions, which would delay the message delivery. This is because such messages typically become useless when delayed.

The lifetimes for monitoring messages should be set to values decided by the monitoring application to allow for different preferences on assured delivery. Also, monitoring messages may need to be throttled to times of reduces wireless capacity to ensure that feedback and control messages are received at best speed. The setting of the lifetime for each message and the throttling of message streams are performed by the functional block located in between the local loop interface and the SCTP sockets (Figure 3).
5. SYSTEMS IMPLEMENTATION AND TESTING

The experimental system implemented encompasses the communications solution described in Section 4 except the measurement function and SCTP tools, which instead are implemented and tested separately to verify their functions. The SCTP part of the system is built with the lksctp tools on Linux, which provides a kernel implementation of the SCTP protocol [25].

These tests of SCTP indicate that lksctp can be used as intended for the communications solution provided that two separate associations are used. The separate association is needed since lksctp implements first-come, first-served scheduling for all streams in the same association [27]. This can cause long delay to feedback and control messages in case they are queued behind monitoring messages.

The experimental system is installed and tested in a Volvo L110G wheel-loader. The means to control the machine are via two electronic breakout units designed and implemented for this purpose [28]. These units allow the Controller to send commands to the Electronic Control Units (ECUs) of the machine as well as receiving observed data communicated with the connected ECUs. That is, they can intercept signals on the cabling to and from ECUs. The machines are thereby made remote controlled from a Control Rig from the Swedish Company Oryx Simulations. This rig has the same controls as in the machine.

Using the experimental system we have measured the total delay from remote stick movements to when actuations take effect on the machine. The resulting total delay for lowering the boom was close to 430ms with hydraulics and mechanics accounting for close to 300ms. In this test the communications delay was about 20ms, which illustrates that delays can appear in many steps from remote control actions to when the machine actually reacts.

The video solution used in these tests gave more than 100ms delay. With this delay in visual feedback and the delay for controls of almost a half second, it became very difficult to perform
tasks such as short-cycle loading efficiently based on remote control. Reducing delays to become short enough may not be possible. Video delays will remain although they can be made shorter, and the same goes for the hydraulics and electronics in the machine. Assuming the visual feedback and machine actuations will remain at levels still causing difficulties, we believe that operator assistance functions related to forced functional restrictions on the machine are essential to ensure the safe operation at remote.

6. CONCLUSIONS

Modern mines will be equipped with high-speed wireless networks. Mining companies like Boliden have already in their underground and open-pit mines deployed IEEE 802.11ac wireless networks for communications as well as real-time localization of both workers and machinery. An important usage of such networks is the remote control and operations of mining machines. Remote operations of such machines is motivated by the harsh working environment in mines and needs to enable excavation at times when personnel cannot be present in the machine, e.g. directly after blasting and during ventilation.

In this paper we have presented key challenges in remote controlling wheel-loaders used for short-cycle load, haul and dump of blasted and fragmented rock. We have identified possible approaches for automated loading and defined a concept of forcing functional restrictions on machines to ensure safe operations in situations of reduced wireless capacity. We further present a generic communications solution, which is partly verified with a test implementation. Delay measurements made with this experimental system illustrates the need for adaptive operator assistance functions such as the functional restrictions suggested in this paper.

ACKNOWLEDGEMENTS

The work presented in this paper is supported by the Swedish Innovation Agency VINNOVA under contract 2014-01882.

We thank Fredrik Bengtsson, Robin Bond and Håkan Therén, Luleå University of Technology, for conducting delay measurements on the experimental system presented herein.

REFERENCES


Transmission Protocol (SCTP) Partial Reliability Extension, Request for Comments 7738, IETF.


Paper B

Key Challenges in Automation of Earth-moving Machines

Reformatted version of paper originally published in:
Key Challenges in Automation of Earth-moving Machines

Siddharth Dadhich∗, Ulf Bodin† and Ulf Andersson‡

Abstract

A wheel loader is an earth-moving machine used in construction sites, gravel pits and mining to move blasted rock, soil and gravel. In the presence of a nearby dump truck, the wheel loader is said to be operating in a short loading cycle. This paper concerns the moving of material (soil, gravel and fragmented rock) by a wheel loader in a short loading cycle with more emphasis on the loading step. Due to the complexity of bucket-environment interactions, even three decades of research efforts toward automation of the bucket loading operation have not yet resulted in any fully autonomous system. This paper highlights the key challenges in automation and tele-remote operation of earth-moving machines and provides a survey of different areas of research within the scope of the earth-moving operation. The survey of publications presented in this paper is conducted with an aim to highlight the previous and ongoing research work in this field with an effort to strike a balance between recent and older publications. Another goal of the survey is to identify the research areas in which knowledge essential to automate the earth moving process is lagging behind. The paper concludes by identifying the knowledge gaps to give direction to future research in this field.

1 Introduction

Earth-moving machines comprise a large set of industrial machines used in construction, mining, forestry, agriculture, cleaning and many other industries. Such machines generally include a vehicle (i.e., a main body) and a robotic mechanism mounted on the vehicle. Many types of earth-moving machines are available with different combinations of vehicle and robotic mechanisms. The robotic mechanism typically consists of a robotic arm (a combination of links and joints) powered by a hydraulic system and a tool designed for tasks such as loading or excavation of materials. It is often possible to change the tool to adapt to different tasks. Wheel loaders and excavators are two common examples of mobile earth-moving machines.

Wheel loaders are extremely versatile and often used as multi-purpose machines at production sites [1]. Applications for which wheel loaders are used every-day include the transportation of soil, ore, snow, wood-chips and construction material. Wheel loaders have extensive use in the mining industry, where they are used to transport ore in both open-pit mines and underground mines. In underground mines, special types of wheel loaders are used: LHD (Load-Haul-Dump) machines. Fundamentally, LHD machines are the same as wheel loaders except that they are adapted for the low ceilings of underground mines.

∗S. Dadhich is a PhD Candidate at the Luleå University of Technology, Sweden (siddharth.dadhich@ltu.se).
†U. Bodin is a senior lecturer at the Luleå University of Technology, Sweden (ulf.bodin@ltu.se).
‡U. Andersson is a project leader at ProcessIT Innovations at the Luleå University of Technology, Sweden (ulf.andersson@ltu.se).
Automation of wheel loaders and excavators has been an active area of research over the past three decades [2]. As claimed by [3], despite much research in this field, a fully automated system for a mobile earth-moving machine has never been demonstrated. In [2], the authors conclude that the subject demands more research, together with industrial support, to speed up the process towards successful autonomous loading of bulk material.

In this paper, the focus is on automation and remote control of earth-moving machines such as wheel loaders and LHD machines. The main contributions of the paper are the review and assessment of different approaches for automating the steps involved in short cycle loading and the survey of publications on automation of earth-moving machines. We also provide an in-depth review of different automatic bucket loading strategies and discussion on possible approaches (section 4.2). In the paper, we highlight important knowledge gaps in the areas of automatic loading of fragmented bulk material, wireless communications, and operator experience and performance in tele-remote operation.

We find that automating the complete short loading cycle is not viable in the short to mid-term. Given the identified challenges in full automation of the earth-moving process, we consider semi-automation through assisted tele-remote operation to be an important step to collect experience for further research and development. Reliable wireless communication becomes essential when machines are tele-remotely operated. This paper also gives a brief overview of communication-related challenges and possible solutions.

The difficulty in automating the entire process can be attributed to the fact that it is impossible to accurately model the earth-moving process, especially the interaction between the tool and the environment. The properties of media to be excavated or moved are central to the problem. Examples of different media are snow, soil, gravel, wood chips, fragmented rock, mud, etc. Autonomous excavation of soil is a well-studied problem, and yet fully automated excavators are rare [4].

Because full automation of the earth-moving process is difficult, researchers commonly aim for small steps in moving towards automation. In [5], a five-step approach is suggested, from fully manual operation at step one to fully autonomous operation at step five. In [1], another nomenclature for these steps is proposed. Our review and assessment of different automation approaches relate to these steps from manual towards fully autonomous operation, as well as the procedural steps in the short cycle loading process. We define a versatile set of requirements on the semi-automated and fully autonomous short loading cycle, among which some relate to the complete process, while others apply to one or more of these procedural steps.

The survey of publications on the automation of earth-moving machines presented here is categorized into different areas: modeling for control, automatic loading, pile characterization, localization and navigation, and path planning. Our most important contributions are the survey of automatic bucket loading strategies and the assessment of the viability of different approaches. We provide arguments in support of reinforcement learning methods as a possible solution for the automatic bucket-loading problem.

The reminder of the paper has been organized as follows. Section 2 assesses the problem of automating earth-moving machines. It presents the automation steps and the procedural steps involved in the short loading cycle. This section also defines operator assistance functions and presents a previously reported case study on tele-remote operation and assisted loading. In section 3, the fundamental requirements for autonomous and tele-remote earth-moving operation are discussed from the standpoint of safety and efficiency. Section 4 address the machine side of the problem, discussing the different aspects of autonomous operation that can be realized via operator assistance functions. In section 5, communication requirements in tele-remote operation are discussed. Section 6 addresses the operator station for a remotely operated earth-
moving machine. Section 7 presents various research areas and publications that could not be categorized in section 4, 5 or 6. Section 8 presents identified knowledge gaps and section 9 summarizes and concludes the paper.

2 Problem assessment and breakdown

The challenges in automating earth-moving machines are multifaceted, motivating us to separately address the different parts of the problem. For breakdown and assessment of this problem, we need to envision the possible steps from fully manual to completely autonomous operation and understand the procedural steps that are performed in the short cycle loading process. Because the intermediate steps towards full automation most likely involve tele-remote operation, we also need to understand possible ways to assist a remote operator. After providing these tools to better understand and assess the problem, we present a case study on tele-remote and assisted loading from an iron-ore mine in Kiruna, Sweden. This case study illustrates how an intermediate step towards fully autonomous loading can be implemented and how operator assistance functions can improve the performance in terms of average bucket weights.

2.1 Steps toward full automation

A five step approach from manual operation at step one to fully autonomous operation at step five are discussed in [1] and [5]. These five steps to full automation tailored for short cycle loading operation are listed below, stressing the point that remote control issues are important when moving from in-sight tele-operation to remote-operation of mobile earth-moving machines. This is because the remote operation introduces more uncertainties in the form of delay and loss of the data communicated over the network. The steps towards fully autonomous operation are:

- Manual operation: The operator is sitting in the machine manually performing all the tasks.
- In-sight tele-operation: The operator is outside, in the vicinity of the machine, performing all the tasks by a hand held remote.
- Tele-remote operation: The operator is in a control room far away from the loading site but still performing all the tasks with the help of a remote and audio-video feedback from the machine (Fig. 1).
- Assisted tele-remote operation: The machine performs many tasks by itself via the use of operator assistance functions (Sec 2.3). The operator intervenes in the tasks where human supervision is of importance.
- Fully autonomous: The machine performs all tasks by itself. The operator is only present to give high-level commands, take care of emergencies and handle failures.

2.2 Short loading cycle

Most commonly, the mobile earth-moving machines perform the following three tasks during one cycle of operation. Because this cycle is repeated thousands of time in many applications, it is important to ensure that efficiency is respected in each step.

1. Loading
2. Navigating

3. Dumping

The mobile earth-moving machines transport material (soil, fragmented rock, gravel, etc.) from one place to another, where the distance between the source of the material to its destination can be from a few meters to a few hundred meters. This differentiation creates two classes of operating cycles, the load and carry cycle and the short loading cycle. In the load and carry cycle, there is a significant distance between the loading point and the dumping point, and thus a larger amount of time is spend in navigating. In a short load cycle, the dumping site is in close proximity to the loading machine, which may be in the form of a dump truck or conveyor belt. The focus of this work is on the short loading cycle which, puts stricter constraints on the cycle time of operation of the earth-moving machine.

Most commonly, the mobile excavating machine performs a V-Y curve (as shown in Fig. 2) between the loading site and the dumping site, but in the case of a side dumping bucket, the motion of the machine is close to a straight line. The loading of some granular material on a nearby dumper in a short load cycle takes place in a small time frame of 25-30 seconds [6], and the challenge for the assisted remote-control operation is to perform at least equal to an expert driver in manual operation.

Intensive research efforts are needed to close the gap from remote-control operation to assisted remote-control operation. In relation with Fig. 2, different procedural steps for implementing assisted remote-control for a short loading cycle operation have been identified in Table 1. The control algorithm for loading the material is the most important and the most discussed step, but it still remains an open area of research [3]. A general control strategy for loading does not work because the properties of the material (density, hardness, moisture and composition) being loaded varies significantly.

2.3 Operator assistance functions

Operator assistance functions are tools for striving toward full autonomy of the earth-moving process. In pure tele-remote operation, operator assistance functions can, for example, warn the operator before collision or alert them about inefficient and unsafe use. In assisted tele-remote operation, these functions can mostly take over the operator. Examples of operator assistance functions are:

- Path planning
- Collision detection, avoidance and navigation
The steps performed by a wheel loader in one operation cycle are as follows: 1: Approach to the pile, 2: Loading, 3: Retract from the pile 4: Approach the dumper, 5: Dumping, 6: Retract from the dumper.

**Figure 2: Short Loading Cycle**

<table>
<thead>
<tr>
<th>Steps</th>
<th>Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approach to the pile</td>
<td>1. Locate the best loading spot.</td>
</tr>
<tr>
<td></td>
<td>2. Navigate to the loading spot safely and efficiently.</td>
</tr>
<tr>
<td></td>
<td>3. Place the bucket in the right position for loading.</td>
</tr>
<tr>
<td>Loading</td>
<td>1. Using the sensor input, run the control algorithm for loading the pile for the specific conditions.</td>
</tr>
<tr>
<td></td>
<td>2. Adjust the load in the bucket to prevent spillage.</td>
</tr>
<tr>
<td>Retract from the pile</td>
<td>1. Locate the pose of the dumper.</td>
</tr>
<tr>
<td></td>
<td>2. Identify a good target location for reversing.</td>
</tr>
<tr>
<td></td>
<td>3. Reverse in a safe way avoiding any obstacles.</td>
</tr>
<tr>
<td>Approach the dumper</td>
<td>1. Navigate to the dumper safely and efficiently.</td>
</tr>
<tr>
<td></td>
<td>2. Prepare the boom and bucket for dumping.</td>
</tr>
<tr>
<td>Dumping</td>
<td>1. Ensure that alignment is as desired.</td>
</tr>
<tr>
<td></td>
<td>2. Activate the boom and bucket for dumping.</td>
</tr>
<tr>
<td>Retract from the dumper</td>
<td>1. Locate a reversal point.</td>
</tr>
<tr>
<td></td>
<td>2. Reverse in a safe way, avoiding any obstacles.</td>
</tr>
<tr>
<td></td>
<td>3. Lower the boom and bucket for the next cycle.</td>
</tr>
</tbody>
</table>

Table 1: Steps in assisted remote-control operation for a short loading cycle
Table 2: Comparison of manual operation and tele-remote operation in terms of loaded bucket weight averaged over one year (Data from LKAB Mine, Kiruna) [10]

<table>
<thead>
<tr>
<th></th>
<th>Average bucket weight (ton)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manual LHDs</td>
<td>26.7</td>
</tr>
<tr>
<td>Semi-automatic LHDs</td>
<td>23.3</td>
</tr>
</tbody>
</table>

- Preparing the boom and bucket for loading and dumping
- Loading algorithm
- Dumping algorithm

A combination of manual operation with operator assistance functions for path planning and navigation is described by [7] as semi-automation. In [8] and [9], a semi-autonomous operation is developed by implementing collision detection and avoidance, and navigation functions to assist the operator. Assisted tele-remote operation is a combination of remote operation and operator assistance functions. It can be seen as an extension of semi-automation that finds the right balance between remote control and automation.

2.4 Case study on tele-operation and assisted loading

During a 10-year period from 1999 to 2009 in the underground mine at Kiruna, Sweden, the iron ore was partly transported by semi-automatic tele-remote controlled LHDs [10]. It was discovered quite early that the average bucket weights of remotely operated LHDs were lower when compared to manual LHDs. To address the problem, an operating assistance function was introduced to the tele-remote LHDs that automatically controlled the robotic mechanism (the boom and the bucket) during the scooping. Tests with two machines indicated that the average bucket weight increased by nearly 5% when using the assistance function (semi-automated LHDs) compared to pure tele-remote controlled scooping [10]. The remote operators were able to use the operator assistance function at their own decision so there is no knowledge of how frequently the function was invoked. Table 2 summarizes one full year of production with five semi-automatic LHDs and eight manually operated LHDs.

As is clear from Table 2, the productivity of the semi-automatic LHDs was still far less than that of the manual LHDs when considering the average bucket weights. It should be noted, however, that the material transported was blasted rock, and in the case of a failed blasting, the blast contained a large number of boulders, which would mean that the volume of the load in the bucket contained more air than when the blasting produced well-fragmented rock. The figures in Table 2 should therefore be interpreted as indicators rather than absolute facts.

In underground mining, there are both pros and cons with semi-/automated machines. An advantage with semi-automated LHDs is that they can operate directly after a blast whereas manual LHDs need to wait several hours before gases and dust produced from the blast are ventilated. However, a drawback with semi-/automated LHDs is the need of isolating the area in which they operate, due to safety regulations, which heavily constraints other activities in those areas. The pros and cons pose an optimization requirement for the most efficient use of semi-/automated machines alongside manual machines.
3 Requirements of operation

Earth-moving operation requires heavy construction machinery, which necessitates the safe and efficient use of such machinery. Because any construction operation cycle, including the short loading cycle, is repeated thousands of times, it is important to define stringent requirements for the operation. Two aspects in which these requirements can be classified are safe operation and performance.

3.1 Safe operation

Safety is a priority for companies in developed countries [4], but reducing the maintenance cost of operation is of interest to all companies around the globe who are using mobile earth-moving machines. Human safety comes before any other priority. Normally, this is performed by separating the zones of remote-operated (or automated) machines by the zones where humans could be freely working. Safety to the machine is also very important because, apart from the direct cost of repairing a broken machine, the maintenance cost also includes the cost of production loss during the down-time of the machine. Given the importance of safe operation, below is a discussion of major safety threats during operation and their mitigation.

3.1.1 Wheel slip

Wheel slip is an undesirable phenomenon that results in the loss of traction. It occurs when the torque applied to the wheels greatly exceeds the friction available from the surface. Reasonably, this can occur when the torque applied to the wheel is too high or when there is not enough friction on the surface (e.g., icy and wet surfaces). For the wheel loader operation, this can occur during the loading phase when the resistance force on the tool is very high, leading the operator to apply more and more throttle. This practice is common with novice drivers, and wheel slip becomes a larger risk with such drivers [11].

According to [10], wheel slip can greatly damage the tires, and it contributes to 20-25% of the machine’s total maintenance cost. Therefore, wheel slip is highly undesirable and should never occur [12]. To avoid wheel slip conditions, traction control algorithms can be incorporated during the loading step in the operation cycle.

3.1.2 Collision detection and avoidance

Wear and tear to the machine due to collisions with the side walls in underground mines are very common in tele-remote operation during hauling (also called tramming), even at low speeds [8]. This results in increased maintenance costs, and hence, collisions are considered a large disadvantage of tele-remote operation [9]. In the short loading cycle, driving backwards is one of the more critical steps where the chances of collision are even higher. Slamming the tool into an obstacle while driving backwards is not very uncommon during remote-operation [8]. There can also be collisions with boulders fallen off from loaded trucks working in the same area, and therefore it is important to have the collision detection and avoidance mechanism as an integral part of the remote control system of these machines.

In certain underground mines, there are ditches along the tunnels that are part of the water drainage system in the mine. The drivers regularly driving in these tunnels are trained to drive close to the wall opposite to the ditch [8]. Because all mobile earth-moving machines working in an underground mine will traverse the tunnels once in a while, an algorithm to avoid driving into the ditches must also be part of the remote-control system.
Much research on the topic of collision avoidance already exists in the field of mobile robotics, and it must be exploited when developing control systems for automated or tele-remote-operated mobile earth-moving machines. Most of the collision avoidance systems use laser range finders, as in [5], [8], [9] and [10]. Some researchers have also experimented with radar-based collision avoidance systems [13]. It is important to mention that both laser- and radar-based systems can suffer from performance degradation due to dusty and foggy conditions.

3.2 Performance

Performance is an important aspect for companies to be able to remain in business against their competitors. The performance of a short loading cycle or a load and carry operation can be captured in terms of productivity and fuel efficiency. As mentioned in [8], the remote-controlled machines are often less productive than manually controlled machines. Therefore, to realize the vision of full automation of these earth-moving machines, it is necessary to dissect the operation cycle in pieces and study the possibility of improvement in performance for each piece. The performance of a short load cycle operation and that of other operations can be captured by measuring the fill factor, fuel efficiency and cycle time of the operation.

3.2.1 Fill factor

Fill factor or bucket fill factor is the amount of material loaded in the bucket in one scoop. The fill factor can be measured by a weighing scale system in the machine when lifting the bucket. A weighing scale system uses the pressure in the cylinders to calculate the loaded weight. Therefore, in the absence of a weighing system, the loaded weight can be computed by the measurements from the pressure sensors of the boom and bucket cylinders in a wheel loader, for instance. In [12], one theory for developing an automatic scooping function is presented, wherein a zigzag motion strategy is proposed for the bucket. In this report, the conclusion is that it is very difficult to fill the bucket via an automatic function as good as a manual driver can, even with soil.

The lower productivity of remote operation is primarily due to the lesser fill factor compared to manual operation [10]. Keeping this information in mind, it is important to consider fill factor as a requirement while developing an automatic loading function for mobile earth-moving machines.

3.2.2 Fuel efficiency

The fuel efficiency of the machine directly affects the operational cost. In [1], arguments are presented to support an operator assistance function for increasing the fuel efficiency. They claim that fuel consumption roughly contributes 30-60% of the operations cost measured per unit of the loaded material. Moreover, pollutant emissions increase with decrease in operational efficiency [14]. Therefore, it is important to ensure that the fuel efficiency of an automated solution is at least close to the most fuel efficient drivers.

In some publications, productivity and fill factor are considered to be the same, and the use of full engine power to load the material is suggested, as in [15] for instance. The use of full power may not be a good solution, as not only can it result in reduced performance due to the increased fuel consumption, but it can also result in increased wear and tear of the tool.
3.2.3 Operation cycle time

Operation cycle time is also important, as the short loading cycle is repeated over and over again. A small improvement in cycle time can result in many more extra loading cycles, resulting in improved productivity. The loading step in the short loading cycle has greater potential for improvement with regard to the cycle time than navigation and dumping. A shorter operation cycle time demands increased fuel consumption due to the higher acceleration and deceleration. Therefore, a trade-off is necessary between the cycle time and fuel efficiency. This particular trade-off problem has been considered in [16].

3.2.4 Unified performance indication

It can be useful to capture the two aspects of performance, i.e., productivity and fuel efficiency, in one figure and to access the performance at a lower time resolution for each individual operation cycle. This can serve as a tool to compare and critique different operator styles and also different automatic bucket loading algorithms. The productivity is defined as the ratio of the fill factor and operation cycle time and thus is measured in weight of loaded material per unit time. In [6], it is argued that the operator’s mental and physical workload should also be captured in the performance of the operation.

4 Toward autonomous operation

Although research toward automation of earth-moving machinery has long been active, in practice, only a handful of construction and mining companies use remote controlled or semi-autonomous machines. In this section, several challenging problems involved in the automation of heavy earth-moving machines are highlighted. In the next two sections after this section, the focus is moved to aspects related to remote control of earth-moving machines due to their significantly growing presence in industry.

The majority of the reviewed papers aimed towards automation of earth-moving machines can be categorized in one of the following areas.

4.1 Modeling for control

A machine model is required for developing automatic control functions for all three steps of a short loading cycle i.e., loading, navigation and dumping. An automatic control function for loading also requires a model for the bucket-media interaction. In Fig 3, a block diagram depiction of this approach is presented in the form of a closed-loop control framework. There are some issues with this representation of the system. First, as highlighted in the diagram, the bucket-media interactions are too highly complex and stochastic to be accurately captured by any practical measurement system. Second, the model of the pile \( G_p \) in (3) is also unknown and changing during each loading cycle. Modeling the machine \( G_m \) in (3), alternatively, is an easy task comparatively.

4.1.1 Modeling the kinematics-dynamics of the machine

Modeling the machine boils down to representing the robotic mechanisms (links, joints and the tool), the hydraulics and the power train of the machine in terms of kinematic or dynamical equations. Several pieces of literature exist that present the model of excavators or wheel loaders. In [17], a dynamic model of a back-hoe excavator has been developed. In [18], the kinematic and
dynamic model of a tracked earth-moving machine is presented. The robotic mechanism of the machine in this paper is similar to that of a typical wheel loader. In [10], models are developed for an LHD machine to be used for autonomous navigation.

4.1.2 Modeling of bucket-media interactions

Many efforts, from as early as 1960’s, have been conducted to create models that represent the bucket-media interactions. These early models were based on the interaction forces between the tool and the media, and many of them converge to a five-force model, presented in [19] and [20]. A good review of many investigations into determining bucket media interaction is presented in [21]. These models are often very complex and so computationally expensive that they remain unusable for real-time automatic control. However, in [22], an over-simplified model based on the 5-force bucket-soil interaction model is used in a closed-loop compliance control scheme. Despite a considerable amount of discussion on such models, a reliable bucket-media interaction model has not yet been achieved.

4.2 Automatic loading

Due to the complex nature of the bucket-media interaction, developing automatic loading functions that are better than or equal to expert manual drivers with regard to performance is a highly difficult task. One of the main questions for the automatic loading control problem is which signal should be controlled [2] and which signal should be used for the feedback. Due to the existing challenges in this problem, only a few control philosophies can be implemented. In this subsection, the possible candidates for solving the automatic loading problem are discussed.

With the aim to develop an automatic loading function, most research works start by studying the actions of expert drivers during loading. Full-scale experiments with instrumented wheel loaders and excavators are performed to interpret the driver’s philosophy of loading. Researchers use these results to give direction to their research work. In [1] and [11], experiments with a wheel loader are performed, with the loading of sand, gravel and fragmented rock by 80 different drivers ranging from novice to skilled. The aim of this experiment was to establish the basis for an automatic loading function. In [23], full-scale experiments are performed with an LHD machine loading fragmented rock. In [24], another study on the actions of drivers while excavating soil with an excavator is presented.
4.2.1 Position (trajectory) control

One idea for loading the bucket is to follow a planned trajectory. This idea is based on the early work by [25] in which the aim is to maximize the volume between the trajectory cut and the profile of the pile. A limiting factor for this approach is that, with the available technology for pile characterization (laser scanners or vision-based systems), only the surface of the pile is illuminated, which is not enough information to define an optimal trajectory. Although the idea of trajectory control is comprehensible, it fails to capture the fact that following the desired trajectory may be impossible in a real-world situation of non-homogeneous media.

Many current researchers take trajectory planning as a starting point for their work, as in [12] and [26]. Although a trajectory may be approximately followed for low-density sand or wood chips, it is impossible to follow a trajectory for high-density media, such as fragmented rock. This is because of the immense amount of resistive forces on the tool by the media, which drives the actuators into saturation and sometimes also results in wheel slip. In [23] and [27], it is noted that, since the aim of the control system is to fill the bucket and not to follow a predefined path, trajectory control should not have priority.

4.2.2 Compliance control

It is not surprising that strict position (trajectory) control can only be realized in extremely low-density media and not while moving through a pile. To address this fact, several opinions have converged on the idea of modifying the trajectory of the tool on the fly in compliance with the resisting forces on the tool. This type of control philosophy named here as compliance control, is also found under several other names, such as two-level (force, position/velocity) control, force-feedback control, inner-outer loop control, admittance, impedance control and more. Compliance control is a fundamental area of research in robotics [28].

A clear and basic formulation of compliance control with an improvement in its formulation is presented in [29]. In [3], [22], and [30], compliance control is applied to excavators. In [23], it has been suggested to use the bucket cylinder pressure as an input for admittance control for automatic loading of fragmented rock. Research in the mobile robotics field that combines the ideas behind admittance and impedance control is presented in [31]. A small-scale laboratory experiment designed around wheel loader operation to advocate a compliance control strategy to modify tool trajectory is presented in [32]. Recent industrial interest towards automation of earth-moving machines can be seen in a patent based on velocity control of the digging work cycle of an excavator in [33].

4.2.3 Feed-forward control

In a feed-forward control scheme, the focus is on measuring the effect of disturbances to the system and pre-compensating their effect by modifying the controller actions. In the setting of an excavation process, the disturbances would be the tool-media interaction forces for a trajectory control problem. Some researchers argue that the un-modeled dynamics of the pile (\(G_p\) in Fig. 3) can be modeled as a disturbance to the process. For example, in [34], the interaction forces from the pile are assumed as a disturbance, and it is suggested that a robust controller could be sufficient to counteract the resisting forces. However, this study is only backed up by a simulation study. In [3], a disturbance observer for the resisting forces is proposed, and an iterative learning algorithm has been used to model the repetitive part of the resisting forces. In this work, experiments are performed by a 1.5-ton excavator but only on near homogeneous soil, which does not resemble, for instance, a fragmented rock scenario. In summary, it is hard
to conclude that modeling the pile only as a disturbance to the excavation process can be used
as a general approach for the autonomous excavation problem.

4.2.4 Artificial intelligence methods
The automatic bucket loading problem has also received attention from the artificial intelligence
research community. Modeling the tool-media interaction is impossible [35], and the traditional
control techniques can be impractical or infeasible, especially for rock excavation [36]. This
is often the motivation behind exploration of artificial intelligent techniques, such as neural
networks and fuzzy logic, to address this problem. In [35] and [36], a small-scale experiment
is designed to investigate the excavation process and involves digging out two rocks of varying
sizes from a pile of muck. Their approach for handling the excavation goal is to break the goal
down into different tasks, which are further broken down into excavation behaviors and actuator
actions. In their work, the excavator behaviors and actuator actions are coded using fuzzy logic
and a neural network based on finite state machine methods. [37] further continues the work on
fuzzy logic control for robotic excavation presented in [35] and [36].

Other works that also use rule-based methods for robotic excavation are [38] and [39]. These
data driven methods rely more on the experiment than theory, and a common idea behind
these artificial intelligence-based methods is to code the intelligence of an expert operator into
a computer program. A rational criticism against the proposal of being inspired by an expert
operator comes from [27], which states that the way an operator has learned to use the earth-
moving machine might not be the most efficient method to control the machine.

4.2.5 Reinforcement learning methods
Reinforcement learning is a field in machine learning that finds some of its applications in the field
of automatic control. In reinforcement learning, an autonomous agent (controller) interacts with
the environment (via sensor and actuators) in real-time and learns to choose optimal actions
to achieve its goal [40]. Because several reinforcement learning algorithms are model-free, it
is attaining the interest of many research groups. A good survey of several algorithms and
challenges for applying reinforcement learning in robotics is presented in [41].

Although reinforcement learning has never been applied to robotic excavation to our knowl-
edge, it is a promising potential candidate to address the automatic loading problem. Because
excavation tasks take place in an episodic setting with a significant interval between two bucket
loadings, the real-time constraints on reinforcement learning are not so harsh. Furthermore,
if excavation data from an expert driver is available, it can be included in the framework of
imitation learning to create a baseline controller for learning experiments [41].

Reinforcement learning is applied in robotics to control humanoid robotic arms in [42]. They
use a Q-learning algorithm where the Q-value function is learned by neural networks. In [43], a
review of reinforcement learning is presented from the view point of adaptive control. Despite
reinforcement learning and optimal control being somewhat related fields, reinforcement learning
cannot guarantee optimal performance for autonomous loading, mainly because of the absence
of a complete model of the earth-moving process.

4.3 Pile characterization
Pile characterization is an area of interest in robotic excavation that uses machine vision tech-
niques to aid autonomous and remote operation. Some applications of pile characterization via
vision-based systems are identifying a good excavation location for short-term (e.g., next scoop)
and long-term action (e.g., task planner), and computing the most suitable pose of the machine to scoop the next bucket. Other applications include identification of the quality of blasted rock and estimation of the volume of the loaded material in one scooped bucket.

In [44], stereo vision is used to identify the best loading location on the pile of material to be moved. In [45], a laser-based task planner is developed for an excavator and has been shown to be capable of excavating the ground as fast as a human driver. A similar method for determining the attack pose for wheel loaders is discussed in [46].

Apart from the attack pose, laser scanner data has also been used to identify large boulders in the pile [47]. In [48], a stereo vision system has been demonstrated to estimate the fill factor of soil in the bucket.

4.4 Localization and navigation

Localization and navigation are relatively more discussed topics, especially in the field of mobile robotics. From this heritage, the navigation techniques for mobile earth-moving machines are already quite advanced. Several companies, including Caterpillar, Atlas Copco and Sandvik, offer navigation products for the mining industry, and many sites already use automatic hauling in their mines [49]. Laser-based techniques are dominant in localization and navigation in underground mines. Some good references that use laser scanners in their work are [5] and [8]. In the scope of a short loading cycle, a relative localization technique between the dump truck and the wheel loader is also a viable solution. The main challenge during navigation in a short loading cycle is to avoid collisions with the walls, boulders and other vehicles. Recent advancements in ultra-wide-bandwidth technologies [50] can also be exploited for the relative navigation between the wheel loader and the dump truck.

4.5 Path planning

In the short loading cycle, the wheel loader moves on a slightly varying V-Y curve, as shown in Fig. 2. The aim of path planning is to generate this V-Y curve given the starting pose of the machine, the pose of the dump truck and other constraints (walls and obstacles). Different objectives for optimizing this V-Y curve as noted in [51] are fuel efficiency, travel distance, travel time and more. Another recent publication concerning path planning for a short loading cycle is [52]. The surfaces at earth-moving operation sites can be bumpy and uneven due to pebbles and small rocks, and for this reason, a 3D relative localization could be a better alternative than 2D localization methods.

5 Communication for remote operations

It is identified in [2], [10] and [38] that operators make their decisions based on their vision, the sound from the surroundings and the vibrations from the machine. Because an operator in manual operation uses all his visual (3D), auditory, tactile and other sensory organs to operate the machine [27], the tele-remote operator should also be provided with more feedback than just plain video streams for different views around the machine. Although it is undesirable to trouble the tele-remote operator with noisy sound feedback and uncomfortable vibrations, some reduced form of audio and vibration feedback will certainly help the remote operator. In total, there can be four types of streams of feedback data to the remote control station along with the upstream of control commands as shown in 4.
5.1 Wireless network properties

Because mobile machines usually need to communicate over wireless links, the adverse effects of wireless channels, such as multi-path propagation, varying signal strength and interference, can plague the communication performance. Even a small glitch or delay in the feedback data can significantly destroy the experience of the remote operator, affecting their ability to control the machine. Therefore, the design of a good communication setup should not be overlooked when designing a tele-remote control system for mobile earth-moving machines.

Although specialized wireless networks could potentially offer highly predictable performance, the benefits of using multi-purpose wireless networks that can not only be used for tele-remote operations but also for other applications motivate the choice of network technologies that can carry Internet Protocol (IP) traffic. Choosing a technology such as wireless local area networks (WLANs) is also attractive for reasons of cost savings since WLAN equipment is widely popular and therefore less expensive.

A reliable wireless communication system is also very important to a fully autonomous system to monitor the safety of the operation, e.g., by overseeing the operation and acknowledging safety-critical tasks and actions. Although communication is critical for the remote earth-moving operations, it is far less discussed in the literature. A valuable discussion of communication solutions for underground mines is presented in [53]. The requirements of the tele-remote control solution from the communication system are low latency, minimal loss and high throughput. In [34], a Simulink-Opnet simulation is implemented to test a proposed communication system for a tele-remote control solution.

Wireless communications at construction sites and in industrial and mining environments may be provided with a combination of different network technologies. For example, IEEE 802.11ac [54] or IEEE 802.11n [55] WLANs can be deployed and controlled specifically for a construction site, industry or mine. To extend the wireless network coverage, such WLAN deployments may be complemented with 4G cellular infrastructures based on ETSI 3GPP LTE-Advanced [56]. These wireless networks technologies are capable of several hundreds of Mbps to Gigabit speeds, but as with most wireless communications, the actual speed varies with radio conditions. When disturbances such as undesired reflections causing multi-path propagation and interference appear, receiving devices experience errors in the received data, which makes the system adapt to stronger coding and consequently lower transmission rates.

In datagram-based networks, queuing delays, jitters (i.e., delay variations) and eventually loss of data appear when the communication speed falls short of the data consumption rate of the application. The amount of buffers allocated for queuing in WLAN devices is decided based
on a trade-off between delay and throughput. For example, a maximum of 1600 datagrams may
need to be buffered at outgoing IEEE 802.11n interfaces to ensure that the network can operate
at its full capacity [57]. With such an allocation of buffer space, delays of more than 300 ms
can appear when the network is saturated. In addition to the latencies that occur when data is
queued for transmission, link-layer retransmission of data can also cause delay and jitters.

For tele-remote operation of earth-moving machines, the risk of being exposed to throughput
degradation and excessive delay and jitters can be reduced by designing a system in which the
demand for capacity stays well below the available network capacity. However, this approach
alone can prove fatal when the wireless network suffers from unpredictable variations in radio
channel quality. Recent IEEE 802.11 standards offer schemes and mechanisms that provide
Quality-of-Service (QoS) satisfaction for real-time multimedia flows over WLANs, allowing the
prioritization of mission-critical streams for tele-remote operations [58]. Still, available wireless
capacity can vary greatly and can cause severe problems for the operation.

5.2 End-to-end transport services

Varying wireless capacity can be handled by adapting the sending rates of the different data
streams for tele-remote control. In Internet Protocol (IP)-based networks, such adaptation is
typically performed at the endpoints of the communication system. The widely used Transmis-
sion Control Protocol (TCP), originally published as an Internet standard in 1981, provided
congestion control and avoidance for applications on IP-based networks [59]. TCP, however, has
some disadvantages for the real-time communication required for tele-remote operations. That
is, TCP may introduce undesired delays due to its mandatory in-order delivery feature since it
buffers data awaiting successful re-transmission of lost packets [60]. This problem is referred
to as head-of-line blocking. Alternatively, the User Datagram Protocol (UDP), the other most
commonly used transport layer protocol on IP networks, does not implement congestion avoid-
ance and control, and applications using this protocol may hence overload wireless networks,
resulting in high loss rate, jitters and extensive delays.

The end-to-end communications for tele-remote operations over IP networks share many
requirements for telephony signaling transport. The need of telephony signaling transport over
IP motivated the design of a new protocol for signaling transport. As a result, the Stream
Control Transmission Protocol (SCTP) was published by the IETF (Internet Engineering Task
Force) as a standard track document in 2007 [61]. SCTP provides similar congestion control
and avoidance as TCP along with additional features, such as avoidance of head-of-line blocking
of messages and multi-homing for endpoint devices.

Head-of-line blocking can be avoided with SCTP by using the unordered delivery service
offered by this protocol. The multi-homing feature allows an endpoint device to be connected
to its peer endpoint via more than one network interface. This feature is highly desirable for
tele-remote operation as it allows for the possibility of switching to a backup wireless network
if the primary one becomes unavailable, e.g., from a WLAN to a 4G network. Extensions to
SCTP for partial reliability (PR-SCTP) further allow for the early discard of stale data, such as
delayed video frames or control messages [62]. In [63], it is shown that limiting the maximum
number of retransmissions with the H.264/AVC video standard can provide reliable delivery
similar to TCP along with lower delay. In general, the scalable video coding extension of the
H.264/AVC standard offers temporal, spatial, and quality scalability to video streams, which
allows the use of rate-adaptive transport protocols, such as TCP and SCTP [64].

Given the several advantages of SCTP over TCP and UDP, it appears as a valid alternative
for the end-to-end transport of streams for tele-remote control of earth-moving machines. An-
other alternative for video transport is the TCP Friendly Rate Control (TFRC), which offers a much lower variation of throughput over time compared with TCP or SCTP. This makes TFRC more suitable for applications where a relatively smooth sending rate is of importance [65], such as streaming media. TFRC can be used with the Datagram Congestion Control Protocol (DCCP), which is a transport protocol that provides bidirectional unicast connections of congestion-controlled unreliable datagrams [66]. Multi-homing support for DCCP is currently being considered by the IETF for possible standardization [67].

5.3 Key communication aspects

As discussed above, the importance of good wireless communication for tele-remote operation of earth-moving machines should not be underestimated. Modern wireless technologies, such as IEEE 802.11ac, IEEE 802.11n and 3GPP LTE-Advanced, are likely to provide the desired communication quality, but the network load and varying radio condition need to be carefully considered and properly handled through careful design and planning. Available schemes and mechanisms for QoS should be used to prioritize mission-critical messages. Additionally, transport layer protocols offering features such as congestion control and avoidance without head-of-line blocking and support for multi-homing can prove valuable for tele-remote operations.

6 Remote control station

The tele-remote operation of earth-moving machines is gaining popularity in some industries. Remote-controlled equipment does provide a present-day solution while autonomous solutions evolve. In this section, a remote control station is discussed in brief.

6.1 Human-machine interaction

Because remote control demands real-time interaction with the operator, the Human Machine Interface (HMI) should provide only the necessary information for efficient remote operation. Irrelevant information should be suppressed to lessen the stress on the remote operator. An advanced HMI is proposed for excavators in [68], where a complete virtual environment of the excavation task has been envisioned with heads-up displays. Virtual reality may be suitable for a minimally moving excavator, but it may not be so useful to apply to a short loading cycle due to the mobility of the machine. Stereo vision displays have been proposed in [69] for presenting augmented reality of industrial robots. In [70], haptic feedback joysticks are proposed for excavators. Many of these techniques can be used to present feedback from the wheel loaders to the remote-operator, but they should only be included if they improve the conditions for efficient remote operation.

6.2 Task planning

Some researchers strive for automation of the mobile earth-moving machines from the highest level, and they aim to break the main objective down into smaller tasks much like how a human operator will see the work. A task planner software implements such an architecture to help the operator or the autonomous agent in making high-level decisions (e.g., discretization of the working area into a grid for planning the excavation). A task planner for an excavator using
state chart flow diagrams has been developed in [71] and [72]. Another task planning algorithm for excavators working in a wide-open area is proposed in [73].

7 Other related works

In this section, research areas that do not fall into the previous categories but which are still quite interesting with regard to automation of earth-moving machines are discussed in brief.

7.1 Power-train and traction control

The research in traction control and power-train technologies also addresses autonomous earth-moving aspects by posing certain requirements. The problem of wheel slip during loading of heavy and dense media already raises enough questions to open the scope. Efficient transmissions aim to minimize the fuel consumption and wear and tear of tires. In [10], improvements in the traction control of LHD machines are proposed. In [74], advanced control theory has been applied on the wheel loader transmission to improve fuel efficiency.

7.2 Simulation of the environment for development and training

Detailed computer simulations are used to design control systems and to develop operator training simulators. Unfortunately, for wheel loaders and excavators, the environment is unpredictable, and the forces exerted by the media (soil, sand, gravel, rock, etc.) are random and unpredictable. Nevertheless, efforts to simulate the environment can be seen in some of the literature. In [26], a pile of consistent gravel is simulated to study different bucket trajectories for wheel loaders, and in [75], a simulation of soil is developed to test automatic loading functions for excavators.

7.3 Connected things at mobile machines

Earth-moving machines are for different reasons equipped with various types of ad-on sensors. For example, construction equipment for autonomous and remote operation requires video cameras and laser sensors [5, 8, 32, 45, 47, 48] and autonomous loading could further require speed and pressure sensors [10, 23]. Additionally, construction equipment industry strives toward remote health monitoring of key components in machines to facilitate proactive and predictive maintenance [76]. Remote monitoring includes logging, pre-processing, and wireless transmission of controller area network (CAN) signals, and data from ad-on sensors [77]. For example, accelerometers may be mounted at a strategic location on machines to detect wear and fatigue of critical components such as a wet clutch of a wheel loader [78].

The increasing need for connecting sensors to construction machines turns them into mobile cyber-physical systems (CPS) and a part of the Internet of Things (IoT). The communication techniques discussed previously not only facilitates remote operation, but also the transport of sensor data to an Industry Control System (ICS) and to advanced machine analysis systems [78].

7.4 Survey work

There is much evident interest in automation of mobile earth-moving machines, which has generated quite a selection of survey papers. Two papers, [2] and [19], provide excellent background
and knowledge for automation of the loading step. A survey work specially targeting automatic loading of fragmented rock is [79]. An overview of navigation technologies for LHD machines is presented in [13]. A couple of good survey papers in the field of the automation of excavators are [4] and [80]. Some recent work towards automation of wheel loaders is presented in [81] and [82].

8 Knowledge gaps

Despite the long on-going research for automation of earth moving machinery, there are some under-explored areas. In this section, such knowledge gaps are discussed to motivate further work in this field. Some areas, such as navigation, dynamic modeling and optimal trajectory for the bucket, have received much attention, which has helped the research in these areas to move forward significantly. Alternatively, some areas lack attention or are relatively new.

8.1 Fragmented rock

In [79], the need for specific research on the loading of fragmented rock has been noted, highlighting the fact that bucket-rock interactions are much more complex than bucket-soil interactions. While developing automatic loading functions for fragmented rock, it might be necessary to adapt the loading algorithm for different grades of blasted rock. In [83], a method to estimate the fragment size distribution after blasting has been discussed. Many papers develop methods for automatic loading of rock, but very few perform experiments on fragmented rock. More experimental research is required in regard to the loading of fragmented rock mainly because the pile cannot be modeled in this case. Additionally, the potential use of artificial intelligence or machine learning methods, or a combination of these methods, needs to be further explored.

8.2 Communication performance for remote operation

The latency in audio and video are important issues for tele-remote operation. Humans can tolerate audio delays up to 400 ms [60], but beyond that, it can hamper the control. Wireless network jitters can cause many frames to be dropped, resulting in sluggish video. Although one argument says that these problems can be mitigated just by upgrading to higher bandwidth or by using available schemes and mechanisms for QoS, a good throughput can never be guaranteed over wireless network due to signal degradation, multi-path propagation and interference. Therefore, it is important to use the network bandwidth efficiently by choosing the most suitable protocol suite for tele-remote operation, especially at the end-to-end transport layer.

Candidate transport layer protocols for tele-remote operation include SCTP [61], DCCP [66] and TFRC [65]. TFRC can prove beneficial for the scalable video coding extension of the H.264/AVC standard, which offers temporal, spatial, and quality scalability to video streams [64]. The use of these transport protocols (or others) for tele-remote operation remains to be explored and tested together with wireless network technologies to gain more knowledge on how a dependable communication solution should be designed.

8.3 Operator experience during remote operation

Operator experience makes a big difference in remote control performance. In manual operation, drivers use their vision, hearing and balance-detecting capacities to judge and make decisions in real-time. It is possible to create a virtual reality for the remote operator with a motion simulator
and head-mount display with surround sound. However, doing so dilutes the main reason for removing the operator from the harsh environment. Additionally, any form of feedback to the remote operator will be slightly delayed, which should be minimized as much as possible. Force feedback-enabled joysticks and pedals can be of interest for improving the operator’s experience, especially during loading. Hence, suitable means of feedback to tele-remote operators of earth-moving machines require more attention.

9 Summary and future work

There is increasing interest in the automation of mobile working machines. Automation of wheel loader operation has its own challenges because of high levels of interaction with its environment during loading.

This paper provides background for the problem of autonomous excavation, presents a wide literature survey covering several research topics and concludes with the identification of knowledge gaps for autonomous/tele-remote operation of earth-moving machines. Automation of mobile earth-moving machines involves many different research areas. Although the article is slightly inclined toward operation of wheel loaders in a short loading cycle, this setting covers several aspects of autonomous earth-moving, which is seen as the future by several industries, including mining, construction, and forestry.

The research relating to excavators has advanced ahead of the research relating to wheel loaders, which can be noted from the fact that the majority of citations listed in this article have performed experiments with excavators. However, excavators, unlike wheel loaders, are much less mobile during operation, which makes wheel loader automation more challenging. The more extensive movements of the wheel loader challenge the wireless communication needed for tele-remote operations. This motivates the need for careful consideration and planning to balance the communication load and wireless network capacity as well as the proper use of available schemes, mechanisms and protocols to obtain the desired quality of the communication services.

There is a split between researchers regarding which approach is more suitable for the automatic bucket loading problem. Two main strategies attempted by research communities are artificial intelligence-based methods and compliance control. However, very few papers have reported results on fragmented rock, which appears to be a mountain not yet climbed.

Future work

Fully autonomous systems that can perform equally well as manual operation are still far-fetched. Future work towards fully autonomous operation needs to address different areas encompassing the following topics.

Autonomous loading algorithms that can adapt to different materials and machines, and can still perform better than or equal to human drivers are important for autonomous operation. Rather than programming based methods, we advocate for learning based methods like reinforcement learning. Model free deep reinforcement learning [84] is an interesting approach which can be build to support variations in machine and material, and could potentially optimize over multiple performance metrics.

Machine to machine communication technology enables task coordination between machines. For example, an autonomous loader and an autonomous dumper working together at a draw point in a narrow corridor in an underground mine needs to communicate with each other and use coordinated path planning and navigation.
Pile shape and geometry characterization enables cognitive decision making by the machine for the loading process. Existing technologies such as laser based lidar system can address this requirement. Autonomous navigation and path planning in a constantly changing environment such as a blasting site should be done with an accurate map of the environment. Simultaneous localization and mapping (SLAM) technology can be used to create the latest and accurate map of the site to be distributed to other machines and to the site management software. The site management technology also requires further research and development to incorporate autonomous machines for their operation, monitoring and maintenance.

The requirements of the construction and mining industries to be more efficient can be met by automation of earth-moving machines, and doing so, also relieve humans from harsh working environments. Adding operator assistance functions over tele-remote operation is a good enabler for companies to increase automation in their operation.

Acknowledgment

The work presented in this article is supported by the Swedish Innovation Agency VINNOVA together with the Energy Agency and Formas under contract 2014-01882. The authors would also like to acknowledge the support of the Swedish companies, Volvo Construction Equipment AB, Boliden AB and Oryx Prototyping AB.

References


Paper C

Machine Learning approach to Automatic Bucket Loading

Reformatted version of paper originally published in:
Machine Learning approach to Automatic Bucket Loading

Siddharth Dadhich*, Ulf Bodin†, Fredrik Sandin‡ and Ulf Andersson§

October 19, 2016

Abstract

The automation of bucket loading for repetitive tasks of earth-moving operations is desired in several applications at mining sites, quarries and construction sites where larger amounts of gravel and fragmented rock are to be moved. In load and carry cycles the average bucket weight is the dominating performance parameter, while fuel efficiency and loading time also come into play with short loading cycles. This paper presents the analysis of data recorded during loading of different types of gravel piles with a Volvo L110G wheel loader. Regression models of lift and tilt actions are fitted to the behavior of an expert driver for a gravel pile. We present linear regression models for lift and tilt action that explain most of the variance in the recorded data and outline a learning approach for solving the automatic bucket loading problem. A general solution should provide good performance in terms of average bucket weight, cycle time of loading and fuel efficiency for different types of material and pile geometries. We propose that a reinforcement learning approach can be used to further refine models fitted to the behavior of expert drivers, and we briefly discuss the scooping problem in terms of a Markov decision process and possible value functions and policy iteration schemes.

1 Introduction

The automation of earth-moving machines is attractive for several reasons including the possibility to avoid having personnel located at dangerous and inhospitable workplaces such as underground mines. Productivity can also be improved by eliminating the time to transport personnel to and from the workplace and by reducing other human related delays. Tele-remote operation is considered as an intermediate step towards fully autonomous operation. Although operators are still needed with tele-remote operation, benefits such as improved safety and reduced transportation time for the personnel can be achieved. With a combination of tele-remote machines with autonomous capability, the operational cost can also be reduced by having each operator drive more than one machine at the remote control site.

This paper focuses on the automation of bucket loading for front-end wheel loaders. An autonomous loading function is useful for both fully autonomous and tele-remote operated machines. This is because a remote operator lacks proper visual, auditory and tactile feedback needed to perform the bucket loading efficiently. A case study included in [1] demonstrates

---

*S. Dadhich is a PhD Candidate at the Luleå University of Technology, Sweden (siddharth.dadhich@ltu.se).
†U. Bodin is a senior lecturer at the Luleå University of Technology, Sweden (ulf.bodin@ltu.se).
‡F. Sandin is an associate senior lecturer at the Luleå University of Technology, Sweden (fredrik.sandin@ltu.se).
§U. Andersson is a project leader at ProcessIT Innovations at the Luleå University of Technology, Sweden (ulf.andersson@ltu.se).
that the average bucket weight during loading of fragmented rock by a Load-haul-dump (LHD) machine by an operator on tele-remote remains significantly lower compared to that of a driver loading a bucket, even with a driver assisting function for loading. This motivates the need for developing an autonomous loading algorithm for front end loaders.

This paper presents analysis of data recorded during loading of different types of gravel with a Volvo L110G wheel loader. We argue that a reinforcement learning (RL) approach can be used to further refine a model fitted to the behavior of expert drivers, for example by fine-tuning regression model parameters. With an RL approach the loading operation can be optimized in mathematical terms, possibly beyond the capability of expert drivers. A learning based algorithm can combine multiple optimization criteria like high average bucket weight, short loading time and low fuel consumption better than a driver.

Wheel loaders are versatile machines that are used in many industries including mining, quarries and construction. These machines come in different sizes and may have different types of linkage for the boom and bucket depending on the intended use. The LHD machine is a type of lower built wheel loader optimized for tough excavation of fragmented rock in underground mining. These machines are typically operated in load and carry cycles, where the material is transported from a draw point to a dumping place. They have a Z-link for high breakout force and have bigger sized buckets for good performance at longer hauling distances. More general wheel loaders come in many different sizes and may have other types of linkage to enable for more general use. For example, Volvo uses a TP linkage for most of their wheel loaders.

The diversity in wheel loader machine construction, size and their usage motivates the search for a general solution for automatic bucket loading. In this paper, we outline an approach for
developing a general solution that can be applied to different machines and different material and pile geometries. In particular, we examine the possibility to fit regression models to the scooping actions by an expert driver, and we outline an RL approach for further optimization of automatic bucket loading models like regression models.

Alternatives to learning based methods include position (trajectory) control approaches, which require having the bucket follow a planned trajectory as described by [2]. Although this approach has been used as a starting point in many works as in [3], it is impossible to follow a trajectory in high-density material such as fragmented rock. This is because actuators are typically driven into saturation by the immense amount of resistive forces on the tool by such material. Also, wheel slip may occur in the attempt to follow the planned trajectory. It is pointed out in [4] and [5] that the aim of the control system is to fill the bucket and not to follow a predefined path and thus trajectory control should not have the priority.

Accurate trajectory control is only possible in extremely low-dense material and not while traversing through a pile of gravel. One strategy for addressing this problem is to modify the trajectory of the bucket in compliance with the reaction forces on the bucket [6, 7]. More importantly, this idea has recently been shown to be applicable for LHD machines [8]. We argue that compliance control does not address all aspects that a general automatic loading algorithm should have, e.g. variation in machine construction, size and use as well as performance parameters like fuel efficiency. This motivates an investigation of learning-based methods in search for a general solution that is invariant with respect to changes in such variables.

Methods for rock excavation based on artificial intelligence have been considered in former studies. For example, [9], [10] and [11] have examined the use of fuzzy logic control for robotic excavation. Also, [12] and [13] have presented rule-based methods for such excavation. These data-driven methods rely on experiment rather than theory and a common idea behind these approaches is to code the intelligence of an expert operator into a computer program. That approach has been criticised [14] because operators may not use the most efficient strategy and control methods when operating a machine. Also, mimicking an expert operator is not easy given the substantial variation in machines and type of piles to load. We believe that a reinforcement learning approach could capture such variation, although to our knowledge it has never been applied to robotic excavation. In particular, we suggest that model-free reinforcement learning algorithms [15] combined with deep learning is an interesting approach for a generic solution for automatic loading of bulk material of different types.

2 Problem description

The problem of automatic loading for front end loaders has been studied since a long time [14]. In [1], the aim of loading is defined as scooping the maximum possible amount of material in the least amount of time with minimum fuel consumption. In order words, productivity and fuel efficiency are two optimization criteria for an automatic loading operation. The absence of an accurate model of the material to be scooped prevents the use of optimisation methods like model predictive control. Fig. 1 illustrates the automatic loading problem in terms of a control block diagram and the interaction forces between the machine and pile.

2.1 State of art

Recently, it is shown [8] that an automatic loading function for a difficult material to be scoped (fragmented rock) can be based on the force acting on the lift hydraulic cylinder. In that solution, a fixed gain proportional controller is used to command the tilt cylinder with an error signal
computed as the difference between a fixed reference signal and the actual value of the force on the lift cylinder. They therefore treat the problem as a Single-Input-Single-Output case by not actively using the lift cylinder and keeping the throttle value always at maximum. In [7], a combination of iterative learning with impedance control is presented for soil excavation with excavators. A study of four different trajectory based loading algorithms is presented in [16]. They also discuss fuel efficiency of different scooping styles and present results from a discrete element method (DEM) for particle simulation of soil.

Figure 2: Variables involved in a loading operation. A general automatic loading solution should address variations among the machines and the material to be scooped.

### 2.2 Variables in the loading operation

There are several operational variables in the general automatic loading problem as pointed out in Fig 2. Some of these variables influence the problem significantly. For example, the newer generation of wheel loaders with hybrid and electric drive-trains will pose different conditions, requiring significant modifications of automatic solutions developed for diesel machines. The geometrical dimensions, the hydraulic construction and the shape and size of the pile also play a significant role for the relative usage of lift and tilt to scoop with maximum productivity and fuel efficiency.

A general automatic loading solution is an approach which can address more than a few variables pointed out in Fig 2. We argue that the state of art approaches needs to be extended with learning based methods to address several aspects of the general automatic loading solution. These aspects include operation variables like machine dimension, specifications of the drive-train and hydraulic system and performance parameters like fuel efficiency.

### 3 Experiment

We conducted bucket loading experiments with a Volvo L110G machine driven by an expert driver from Boliden AB on a few different types of piles. Before the experiments, the machine was modified with custom instruments in order to do specific measurements. In this section we
discuss the instrumentation of the machine and the experiments conducted on the different pile types.

3.1 Instrumentation

The machine used in the experiment a Volvo L110G, is a front-end wheel loader with a breakout force between 145-158 kN with a general purpose regular bucket (without teeth) [17]. The machine was equipped with pressure sensors in the hydraulic system and an accurate speed sensor solution consisting of a cogwheel and proximity sensors. We mounted four pressure sensors, two at each end of lift and tilt pistons to compute the forces \( f_L \) and \( f_T \) (see Fig 1). The position of lift and tilt cylinders \((l_L, l_T)\) are extracted from the machine’s internal Canbus using a system developed in [18].

The pressure data is logged at a sampling frequency of 20 Hz which we find to be sufficiency high given the delays present in the hydraulics system, which slows down the dynamics of process. The motion of machine components (buckets, pistons, body) are also damped due to their inertia and presence of software filters in the machine computers (ECUs) further limits the dynamics of the signals.

Based on the pressure sensors, we developed a simple weighing scale solution shown in Eq. (1) to estimate the scooped weight in the bucket where the coefficients \( c_0 = -6.4342, c_1 = 0.0476, c_2 = 0.2568, c_3 = 0.9878 \), are obtained with a least square fit and tested to be accurate to 8\% (\( \pm 0.3 \) tonne) on our test examples.

\[
W = c_0 + c_1(P_{LH} - P_{LL}) + c_2v(l_L) + c_3v(l_T)
\]  

where \( P_{LH}, P_{LL} \) are pressures in the bore (high pressure during scooping) and piston side (low pressure during scooping) of lift cylinder in the range of 0-250 bar and \( v(l_L), v(l_T) \) are raw voltages in 0-5V range which corresponds to lift and tilt cylinder lengths.

3.2 Pile

In order to study the general characteristics of an automatic loading solution, it is important to do experiments with a variety of materials. We collected data from two types of piles, two of which are shown in Fig. 3. The Volvo L110G machine is not well suited to load rock such as in pile Type II and thus it becomes difficult to use this data to draw significant conclusions.

![Figure 3: Two types of piles used in the experiments. Type I (left) is gravel and cobbles of size 0-150 mm. Type II (right) is mainly cobbles and rock with high size between 0-500 mm. Type II resembles the most difficult case with fragmented rock like that in mining applications.](image)

In Fig. 4 and 5, we show examples of scooping data in terms of piston lengths, forces exerted on the piston, and the speed of the machine for piles of Type I and II. Based on visual inspection
of data for some recordings with the two types of piles, we concluded that driver actions were more aggressive for rock, resulting in high-magnitude forces on the piston. The bucket trajectory in gravel (Type I) has less variability compared to rock, which had more zig-zag motion in the tilt action. Sometimes, a single attempt at loading rock (Type II) fails, forcing the driver to go for multiple attempts.

In the next section, we exercise supervised learning in the form of regression model on the data from Type I pile to investigate the relationships between reaction forces $f_{LR}, f_{TR}$ (see Fig. 1) and other variables in the data.

4 Regression model of manual operation

In order to understand the relationship between the forces applied by the hydraulic system on the lift and tilt pistons and the reaction forces of the pile on the lift and tilt pistons, a regression
model of the trajectories through the pile is considered.

Since the pile is not prepared in any particular way before scooping, all instances of scooping in this study differ significantly from each other and are biased mainly by the behavior of the expert driver. The high variance of the data is studied with the regression model. There is significant variability in the pile forces and the driver actions between each scooping and we address the question whether there are systematic relationships between the variables approximating the behavior of the expert driver and the pile.

In Fig. 1, the independent variables of the problem are the actions (tilt stick \( j_T \), lift stick \( j_L \) and throttle pedal \( t_P \)) and the forces from the pile \((f_{LR}, f_{TR})\). The dependent variables, the forces from the hydraulic system on the tilt and lift pistons \((f_T, f_L)\), can be expressed as a function of the independent variables as

\[
f_T, f_L = f(j_T, j_L, t_P).
\]

The reaction forces from the pile on the lift and tilt pistons \((f_{LR}, f_{TR})\) are not possible to measure and cannot be included directly in the regression model. Our aim is to study whether a basic regression model can describe the scooping behavior of an expert driver when the forces \(f_{LR}, f_{TR}\) are omitted. With a good regression model the effect of neglected forces \((f_{LR}, f_{TR})\) should be reasonable and the variance of the regression model residual should be low.

For the regression analysis, we treat \( f_L, f_T, l_T \) as input variables for predicting \( l_L \), and \( f_L, f_T, l_L \) as input variables for predicting \( l_T \). Although \( f_{TR} \) is non-measured and included in the regression model, it is related to the variables \( f_T, l_T \) and \( l_T \) by the Newton's laws. A similar argument can be made for \( f_{LR} \). The output variables \( l_L \) and \( l_T \) define the trajectory of the bucket through the pile.

We select the forces \( f_T, f_L \) instead of driver actions \((j_T, j_L, t_P)\) as the basis of regression because the driver actions are non-smooth. Drivers often overshoot and then over-compensate the joystick movements to counter the software filters which are in-place to protect the machine from jerky signals from operators. Doing so we could also avoid the variable delay present in the hydraulic system which varies between 250-300 ms. In the final automatic solution we want to produce smooth commands to the hydraulic cylinders and therefore it is more natural to study the motion of cylinders instead of the joystick signals.

Since bucket loading is a variable mass problem, the impulse imparted \((I_T, I_L)\) to tilt and lift pistons are also important variables for expressing the dynamics of the pistons

\[
I_T = \int_0^t f_T dt \quad I_L = \int_0^t f_L dt.
\]

We use linear regression with feature vector \( \{I_L, I_T, f_L, f_T, l_T\} \) for predicting \( l_L \), and the feature vector \( \{I_L, I_T, f_L, f_T, l_L\} \) for predicting \( l_T \). The coefficient of determination, \( R^2 \), describes how well the data fit the regression model, or more precisely how much of the variance is explained by the model. An \( R^2 \) values close to 1 indicates that the data fits the model well in terms of variance. Here we consider standard \( R^2 \) values that are adjusted for the complexity of the regression model. The adjusted \( R^2 \) of the regression models of lift and tilt actions by the expert driver are illustrated in Fig. 6. The regression model for the length of the lift cylinder is significantly better than that for the tilt cylinder mainly because the tilt actions vary when the bucket exits the pile (breakout). In Fig. 7, the prediction of the regression model is shown for one scooping example. The deviation between the regression model and driver data towards the end of scooping indicates a loss of contact between the pile and the bucket.
Figure 6: Goodness of fit versus the number of training examples. The adjusted $R^2$ coefficient initially decreases with the number of training examples before it settles.

The regression model combines the effect of hidden variables related to the driver (actions) and the pile, and averages over the variation of these variables to give a representative model of manual operation. The output of the regression model for this machine and driver scooping on a Type I pile are promising but not good enough to build a final solution. More importantly, a regression based method does not provide a general solution because the requirements of loading maximum amount of material with least amount of time and minimum fuel consumption have not been included.

This regression model is based on scooping data from one driver. Therefore, it includes the bias of the driver’s level of experience with the test machine and material, and his/her style of scooping. The regression study can be extended by incorporating more data from other drivers to get a better understanding of the limitations of the model.

5 Reinforcement learning

In this section we briefly introduce a reinforcement learning (RL) framework for automatic loading. RL provides a framework to optimize an automatic loading controller for example in terms of the bucket fill factor, cycle time and fuel efficiency. Since a RL solution can be formulated regardless of mathematical model of machine and pile, a general solution is possible to some extent. In this section, we discuss the Markov Decision Process (MDP) which is used to formulate the RL problem and the value function that provides information about preferable solutions. A reward value could be based on the combination of estimate of bucket fill factor, time penalty and fuel efficiency. The aim of the RL algorithm is then to maximize the cumulative reward value for every scooping by solving an MDP model via policy or value iterations.

RL in combination with deep neural networks for flexible function approximation [19] is a promising and highly potent approach to develop artificial intelligence systems that optimize the behavior given a value function, see for example [20] where a deep RL model learns to play atari games better than humans. Although the earth moving process and environment of an atari game are different, the human operator can in principle be replaced by an RL model in both cases.
5.1 Markov Decision Process Framework

In a standard MDP framework, the problem consists of a set of states \( S \), actions \( A \) and a state transition probability model \( T \). The theory of MDPs and RL methods are described in [21].

From the regression analysis of scooping data for piles of Type I, it can be assumed that forces, impulse of forces and the displacement of the pistons are relevant for defining the state \( S \) of the machine during scooping. The speed of the machine is not correlated with the extension of the pistons, hence it could be excluded from the state \( S \) in a first approach towards an RL solution. Function approximation methods can be used to represent states, actions and value functions. They constitute key methodologies when addressing RL problems and become inevitable in continuous state problems [15]. An alternative to function approximation is a tabular representation of the state and action space. For example, a discrete state space \( S \) and action space \( A \) can be defined by a hand crafted discretization of the state and action variables according to Eq. (4). When each state and action is discretized in 10 levels, the size of the state space is one million, and the action space has one thousand states. RL provides different possibilities to improve on the basic linear regression model using model based or model free methods, and some type of function approximation method.

\[
S := [\tilde{l}_L, \tilde{l}_T, \tilde{F}_L, \tilde{F}_T, \tilde{I}_L, \tilde{I}_T] \quad A := [\tilde{J}_L, \tilde{J}_T, \tilde{T}]
\]  

(4)

5.2 Value function and policy iteration

The value function (also called Q-function) gives preferable directions to the learner from the starting state to the exiting state, in an episodic setting such as the scooping problem. At every time step the learner obtains a reward for visiting the state that the machine is in by the value function. In an episodic policy iteration setting, a given policy is followed while collecting the rewards. At the end of the episode (breakout from pile), the value function is modified based on the total reward for the policy and the states visited during the episode. The current policy is then improved based on the new value function to create the next policy.
The agent gets reward (positive value) for fulfilling the predefined goals and punishment (negative value) for undesirable behavior. A typical reward function for a RoboCup bot is a high positive reward for scoring a goal, and small negative rewards for each time step (passing time), energy usage, and bump into walls or other robots [22]. Similar to this, a suitable reward function for scooping would be a high positive reward proportional to the bucket weight at the end of scooping, and small negative rewards for passing time, wheel slip, machine stall and when the fuel efficiency is below a certain level. The negative rewards will encourage the agent to terminate the episode and therefore the relative weights of these reward values are going to be an important step in the RL design.

Although a value iteration using a state transition probability model \((T)\) (model based approach) could be computationally possible, we argue for model free methods as the better alternative to model based. The reason being the non stationarity of the process which can make it difficult for the model \((T)\) to be estimated and for the value iteration to converge within finite number of scooping examples. The value iteration also suffers from the curse of dimensionality as even with a course discretization mentioned earlier, the size of state-action space easily becomes one billion for this problem. A policy iteration method on the other hand has the disadvantage of having a bias based on the initial policy following some greedy policy method. But given the safety requirements of experimentation with heavy construction equipment, starting with an expert driver’s trajectory (policy) is the only feasible and practical solution. The policy bias can however be minimized to some extent by using scooping data from several different drivers scooping similar piles.

6 Conclusions

We discuss the complex problem of automatic loading for a front end loader and address limitations of current research arguing that there is a need for a general solution for the scooping problem, for different types of material and machines. The problem of automatic loading is complex due to the highly complex and uncertain process, which cannot be modeled from first principles. Our experiments with one type of pile reveal a relationship between the forces sensed on the lift and tilt pistons with the trajectory of the bucket (movement profile of lift and tilt pistons). The force data and regression model for predicting trajectories show no sign of high bias or high variance, which suggest that this method is feasible and can be extended further.

Reinforcement learning (RL) is one interesting approach, which potentially could provide a general solution for the automatic loading problem. Deep RL is the state of the art in artificial intelligence today and the automatic scooping problem appears well suited for an approach like that. In this paper, we also explained the basic building blocks of an RL based solution like an MDP model with states, actions and rewards in context of the scooping problem. We outline a potential solution for the autonomous scooping problem based on reinforcement learning. In the future, we plan to conduct more experiments and implement a RL model based on deep Q-learning.

Acknowledgment

The work presented in this article is supported by the Swedish Innovation Agency VINNOVA together with the Energy Agency and Formas under contract 2014-01882. The authors also thank Skanska AB who allowed us to use their quarry to conduct the experiments. The authors
acknowledge the support of the Swedish companies Volvo Construction Equipment AB, Boliden AB and Oryx Prototyping AB.

References


Paper D

Assisted tele-remote operation of mobile earth moving machines in underground mines

Reformatted version of paper to be submitted in:
Assisted tele-remote operation of wheel-loaders in underground mines

Siddharth Dadhich, Ulf Bodin, Fredrik Sandin, Denis Kyelo
Ulf Andersson and Erik Uhlin

Abstract

Tele-remote operation of mobile earth moving machines in underground mines is attractive for safety and productivity reasons. That way operators can avoid hazardous underground environments with poor air quality, and the productivity can in principle be improved by sparing the time required to commute drivers to and from the operational areas. However, the constrained perception and awareness of the machine is a challenging problem for remote operators. In particular, the scooping efficiency for blasted-rock is significantly lower when machines are tele-operated. Furthermore, the narrow corridors and draw points in underground mines, and the varying properties of blasted rock makes the remote-operation challenging. Here we present a study of data from manual scooping experiments with medium-coarse gravel and a machine learning approach to develop operator-assistance functions for scooping. We also present a case study on the use of wheel-loaders in underground mining and discuss assisted tele-remote control based on audio-video and sensor feedback. Finally we simulate and evaluate two transport layer protocols with respect to video quality for tele-remote control over wireless IEEE 802.11 networks. We conclude that, adding operator assistance functions to tele-remote control is a viable approach to move towards fully autonomous operation.

1 Introduction

Wheel-loaders are preferred in underground mines with higher ceiling and narrow corridors that requires machines with high mobility and maneuverability. They are used to load, fill and transport different types of material such as blasted-rock and waste-rock. They are also used to scoop blasted-rock from a drawpoint (freshly blasted location) and dump it onto a truck. This operation of loading the truck is called a short loading cycle. The room where the wheel-loaders load and dump the blasted-rock onto the truck is called a pocket. The truck (also called a dumper) transports the material further once it is full. In most cases, wheel-loaders carry the material for short distances, like in the short loading cycle and, for example, from a waste rock pile to a nearby pocket.

Manual operation of wheel-loaders can be ineffective and unsafe. When waiting for the dumper to arrive, the wheel-loader will stand still with an inactive driver. Furthermore, there are safety concerns involved in having drivers operating the machine in environments with bad air quality and risk of accidents such as fire. Therefore, the option of tele-remote control of wheel-loaders is attractive in underground mines. Tele-remote operation of wheel-loaders is also desirable in other applications, such as open-pit mining, queries and at construction and industrial sites.
Figure 1: Components of tele-remote operation of an earth-moving machine. A remote control station (left) located outside the mine receives video, audio and motion feedback from a wheel-loader (right) inside the mine while it also sends control commands to the wheel-loader. The data is transported by a combination of wired and wireless communication networks.

Short loading cycle in narrow pockets in underground mines require accurate maneuvering of the machine and is a skill learned by experienced drivers. The variation in properties of blasted-rock provide further challenges for tele-remote operation. In this paper, we propose a research roadmap with incremental addition of operator assisting functions to tele-remote control as a viable path towards full automation of earth moving operation. The proposed solution is called assisted tele-remote operation. Fig. 1 illustrates how the components of an assisted tele-remote operation are realized in practice.

Loading of blasted-rock under tele-remote control is inefficient in terms of productivity [1]. This is due to the fact that tele-remote operators lacks 3D-visual, auditory and tactile feedback needed to perform loading with high efficiency. The decreased productivity with remote-loading makes remote control operation economically inferior to manual operation [1]. To address this problem, we propose to develop an operator-assistance function for scooping.

Machine learning methods are well suited to develop operator assistance functions for scooping, which need to be robust against different properties of piles (such as shape, size distribution, moisture and temperature) and preferably also support different machine characteristics (such as type of linkage, traction, bucket and size). The methods investigated in this paper are based on scooping data of medium course gravel, which provide a first step towards understanding drivers’ behavior during scooping. Models of driver behavior are developed to better understand how drivers use lift, tilt and throttle during scooping.

As pointed out in [2], scooping of blasted-rock is more difficult than gravel. As a first step towards assisted tele-remote solutions for rock excavation in mines, we report a case study on strategies of expert drivers who operate standard wheel-loaders for scooping blasted-rock at the Kankberg underground mine in Boliden, Sweden. Based on this study, we discuss different considerations for enabling assisted tele-remote control of short-cycle loading. We also discuss video transmission protocols, in particular the importance of efficient use of communcation network bandwidth.

The contributions of this paper are:

1. An overview of the problem and challenges in efficient tele-remote operation of short loading cycle in underground mines with front-end wheel-loaders.
2. An analysis of data from scooping of medium-course gravel by machine learning methods aiming at assisted tele-remote scooping.
3. A case study on strategies of expert drivers performing short-cycle loading in narrow
loading places highlighting the problem of hidden boulders in blasted-rock.

4. A simulation-based evaluation of two protocols for transporting video streams from mobile machines to a remote control stations for predictable quality over IEEE 802.11 wireless (WiFi) networks.

We argue that operator assistance functions with tele-remote control is a more viable approach than fully autonomous operation in the short to mid term, and that it is also an important step to collect experience to move towards fully autonomous operation.

2 Background and motivation

2.1 Short loading cycle

In underground mines with high ceilings, a combination of wheel-loaders and dumpers is used to transport blasted-rock out from the mines. The short loading cycle in such mines (Fig. 2) requires the wheel-loader and the dumper to give way to each other because of limited space around draw-points. An increased level of interaction between wheel-loader and dumper makes the operation susceptible to inefficiency.

To achieve a cost efficient transportation of material, the matching between the wheel loader and the dumper is important [3]. Matching is defined as the number of buckets needed to fill the truck. A criteria used in the industry is that 3-6 buckets (pass match) can yield an economical loading operation. When too long time is spent on filling trucks to their maximum payload, the loading process becomes a bottle neck in the production, possibly introducing queues with subsequent traffic disturbances.

Side-tipping bucket, if used, on wheel-loaders simplifies the short loading cycle to some extent. With the side tipping bucket, wheel-loaders does not need to reverse too far to make
way for the truck, but instead, they can dump the material by tilting the bucket sideways onto the truck.

2.2 Autonomous navigation in mine corridors

Autonomous navigation for tunnel applications in mine mining has been discussed and reported for a long time. In this context, Load-Haul-Dump (LHD) machines have been in focus in the literature. Fundamentally, LHD machines are similar to wheel loaders except that they are adapted for underground mines with low ceilings and have bigger buckets, more suitable for performing load and carry operation.

Today, at least three major suppliers of underground mining equipment have developed LHD automation systems of their own that are commercially available. This is in contrast to the situation in the late 90’s when mining companies developed their own systems [4].

The Swedish mining company LKAB has since the late 80’s conducted a series of LHD automation projects called semi-automatic loading and transport (SALT) [5], in which scooping is done under tele-remote control and navigation and dumping are performed autonomously. The navigation system used in SALT3 and SALT4 projects are a laser based system, originally developed for AGV (automated guided vehicles) applications. The adapted system, called HUNS (High speed Underground Navigation System), was used as the navigation system during a 10-year production period from 1999 to 2009 in the LKAB iron ore mine in Kiruna [1]. Later development of LHD navigation has been reported in [6], [7] and [8].

The mentioned papers focus on navigation solutions for machines operating without interacting with other machines such as dumpers. An additional challenge in the short cycle loading is the interaction between the loader and the dumper.

2.3 Autonomous scooping

The scooping step in the short loading cycle is known to be inefficient when performed with tele-remote control [1]. A fully autonomous loading operation is, however, known to be more difficult and has been an open area of research since three decades [9]. Although tele-operated LHD machines have been used in underground mines for more than ten years [10], a fully automated system of an earth-moving machine has never been demonstrated despite a lot of research in this field [11].

To address this, [1] developed a scooping algorithm for tele-remote operated LHD machines triggered after the bucket enters the pile. It is to be noted that, LHD machines are required to maximize the volume of each scoop while wheel-loaders in the short loading cycle are required to fill the dumper in least amount of time. Although an operator assisting function for scooping is used by [1], the average bucket weight for scooped rock is reported to be lower than with manual scooping.

In [12], a machine learning approach is applied to understand and mimic driver behavior during scooping of granular material. In this paper, we extend the work in [12] to propose an operator assistance function for scooping of medium-course gravel. Although larger variability in fragmentation size of blasted-rock compared to granular material makes scooping of the blasted-rock more difficult [2], we consider that it is important to gain knowledge of fundamental driver behaviors of by studying scooping of granular material.
2.4 Video transmission and transport layer protocols

For safe tele-remote operation of the short loading cycle, operators require a good quality vision feedback from all around the machine as well as sensor based feedback (e.g., motion, sound and tactile feedback). Because performance of the tele-remote operation depends on the quality (latency, jitter and loss) of the feedback, the wireless transmission of control and feedback data needs to be dependable and robust [13]. In particular, providing a good video feedback over wireless networks can be challenging because of high data rates.

The mining industry seeks to exploit recent advances in wireless technology such as wireless local area network (WLAN), ultra-wideband (UWB) and also cellular networks [14]. For example, Boliden Minerals AB (a Swedish mine company) has deployed IEEE 802.11 wireless networks in several of their mines for communications and real-time localization of both workers and machinery [15, 16]. However, even the most advanced wireless network can get overloaded, for example, due to radio impairments, which reduces its capacity. Therefore, it is important to use the network’s bandwidth efficiently by choosing the most suitable protocol suite for tele-remote operation. The User Datagram Protocol (UDP) protocol is good for real-time data transmission but it does not offer any load control mechanism, and thus floods the network even if the network is already overloaded. To address this, we examine the possible use of the Partially-Reliable Stream Control Transport Protocol (PR-SCTP) as an alternative to UDP to achieve desired robustness against temporarily reduced wireless capacity for video transmission.

3 Machine learning based operator assistance function for scooping

Autonomous loading is a general problem with applications in different earth moving and construction operations that concerns both front-end loaders and backhoe excavators. This problem has been investigated using automatic control theory such as feed-forward control and compliance control, and also using artificial intelligence methods like fuzzy logic. For example, iterative feed-forward control is investigated by [11] for autonomous excavation with excavators. In [17], a fuzzy behavior programming proposed to use to address the autonomous excavation problem. They conducted experiments with a laboratory prototype with a PUMA robotic arm and demonstrated that agent based control can adapt to feedback forces from a pile and change its behavior in a rock digging task. However, excavator tasks are more well defined when formulated as a control problem compared to loading tasks with a front-end loader. For LHD machines, which are more similar to wheel loaders from an automation perspective, [2] developed and tested an autonomous compliance controller for the velocity of the tilt cylinder that uses the hydraulic pressures of the lift and tilt cylinders as input. In [18], it is shown that this method performs better than human drivers of LHD machines.

Machine learning methods have not been applied to the bucket loading problem for front-end loaders as far as we know. In this section we introduce such a data-driven machine learning approach to automation of the short loading cycle scooping process.

3.1 Scope

Consider a scenario where a remote operator is in supervisory control of the machine. The operator chooses the scooping location by driving the machine towards the pile. The question is how to design a scooping assistance function that kicks in once the bucket is inside the pile (as indicated by rapidly increasing forces on the tilt and lift cylinders) and stops at breakout
when the bucket looses contact with the pile. The variables (lift and tilt, angles and forces) vary significantly between different bucket fillings due to the differences in pile shape and surface profile. Similar to [18], we define the entry of the bucket into the pile when the lift force exceeds a given threshold, and the exit from the pile when the tilt angle exceeds another threshold value. The threshold values are inferred from the data set and are exogenous parameters that probably need further adjustment under other conditions.

3.2 Regression model of expert driver trajectories

are several hidden variables in the autonomous loading problem for front-end loaders that are related to the (size, distribution, moisture, temperature etc.) and the machine (linkage, traction, bucket and engine). drivers take some of these aspects into account through complex visual, auditory and tactile ques. These sensory ques are modified in a tele-remote operation situation, which leads to reduced scooping efficiency. We are interested to know how far the scooping behaviour of an expert driver can be modeled using the information that is practically available within the ECU of a machine, and whether such a model could be used to estimate efficient scooping trajectories automatically during tele-remote operation. Therefore, as a first step we develop a linear regression model that is fitted to live scooping data.

The data used to develop the following models have been provided by Volvo Construction Equipment AB. The data contains variables such as the angles of lift and tilt joints and hydraulic pressures in the lift and tilt cylinders of a Volvo L120G wheel loader that is used by an expert driver to load medium-course gravel (8-32 mm in diameter).

the automatic loading problem in terms of a control block diagram and the interaction forces between the machine and pile. The hydraulic system in the convectional diesel engine powered machines is a multi-variable system where the forces applied to lift and tilt pistons come from a non-linear coupled function of operator actions as shown in Eq. 1.

\[
f_{TL, FL} = f(j_L, j_T, t_P). \tag{1}
\]

The resistance forces from the pile \((f_{LR, FR})\) cannot be modeled this poses the main challenge to the bucket loading problem. The tilt and lift angles \((\theta_T, \theta_L)\) define the trajectory of the bucket through the pile. signals from the lift and tilt joysticks are not considered here. in the
Figure 4: An example of linear regression of an expert driver’s trajectory. The model approximately learn the driver’s behavior, but fails to accurately predict when actions are taken. Lift and tilt actions initiated by the driver correspond to steep slopes of the trajectories.

ECUs (machine computers) and are not directly related to the valve control signals and the resulting forces on the pistons, which are the relevant variables.

We train a linear regression model with data recorded during scooping by an expert driver and use the model for prediction of the trajectory of the driver. The pile forces and driver behavior varies significantly during different scoopings. Therefore, one question is whether an accurate regression model can be obtained for these variables, which depend on the behavior of the expert driver and the pile. A linear regression model is implemented for prediction of $\theta_L$ from $FV_L$ and $\theta_T$ from $FV_T$, where the feature vectors are defined by the following expressions.

$$FV_L = [I_L, I_T, f_L, f_T, \theta_T],$$  \hspace{1cm} (2)  

$$FV_T = [I_L, I_T, f_L, f_T, \theta_L].$$  \hspace{1cm} (3)  

Here, $I_L, I_T$ are the impulses (time integral of force) of the lift and tilt forces, respectively.

Example calculated with the regression model is shown. Even though the linear model is simple compared to the complexity of the problem it approximates the actual trajectory to some degree, but it fails to predict the discrete lift and tilt actions initiated by the driver. Therefore, in the following we extend the linear regression model with a classification model that provide additional input to the regression model about the probability that a lift or tilt action is to be taken.

### 3.3 Cascaded classification and regression model

The linear regression model does not predict when the driver initiates the lift and tilt actions, but rather approximates the average change of lift/tilt in a smooth way. In reality the discrete lift and tilt actions by the driver are related to the dynamics of the pile and scooping process, and the sensory cues and experience (priors) of the driver. We extend the linear regression model with a classification model in an attempt to approximate the lift and tilt decision processes of the driver. Since the final goal of the machine learning controller is to take actions autonomously by actuating on the lift and tilt cylinders, we aim to estimate the lift and tilt actions.
Figure 5: The proposed scheme of cascaded machine learning (ML) models. The four classification models predict the lift and tilt actions as active (high) or inactive (low) followed by two regression models which aim to produce commands for autonomous lift and tilt actions.

<table>
<thead>
<tr>
<th>Model type</th>
<th>Feature vector</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>C for $p_{LH}$</td>
<td>$X = [\dot{\theta}_L, \theta_L, \theta_T, f_L, f_T]$</td>
<td>$y = \dot{\theta}<em>L &gt; \dot{\theta}</em>{LH-th}$</td>
</tr>
<tr>
<td>C for $p_{LL}$</td>
<td>$X = [\dot{\theta}_L, \theta_L, \theta_T, f_L, f_T]$</td>
<td>$y = \dot{\theta}<em>L &lt; \dot{\theta}</em>{LL-th}$</td>
</tr>
<tr>
<td>C for $p_{TH}$</td>
<td>$X = [\dot{\theta}_L, \theta_L, \theta_T, f_L, f_T]$</td>
<td>$y = \dot{\theta}<em>T &gt; \dot{\theta}</em>{TH-th}$</td>
</tr>
<tr>
<td>C for $p_{TL}$</td>
<td>$X = [\dot{\theta}_L, \theta_L, \theta_T, f_L, f_T]$</td>
<td>$y = \dot{\theta}<em>T &lt; \dot{\theta}</em>{TL-th}$</td>
</tr>
<tr>
<td>R for $j_L$</td>
<td>$X = [p_{LH}, p_{LL}, p_{TH}, p_{TL}, \theta_L, \theta_T, f_L, f_T]$</td>
<td>$y = \theta_L$</td>
</tr>
<tr>
<td>R for $j_T$</td>
<td>$X = [p_{LH}, p_{LL}, p_{TH}, p_{TL}, \theta_L, \theta_T, f_L, f_T]$</td>
<td>$y = \theta_T$</td>
</tr>
</tbody>
</table>

Table 1: Training data with feature vectors and output vectors for the six models used in the proposed solution. Here C denotes classification and R is a short for regression.

Fig. 5 illustrates the proposed scheme of cascaded models for estimation of lift and tilt. First, the classification model predicts (based on data presented during training) the probability of high ($p_{LH}$, $p_{TH}$) and low ($p_{LL}$, $p_{TL}$) lift and tilt actions. The two blocks in Fig. 5 contain two classification models, one for high and one for low, respectively. The data used for training of these classification and regression models is outlined in Table 1.

Instead of using binary classifiers, we use the confidence values ($p_{LH}$, $p_{LL}$, $p_{TH}$, $p_{TL}$) for each classifier as inputs to the regression model. The two regression models (Fig. 5) predict the lift and tilt actions.

An test example of how the proposed cascaded network of machine learning models performs on an unseen scooping is shown in Fig. 6 and Fig. 7. We observe that the predicted actions approximate the velocity of lift and tilt cylinders under expert driver operation.

From joysticks to valve commands present in the ECU’s of this machine, we expect the model to produce similar motions of the lift and tilt cylinders as the expert driver. Fig. 7 illustrates the predicted trajectories obtained by integrating the lift and tilt actions estimated by the model. We observe that the prediction captures the on-off nature of the lift and tilt commands, and the integrated drift from the driver’s trajectory is moderate. By changing the parameters of the four classification models, $\dot{\theta}_{LH-th}, \dot{\theta}_{LL-th}, \dot{\theta}_{TH-th}, \dot{\theta}_{TL-th}$ (see Table 1), it is possible to reduce the discrepancy between the driver’s behavior and the prediction. However, the aim here is not to fine tune the model to a recorded data set, but to investigate whether there is any hope that a regression modeling approach can be useful to address this challenging problem in practice.

In the current data, large negative values of lift and tilt velocity are not observed. Therefore, two classes for each action type are considered to be enough. For more challenging materials such as fragmented rock, drivers are often required to decrease the lift/tilt to dig below large
Figure 6: Example of scooping by an expert driver and the corresponding estimation of lift and tilt angular velocity by the cascaded ML models.

Figure 7: Example showing the change of lift and tilt angles initiated by an expert driver and the corresponding predictions by the cascaded ML models. The deviation between driver and predicted trajectory can be further reduced by fine tuning of parameters.
rocks to complete the loading. In such cases additional classes may be needed.

3.4 Throttle action

When scooping expert drivers modulate the throttle pedal to operate the machine at an optimal engine RPM, where maximum power is generated from the engine. The RPM for maximum power for Volvo L110G and L120G is around 1600 [19]. The power generated by the engine is divided between the hydraulic pumps and the torque converter in the machine. Maximum power from the engine results in maximum power available to lift and tilt the bucket, and thus to fill the bucket in the least amount of time. However, more engine power also means more power to the torque converter and the transmission which increases the probability of traction loss and wheel slip. Therefore, we intend to use an RPM controller for throttle which is sensitive to wheel slip. A wheel slip prediction method is thus necessary in this scope and is planned as future work.

4 Discussion

The problem of short-cycle loading in underground mines is challenging; hence it makes a good use case for our work on assisted tele-remote operation of wheel-loaders over IEEE 802.11 wireless networks. In this section, we provide discussions in two areas aligned with this work. First, we present a case study on strategies of expert drivers using wheel-loaders in underground mines and then we discuss video transport approaches by comparing two transport layer protocols.

4.1 Case study on strategies of expert driver

4.1.1 Kankberg mine in Boliden, Sweden

The Kankberg mine holds gold and tellurium deposits embedded in rocks and it is mined using the cut-and-fill method. The mine has narrow tunnels ending at draw points where blasted rock is excavated from the faces and loaded onto dumpers. The narrow pockets motivate the use of large volume wheel-loaders instead of LHD machines. In this mine, dumpers have a specified maximum payload of 30 tonnes, and they need to be loaded with material as close as possible to this weight and as fast as possible. Experienced drivers usually succeed in loading a dumper within 3-4 short loading cycles. This means that the target weight for the last scooping may not be the maximum possible, but rather what remains to meet the targeted payload.

In order to fill the dumper efficiently, drivers sometimes prepare the pile before scoopings. Often, there is time for such preparation between when the filled dumper leaves and an empty one takes position for loading. When the dumper is in the position for loading, there is little space at the drawpoint which means that the dumper needs to move in and out for every scooping as shown in Fig. 2.

4.1.2 Drivers' behavior and approaches

The case study was done based on discussions with two experienced drivers. These discussions were triggered by asking the following questions to the drivers:

- What describes a recommended approach and strategy for scooping of blasted-rock in the mine?
- Does different strategies apply to different types of materials?
Two important issues are identified: (1) the event of hitting a big boulder hidden in the pile during scooping and (2) keeping track of moving objects at the draw point to avoid running into the dumper or dropped boulders. Avoiding tunnel walls and other obstacles is a minor problem by drivers in comparison to the issues mentioned above. However, it is important to keep track of the surroundings of the wheel-loader when a boulder falls off the dumper or rolls out from the pile. In such case, the dumper moves to a different position to let the wheel-loader avoid the boulder, which is then cleared by the wheel-loader before the next scooping. Such obstructive events are detected in the unfocused zones of drivers’ vision and must be carefully considered when designing a video solution for the tele-remote operation.

The event of hitting a big boulder is sensed by drivers when the machine makes a sudden stop exposing them to a strong jerk. Alternatively, the machine can also slow down or even stop due to an insufficient lift action, which is interpreted differently by the drivers. When the wheel-loader hits a big boulder during scooping, specific actions are needed to get it into the bucket, if possible. The first strategy applied by drivers is to stop the machine ensuring that the wheel grip is retained. Thereafter, they curl down the bucket with a gradual increase to throttle attempting to move the bucket forward under the boulder. If this does not succeed, a retake is needed aiming at either moving the boulder in the pile or trying the same strategy again.

Finding big boulders in blasted rock is common and it impacts on how drivers approach the pile. Some drivers argue for entering the pile with good speed and lifting the boom at the right moment to obtain enough pressure from the front axle. Alternatively, expert drivers advocate for making a complete stop just before the pile, and thereafter, pushing the machine into the pile while gradually lifting the boom. The latter approach avoids unnecessary wear on the machine caused by hitting boulders at high speed when boulders are present close to the surface of the pile. The scooping is completed by curling up the bucket which helps to prevent the material in the bucket from falling off while reversing. It should be noted that the strategy described here is for Volvo L250H machine with Z-bar linkage and a bucket with medium floor (length of base of the bucket). Other machines with different linkage and buckets may require different strategies. For example, an LHD machine with longer bucket requires only curling action of bucket for an efficient scoop [18].

The scooping strategy also differs depending on properties of the material and the profile of the ground. When loading, waste-rock behaves differently than blasted-rock which is typically heavier. A denser material requires more lift and tilt movements with more careful use of the throttle to move through the pile compared to a less dense material. This means that the driver needs to be sensitive to the pile to perform the scooping efficiently. The slope of the ground also plays a role. Scooping on a slightly uphill ground requires more use of the curl-up action to move into the pile. On the contrary, scooping on a slightly downhill ground requires less lift and curl-up actions but the driver needs to account for the motion of the machine due to the slope.

Drivers’ behavior and approaches vary depending on how each driver interprets and adopts to the commonly known best practices. For example, the approaches accounting for the wear and fatigue on the machine seem to differ between drivers. However, the detection and the approach taken after hitting big boulders in a pile are similar for different drivers. Also, drivers’ behavior with variation in pile density and surface slope apply to all drivers.
4.2 Video transport approaches

Efficient tele-remote control of mobile earth moving machines in an underground mine as well as in other environments demands a good quality audio-video feedback along with other feedback. As shown in Fig. 8, a basic setup has the tele-remote control station receiving video, audio and sensor based feedback and sending commands to the machine. Among these data streams, video streams account for most of the used network bandwidth, particularly when several cameras are needed to give sufficient visual feedback. Although throughput and delay varies with radio channel impairments caused by issues like path loss, multi-path propagation and interference, wireless networks are still essential to transmit data between the tele-remote control station and the mobile machine.

A wireless network such as IEEE 802.11 [20] is shared between all data streams needed for the tele-remote control and other data streams supporting monitoring of the controlled machine. There may be more than one tele-operated machines in the same area for which wireless communications are needed. Therefore, the use of wireless bandwidth need careful planning to reduce the risk of network congestion that can lead to increase in the transmission delay and packet loss. The varying capacity offered by wireless networks such as IEEE 802.11 implies that overload may occur anyhow, resulting in a degraded communication quality negatively affecting the feedback and control streams.

The risk of degraded wireless communication quality motivates the use of congestion responsive transmission of the data streams. UDP protocol does not offer such responsiveness while transport protocols like the Transmission Control Protocol (TCP) reduces the sending rate as response to the congestion indicated mainly by packet loss. TCP is, however, not suitable for real-time video since it may introduce additional delay awaiting lost packets to be re-transmitted, i.e. head of line blocking. The Steam Control Transmission Protocol (SCTP) [21] is an alternative congestion responsive protocol to TCP that can deliver packets immediately to the application while re-transmissions are in progress. In addition, the partial reliability extension to SCTP (i.e. PR-SCTP [22]) allows for defining time-to-live for individual messages thus avoiding re-transmissions of stale data.

With the real-time data which becomes quickly out of date, the partial reliability feature of SCTP can be used to ensure that only useful data is transmitted during the congestion, and thereby making the best out of limited wireless capacity. For example, feedback and control streams typically carry information that is valid only if delivered with very short delay. Partial reliability can also be used to time-differentiate between different types of video frames as discussed in the following section.

4.2.1 Video coding and compression

The raw video recording is compressed to a great extent in cameras by special encoding to save capacity of the communication channel when transferring the video over the network. This discussion considers the case of encoding using the widely accepted H.264/MPEG-4 AVC standard [23]. This standard uses both temporal and spatial redundancy to compress the signal. Spatial encoding provides less compression than temporal encoding but comes with an advantage that parts of the encoded signal do not require any other information for the decoding. Parts of the video signal encoded using the spatial redundancy only are called I-frames, where I stands for intra-coded picture.

Temporal redundancy is used for further compression. In temporal redundancy, the current part of the signal is constructed using the previous part as a reference point and only the difference between these parts is transmitted. The temporal encoding produces P- and B-
frames where P stands for predictive and B stands for bi-predictive. The B-frames are the most compressed type of frame because they use I and P frames as references, both historical parts as well as from the future signal. It is to be noted that the use of the future signal assumes some delay in the encoder.

The different types of frames in the encoding bring a natural priority to them based on the importance of packets. B-frames are least important because the loss of one such frame affects only the part of the video signal represented by the lost frame. Loss of an P-frame destroys not only the part of the signal represented by the frame itself, but all B-frames which refer to the lost P-frame. In the case when an I-frame is lost, all other P- and B-frames related to this I-frame cannot be decoded, hence I-frames are of the highest importance. Clearly, when transmitting H.264/MPEG-4 AVC encoded video over networks in which some packet loss may occur, it is preferable to lose those packets that affect the quality of the video stream as little as possible. Hence, packets with B-frames should preferably be lost before P-frames, while the loss of I-frames needs to be limited as much as possible.

4.2.2 Comparison of PR-SCTP with UDP for throughput of I, P and B frames

This section presents the results of simulations comparing UDP [24] and PR-SCTP [21, 22] protocols when used to carry H.264/MPEG-4 AVC encoded video [23]. Through these simulations we illustrate the use of PR-SCTP to give I-frames the highest precedence, while P-frames are given medium and B-frames the lowest precedence. The different frames are assigned different
time-to-live (TTL) values to achieve this differentiation regarding the delay and loss, thereby offering a smoother decay of the quality of the streaming video compared to UDP.

PR-SCTP reduces the load at congestion by avoiding transmitting stale data and this can provide reduced medium access delay. That is, during the congestion the average transmission delay over IEEE 802.11 should be lower with PR-SCTP than with UDP, which does not reduce the load in response to packet losses.

In [25], it is shown that PR-SCTP can prioritize the delivery of frames by limiting the number of re-transmissions in order to provide different priority to different types of H.264/MPEG-4 AVC frames. They conclude that reliable delivery similar to TCP can be achieved with PR-SCTP while maintaining equal or lower delay in all cases. The policy for number of re-transmissions for each of the different frames is shown to depend on network conditions (e.g. congestion) and the characteristics of the encoded video (e.g. relations between the different frames). Although we consider this approach promising, the number of re-transmissions is a discrete parameter that poorly captures the real-time delay (e.g. time spent in sender buffers), which is important for video streaming with real-time constrains.

Our simulations are performed in the widely used open-source NS-3 simulator [26]. NS-3 includes many of the Internet protocols as well as models of different wired and wireless networks such as IEEE 802.11 and the 3GPP LTE. Although PR-SCTP is currently not supported in standard NS-3, it can still be simulated using the Direct Code Execution (DCE) framework for NS-3. DCE allows execution of Linux kernel implementations of networking protocols. In this work, both UDP and PR-SCTP are simulated using implementations from the Linux kernel. The video stream is simulated by assigning different frequencies and sizes for each type of frames. We have used 1400 bytes for I-frames, 700 bytes for P-frames and 350 bytes for B-frames.

In the simulations, Wi-Fi standard IEEE 802.11g is used at the medium access layer. It allows a maximum bit-rate of 54 Mbit/s. The topology of the network included one fixed Wi-Fi access point and seven mobile client stations. Each client station simulates a source of a video stream, which represents the video feedback from a tele-operated mobile earth-moving machine. During the simulations, the speed of each video stream is varied in range from 1.6 to 4.8 Mbit/s. Average percentage of packets successfully delivered to the access point is calculated for each type of frames. For PR-SCTP, the following TTL parameters are used: 15 ms for I-frames, 3 ms for P-frames and 1 ms for B-frames. These values are selected experimentally to illustrate the intended differentiation giving I-frames the highest precedence. As noted by [25], the policy for re-transmissions needs to be adapted to network conditions (e.g. congestion) and the characteristics of the encoded video, which means that the TTL values need to be adapted as well.

The results of simulations are shown in Fig. 9. Each plot in the figure presents the packet delivery ratio (PDR) for a particular type of frame for both protocols against the speed of the video stream from a single client. It can be seen that when there is no congestion in the network (1.6 Mbit/s speed) both protocols perform equally well, i.e. all packets were delivered to the access point. As expected, UDP does not prioritize any packet type over others which means that for a particular application speed PDR for I, P, and B packets are approximately the same. For PR-SCTP PDRs differ due to difference in TTLs values of the I-, B- and P-frames.

For application speeds in range from 3.2 to 4.0 Mbit/s, PR-SCTP provides higher delivery rates of I-frames than UDP at the expense of decreased PDRs for P- and B-frames. PDRs for P-frames compared to B-frames are slightly higher because its TTL was longer. It should be noted that, during the congestion PDRs for P- and B-frames are lower with PR-SCTP than with UDP because stale packets are dropped before transmission (i.e. packets are dropped due to buffer overflow and by the partial reliability mechanism in PR-SCTP). This means that UDP
may deliver more data than PR-SCTP, but some of the data is likely to be outdated as the delay may exceed the TTL values. This situation occurs in the simulations at the sending speed of 4.8 Mbit/s.

The simulation results illustrate the possible use of PR-SCTP to prioritize the delivery of delay sensitive packets, in particular for the real-time video needed for the tele-remote control of mobile earth-moving machines. Future work is, however, needed to find a function to adapt TTL values to network conditions and the characteristics of the data to be transmitted. Another attractive feature that SCTP brings is the concurrent multipath transfer extension, which is being addressed by Internet Engineering Task Force (IETF) [27, 28]. Multipath transfer is applicable to critical applications such as the tele-remote control since it provides redundancy through the use of several wireless networks in parallel.

5 Conclusion and future work

Tele-remote operation of short loading cycle with wheel-loaders in narrow underground mines is a challenging problem. The constrained human perception when using tele-remote control makes it difficult to scoop efficiently. We propose to solve this problem with machine learning based operator assistance functions for scooping. Classification and regression models are used in cascade to build a system that approximates the lift and tilt actions produced by the joystick commands. The classification model investigated here is able to predict driver behavior in terms of the onset of lift and tilt actions. The trajectories estimated with a cascaded model of interconnected classifiers and linear regression functions are similar to those of the expert driver and motivates further work in this direction.

The case study on strategies used by expert drivers reveal a problem with boulders in the pile, and in the path of wheel loaders. Boulders present in blasted-rock may require operator intervention, when the operator assistance functions fails. Therefore, the tele-remote operator should be alarmed to handle such exceptions.

If congestion control is desired, UDP cannot be used and hence we evaluate the PR-STCP protocol for transport of video between the machine and the remote control station. The ns-3 simulations of PR-SCTP for video streams suggest that TTL values for I-, B- and P-frames of H.264/MPEG-4 AVC encoded video should be modified in real-time based on the network load.

Future work

The work presented in this paper is ongoing and requires further experimental research. With the help of our industrial partners, we plan to conduct field experiments both outside and in underground mines. Field experiments to validate the proposed operator-assistance function for scooping also require wheel slip detection and mitigation algorithms.

The goal of the scooping function is to scoop as fast and efficient as possible to load the truck in a short period of time. In the future, we intend to use reinforcement learning methods based on the cycle time of operation to further improve the efficiency of the scooping function. Reinforcement learning can, for example, be used to improve the parameters of the regression and classification models to improve the performance of the scooping function.

The human machine interface at the remote control station needs to provide the feedback to the tele-remote operator in an effective way. The details of audio-video solution and motion feedback to the operator are also part of future work.
We consider the use of transport protocols with congestion control features important. The question about the best alternative to UDP for real-time performance remains open. Use of other transport protocols such as TFRC and TFRC with Datagram Congestion Control Protocol (DCCP) are also to be considered.

Acknowledgment

The work presented in this article is supported by the Swedish Innovation Agency VINNOVA together with the Energy Agency and Formas under contract 2014-01882. The authors would also like to acknowledge the support of the Swedish companies, Volvo Construction Equipment AB, Boliden AB and Oryx Prototyping AB.

References


