Enabling operational autonomy in earth-moving with real-time 3D environment modelling

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Abstract -

Digital 3D environments are already integral parts of construction and are on the critical path of end-to-end site autonomy. They currently provide human users at all levels of an organisation, access to relevant digital representations of job-critical information at various lifecycle modes, from asset design through to asset maintenance. However, existing solutions lack the real-time functionality, suitable model resolution and machine interfaces which open the door to realising operational improvements from these models. This work proposes a method and proof of concept that enables high-fidelity, real-time 3D modelling of asset construction phase operations using Photogrammetry, Terrain Deformation and Plant Telematics / IoT. This will create a digital twin to act as a platform to facilitate machine automation, which is imperative to catalyse and drive adoption of automation and autonomy in construction. Initially and specifically seeking to facilitate Connected Autonomous Plant (CAP) for earth-moving operations, the work will also give rise to other monitoring, safety, environmental and efficiency benefits, but also be extensible to other site automation tasks.

Keywords -

3D Environments; Terrain Deformation; Photogrammetry; Telematics; Connected Autonomous Plant; Digital Twin;

1 Introduction

Enabling the autonomous future should be a priority for companies to super-charge profitability and safeguard futures. Companies are increasingly reliant on technology-based differentiators to win work, and this will only increase as the remit, quality and abstracted nature of technology solutions increases. We have seen that technology companies have a history of creating new markets and facilitate creation of entirely new business verticals due to radical innovation. Technology native businesses pose a significant risk to incumbent businesses [1] and as such, incumbents need to own differentiated solutions to overcome incumbent inertia and allow them to grow market-share whilst also defending against faster moving new entrants and competition. At a higher level, this work is a response to the ever present demand for safer, faster, better, smarter construction project delivery at less cost, but more granularly, the recent maturity of various technologies which will be discussed and combined to facilitate a subset of autonomy and automation specifically relating to construction Plant and its application within earth-moving. Earth-moving plant presents a good candidate for automation and autonomy due to the scale and repetitive nature of work however it does present unique challenges that differentiate it from manufacturing or automotive automation and autonomy technologies which can be considered more mature [2, 3]. This is also why thus far, extensive applications of autonomous earth-moving have been limited to the mining industry, having less changeable haul routes and far less on-site personnel they are both easier and safer environments. Not only must a vehicle in construction interpret and understand its environment, it must understand and be reactive to the dynamic nature of construction sites, as well as have the facility to manipulate and alter the environment based on a given design and specification. Through the lens of Singh [4] there are three aspects to an operational autonomous machine of which regular reference will be made throughout this paper, sense, plan and execute.

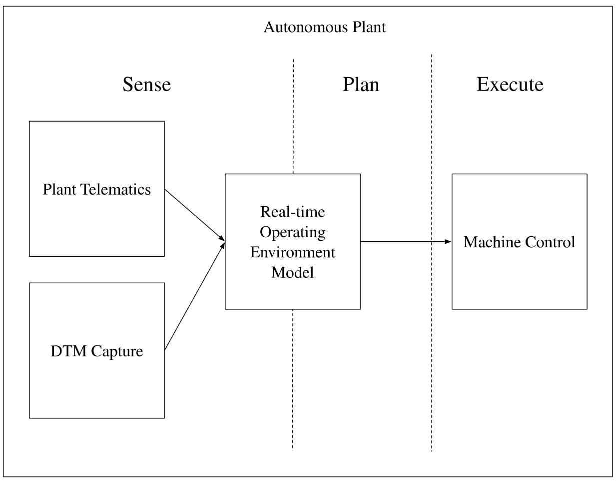

Figure 1. Method Diagram

To that end, this work contributes a method as well as a review of adjacent technologies required to enable the method, and can be seen as a early stage presentation of a much larger investigation which is notable in that the conclusion does not draw on any discrete data. As indicated in Figure 1, the higher level concept is for a telematics integrated, real-time 3D environment that deforms upon interaction by plant that can not only act as the bridge between design and as-built, communicating visually to project stakeholders, but specifically to earth-moving machines acting in semi and fully autonomous capacity too, giving autonomous machines access to detailed information about their environment, and other agents within it. This will also provide the interface to disseminate commands to machines, as well as acting as a central data platform for visualising and manipulating real-time 3D data.

2 The Contribution

BIM uses 3D to help inform decision making for stakeholders, whilst manufacturers provide machine control to assist plant operators. This work proposes that DTMs can be combined with plant telematics thus creating a bridge between the aforementioned, a digital twin or Real-time Operating Environment Model (ROEM) that can ultimately result in fleets of autonomous vehicles completing tasks efficiently. The method to be described here theorises that a digital twin can be used to facilitate autonomous plant by bolstering all three facets of Singh's [4] sense, plan, execute philosophy by creating a two-way relationship between intended design, and operational autonomy. The novelty in this method is the combination of local-sensors which are the commonly referred to environment sensing strategy from Singh [5] with non-local and pooled (drawn from multiple sources) sensing, combined with a DTM that can deform based on the interaction therein of accurately simulated plant in real-time (from telematics / IoT). Other contributions are secondary and are outlined outlined in section 3.

2.1 The purpose of digital 3D visualisations

Graphical processing and 3D environments are not trivial and present various challenges relating to implementation, so why use them, especially if the primary purpose of this work is to facilitate machine control?

3D World In order for machines to execute an activity within their environment (carry out autonomous work), they must first sense their environment and plan the activity based upon it. It follows that having an accurate digital 3D representation of an environment can enable machines to understand it, as it is in reality.

Human Control Secondly, while humans remain primary stakeholders and beneficiaries of construction, and also while they are universally accepted to be in direct control of construction (this will change), they will continue to have a vested interest in acquiring increasingly accurate information from which to generate insight for decision-making. It follows that an accessible 3D environment is a correct method communicate in construction.

3 Use Cases

3.1 Enabling Plant Autonomy

The primary focus of this work is using Digital Twin for facilitation of Autonomous Plant. The benefits and reasons to automate are not new and are widely researched within construction. Paulson [6] indicates the prerequisite technologies and the potential of borrowing from more automation-mature industries like manufacturing in 1985 with further work by Skibniewski [7] indicating progress to date, largely validating Paulson's foresight and further in Singh 1997 [4] where the slow uptake is indicated but with acceleration being identified as a result of progress in safety critical applications in Space and Nuclear outweighing the potential economic drivers in construction. Most recently, a study by National Highways indicated £200Bn in potential productivity benefits by realising effective plant autonomy by 2040 [8].

3.2 Earth-moving Optimization

Having an operational environment tracking precise movements of plant and their interactions with the environment means that we can quickly build up a significant database about the efficiency of the current operation of earth-moving vehicles, but also compare between projects, use transfer learning to incorporate existing models, and most importantly provide a more comprehensive ability to simulate and optimize earth-moving operations. There are many existing models that are useful to study in this area. However, as identified by both Moselhi and Alshibani [9] and more recently by Louis and Dunston [2], they do not support the dynamic changing nature of real-world operations, nor do they have the facility to optimize in real-time. The environment to be outlined helps facilitate this and should assist developments in Reinforcement Learning (RL) based optimisation techniques such as explored by Shitole et al. [10] where an RL agent dictates an approximately optimal policy that can be enhanced with real-world data and then disseminated to autonomous plant to execute the task.

3.3 Monitoring

A real-time 3D environment presents a useful solution to both operational and strategic leaders, showing changes to a site as they occur and enabling time-critical decision making. An example use case for this is as-built monitoring, we should be able to automatically identify when an earth volume has been correctly graded thus saving significant manual survey time. This is explored further by Anwar et al. [11]. Additionally to this, similar to the intentions of Wang and Cho [12], real-time 3D digital twins can be used to give plant operators an additional perspective of their machine and surrounding environment.

3.4 Safety

Construction remains one of the most dangerous industries in the UK and the top priority for construction firms. Accounting for 27% of workplace fatalities in 20/21, and further, 18% of fatalities involving being struck by a moving vehicle [13]. Having a connected site enabled by, for example, wearable IoT positioning locators, integrated into a real-time 3D environment gives rise to a number of safety benefits such as automated proximity detection between machines and humans. This use case builds on design and planning phase safety improvements from 3D Environments (BIM), previously largely targeting fall from height injury and fatality by Zhang et al. [14] into more operational, real-time safety advances as seen in Teizer et al. [15]. Utilising autonomous plant as in 3.1 also further adds to the safety benefit by removing operatives from harm's way enitrely.

4 DTM Capture

In this section we discuss sensors, capture methods and context relating to capturing a DTM. From first principals, the basic requirement for the foundation of this method is to create an accurate digital representation of an environment from which we can measure, manipulate and predict. These environment models have various nomenclature and are often used interchangeably however the following is generally understood from Li et Al [16], Digital Terrain Model (DTM) is the all-encompassing term for digitally representing a physical environment including surface features whereas, Digital Elevation Models (DEM) and Digital Surface Models (DSM) are a subsets indicating bare-earth. Various hardware is available for collecting 3D data at varying levels of maturity. For the purpose of this method, we are primarily considering exterior modelling across larger geographies although the techniques still apply for internal building modelling. UAV is the primary collection method with other methods identified to augment the UAV base model with delta changes and increase the real-time nature of collected data.

4.1 Sensors

4.1.1 Photogrammetry

Photogrammetry is the process of using images to generate information about objects and environments. Initially used for mapping objects, it has become more widely used to map larger objects and environments (DTMs) as collection methods have improved and computer systems have become more capable of handling large amounts of data. This is of particular note because the benefits possible from automation of earth-moving are compounded with larger work areas and as such the ability to map large areas is important for a successful outcome. Photogrammetry creates a higher resolution DTM and is also beneficial because it uses the visible light spectrum and as such, accurate color data is also captured, important for representing the environment to both humans and machines from which further context about an environment can be understood, deducing materials for example using techniques as identified by Rashidi et Al. [17] or surface terramechanics as demonstrated by Bretar et Al [18].

4.1.2 LiDAR

LiDAR (Light detection and ranging) uses lasers to directly measure distances from which DEMs can be created. LiDAR has lower absolute accuracy and by default does not enable a coloured point-cloud (although they can be coloured in post-processing by using traditional coloured digital maps). The technology can provide a better result when the survey area has moderate levels of foliage as light pulses can penetrate gaps in and around foliage, thus reaching ground-level and producing a more complete DTM. It is most commonly therefore used in a forestry setting for canopy height mapping, and is less commonly found on a construction site vs. Photogrammetry.

4.1.3 Combining LiDAR and Photogrammetry

Using a hybrid approach and merging the two techniques has been done and can attain an optimal model for certain use-cases, see [19] or [20] where two respective data sets are combined to create a single resultant DTM, although unless the site has moderately dense vegetation, the additional payload weight of suitable LiDAR scanner is not worth the reduced flight range. It is also noted that although it has been done, there is a literature gap in simultaneous capture of Photogrammetry data and LiDAR data using a dual gimbal of which the method to be described here would use.

4.1.4 Radar

Radar (Radio detection and ranging) uses radio waves in a similar strategy to LiDAR but is not to the same extent vulnerable to poor lighting and weather conditions which makes it an attractive candidate for use on a construction site. It is currently less commonly found due to the sparse point clouds it generates due to low spatial resolution and specularity, although a recent technique by Qian et al. [21] appear to increase point-cloud density, although still far from the density and overall quality of both LiDAR and Photogrammetry.

4.2 Platforms

4.2.1 UAVs

UAVs are the primary way in which 3D Data is collected today, principally using structure-from-motion photogrammetry as described above. It is the collection of data points across a wide range of different locations at a given altitude above ground that makes it well suited. Due to recent advances in battery technology UAVs have improved greatly in the past 5 years with many consumer and more advanced commercial solutions being developed with increased range, payload capacity and control system quality which has made them the obvious choice for surveyors.

Autonomy The primary challenge of site use of UAVs through the lens of this framework is the supervised nature of their operation which is prohibitive to high-frequency operation. The process currently requires manual setup and calibration of Ground Control Points (GCPs) or Real-time kinematic (RtK) base-stations to yield the centimeter precision needed for accurate surveying, combined with the need for a pilot to be physically located on the site to fly and have visual line of sight to the aircraft and also to change the aircraft battery means that remote piloting and autonomous recharging solutions need to be in place and aligned with the regulator. Notable attempts at overcoming this are power-tethered design in [22] or ground task automation designs proposed in [23]

Sortie Frequency The frequency of airborne scans be increased to reduce delta drift in the environment, however it is noted that sorties are best conducted when site activity is minimal to reduce unwanted artifacts arising from active operations. A combination of telematics, machine learning and diffs between sorties can be considered to filter out plant and other unwanted dynamic artifacts from images and would allow continuous sorties and data capture.

4.2.2 Static

Static hardware can also be used to assist with DTM capture, for example Wang in 2015 [12] sets up a multi camera and scanner system to create a DSM augmented with live video feed give operators a external perspective of their vehicle. By mounting capture hardware statically in this way or for example a on a high point, e.g. crane, it is possible to get a near real-time point cloud data of a specific area.

4.2.3 Vehicle Mounted

Mounting capture hardware on vehicles, specifically the plant machinery that is the focus of this study is an optimal way to capture local environment data, as is stipulated by Singh [5]. The quality of data is also higher as the roving nature of the vehicles gives a wider range of perspectives from which to interpolate.

4.3 Location considerations

Accuracy and ultimate usability of models is largely dependant on the synchronicity between the captured data and its alignment with real-world 3D vector space, as identified in [24]. The importance of accurate location information increases as we want to superimpose plant machinery on our DTM as well as use our DTM to inform plant operationally. There are three primary methods of attaining this alignment: Ground Control Points (GCPs); Real-time Kinematic (RTK); Post-processing Kinematic (PPK).

GCPs are the most commonly used method and they are often used alongside more advanced techniques. They rely on physically marked locations which are geo-referenced using traditional survey equipment, these points are then identified in post-processing to align the model. RTK and PPK use a drone based receiver with an accurately positioned base-station/s and enable highly accurate location information to be recorded directly into the 3D data by using carrier phase signals which can be thought of as a local coordinate reference. These measurements are either converted in real-time to real-world vector coordinates with RTK or in post-processing in PPK. Kinematic technologies require more specialist equipment and cost more, and of the two Kinematic methods, PPK is preferred for reliability due to reduced number of persistent reliable connections required and its compatibility with longer flights, especially beyond visual line-of-sight.

4.4 Software

Once data has been captured, it must be processed. The goal of this processing is to generate an accurately geo-referenced point cloud to form the basis of a DTM. This process varies in complexity dependant on the sensor technology used, and the specifics are outside the scope of this work. The steps are outlined here at a high-level and for this work are handled by Pix4D (7.2) and LGSVL (7.3).

Point Cloud Generation This first step in processing is to create a point cloud from the captured sensor data.

This process involves stitching together collections of photographs or distance data.

Coordinate Plane Alignment The second step is to align the point cloud with a real-world coordinate system. This process depends on the accuracy embedded location data of the captured images and is largely manual in the field, however the method in this paper will seek to make use of an server-based processing engine to create a robust and automated data pipeline that makes use of new techniques such as automated GCP identification.

5 Plant Telematics and IoT

In this section we explore the second part of our method, relating to plant telematics and IoT sensor data that can be used to accurately model and superimpose vehicles (and more) into an environment. We again look at context and important aspects for informing the ultimate system design.

5.1 Real-time Requirement

Although it is generally accepted that 30fps is the minimum frame-rate for which the human eye deems to be smooth, the definition of real-time, relating to the latency between an event taking place and being observed in a digital system is not very well defined, this is largely because any definition negates itself as in-fact any latency makes a system no longer technically real-time, however the commonality and the one that we will use for this method relates to the perception of humans to a delay which sets the requirement for latency from the event happening to it being displayed to the end-user in the low tens of milliseconds.

5.2 Data Communications Requirement

To attain sub 30ms latency, 5G technology is proposed in this work. Having superior performance and higher range than WiFi technology, 5G has as low a 1ms latency and has reached a suitable maturity to make it the obvious choice for data transfer between site-based devices in this system and cloud-based processing.

5.3 Location and positioning

In a similar way to the requirement for highly accurate location information for DTM sensor platforms, any vehicle wanting to interact as part of the environment must have accurate real-time positioning data available. In practice, this means employing RTK base-stations from which all agents interacting in the environment can operate from the same local reference frame.

5.4 Required sensor data

The sensor data we require for accurate synchrony is quite comprehensive and also dependant on the specific vehicle we want to support. Additionally, the precision of this sensor data must again be sufficient to ensure that real-world and digital environments do not diverge. The availability of plant-integrated sensor data is increasing with time, although the majority of systems currently are designed for non real-time reporting, such as idle-time monitoring. Legacy plant can be equipped with IoT sensors to allow them to participate in ROEM.

Standards There are numerous standards that outline how telematics data should be formatted and specifically the ones of interest as identified in ISO/TS 15143-3 [25]. Each plant manufacturer has slightly differing mechanisms for formatting and accessing its telematics data, despite the existence of [25]. For each plant manufacturer supported by the method, a unique feed of raw data must be secured with appropriate resolution and then cleaned and standardised.

6 Real-time Operating Environment Model (ROEM)

Telematics, IoT data and DTM are combined to create ROEM, a real-time environment containing data from multiple sources to create an interactive digital representation of a site. Given the input data from sections 4 and 5, this section identifies the required capabilities of this model in order that it maintains an accurate representation of the real-world.

6.1 Terrain Deformation

In this work, terrain deformation is the process of manipulating ground mesh and point cloud data to allow us to synchronise the built environment with ROEM by updating it based on plant sensor data from section 5. This will be achieved in real-time by mirroring the actions of real-world plant within our model to create delta changes from our base-model provided by DTM sensor data. To achieve delta deformation for model synchronicity, we use the Unity3D Vector3 API to manipulate the meshes by transforming mesh vertices through a vector based on the collisions of the digital representation of the plant machine on the environment.

6.2 Agent State Representation

In order to represent agents (Vehicles, humans etc.) correctly within ROEM, alongside telematics/IoT data, we must also have geometrically accurate 3D representations of the respective agent that we want to represent. This is to ensure that we can accurately represent the state of an agent within the environment and ensure that machine interaction with the terrain and environment is correctly modelled, critical for correct terrain deformation.

6.3 Data smoothing

Despite intentions for low latency, high frequency data, to project data into an environment that is perhaps running in excess of 100fps, data will be smoothed using a Kalman Filter see Welch et al. [26] to facilitate gaps in data between frame renders and to ensure accurate representation of machine state.

7 System Architecture

There are two sub-systems making up the architecture of ROEM as outlined in Figure 2. The first is the data processing and facilitation system, transforming and persisting data. The second is the 3D environment itself which consumes input data, enables it's manipulation as well user interaction and monitoring, plus additional sub-modules to enable use-cases defined in Section 3. Both sub-systems will be contained within an AWS virtual private cloud environment. This section considers each ROEM input, process and output step at a high-level.

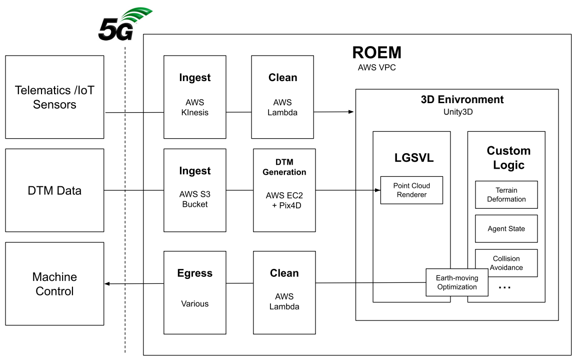

Figure 2. High-Level System Architecture

7.1 Telematics and IoT (Input)

Ingest Real-time telematics data will be ingested from various sources using AWS Kinesis, a real-time big data streaming platform.

Clean Data contained within Kinesis shards will be cleaned using an AWS lambda function and formatted to a unified format understood by ROEM before being persisted in an S3 bucket and passed directly onto Unity.

7.2 DTM Data (Input)

Ingest Raw DTM image and LiDAR data will be directly uploaded to an S3 Bucket, this will trigger an upload event on SQS (Secure Queuing Service).

DTM Generation The upload event will be detected by an SQS consumer running within an EC2 (Cloud Compute Resource) instance, also running Pix4D engine. The respective 3D data will be processed and combined to create a single LAS point cloud file. Any post-processing will be carried out (Diff generation, M/L etc.) on this file before it is persisted in an S3 bucket where it is fetched by the ROEM environment and the point cloud and associated ground-mesh reconstructed.

7.3 3D Environment (Processing)

The environment is the physics engine and 3D model that combines data to enable us to create a real-time digital twin, but also allows us to feedback sense, plan and execute information back to plant whether operating in autonomous or manual modes.

Unity3D A versatile 3D engine is required to power ROEM and to enable the user to view and interact with the environment. Unity3D is a widely used cross-platform 3D engine originally created for game-development that now has applications across industries and is seeing growing use in construction, most commonly for VR and XR purposes. It is the flexibility of this engine, which handles the complexities of an efficient 3D engine that allows the developer to focus on implementing differentiating features and makes it the suitable choice for this method.

LGSVL LGSVL [27] is an open-source project developed LG Electronics America Research and Development Lab in California. It provides a set of tools to build autonomous vehicle simulations based on Unity3D as well as containing a solution to process point clouds and create associated ground meshes. It also provides vehicle driving mechanics, important for agent state representation.

7.4 Machine Control (Output)

Once an activity has been planned within ROEM, it can be disseminated back to the plant machinery where machine control can execute the activity.

Clean ROEM output data must be cleaned and formatted to match the receiving machine control system. An AWS lambda function will be created for each receiving system.

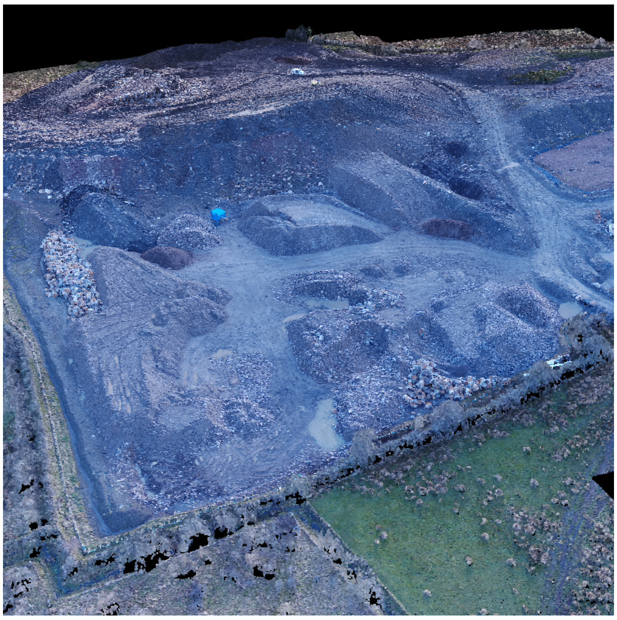

Figure 3. Earth-moving site

Egress Different providers of machine control systems also have different methods of receiving control data. Provider specific connectors will enable support for these systems.

8 Case Study

The case study shown in Figure 3 is a proof of concept of the ROEM 3D environment whereby a 1cm precision scan of an earth-moving section of a complex real-world road-building site has been ingested, a point-cloud generated along with a ground mesh.

9 Conclusion and Future Work

In this paper we introduce the concept that Plant Telematics and IoT can be combined with Digital Terrain Models to create a Real-time Operating Environment Model that can be used to accelerate plant autonomy adoption by providing a mechanism to fulfil Singh's [4] sense, plan, execute philosophy alongside other benefits outlined in Section 3. We explore the relevant adjacent, enabling technologies and associated literature, before outlining a system architecture along-side presenting early proof of concept implementation of the architecture using data from a real-world construction project. Future work is listed below and is largely relating to validation of the concept.

- Complete the implementation of the method outlined.
- Integrate ROEM in a live site trial.
- Utilise ROEM to manage, optimize and monitor autonomous tasks.
- Gather and synthesize data from this trial and quantify findings and benefits in further papers.

References

[1] Charles W. L. Hill and Frank T. Rothaermel. The performance of incumbent firms in the face of radical technological innovation. *The Academy of Management Review*, 28(2):257–274, 2003. ISSN 03637425.

[2] Joseph Louis and Phillip S Dunston. Integrating iot into operational workflows for real-time and automated decision-making in repetitive construction operations. *Automation in Construction*, 94:317–327, 2018.

[3] S. Dadhich, U. Bodin, and U. Andersson. Key challenges in automation of earth-moving machines. *Automation in Construction*, 68:212–222, 2016. ISSN 0926-5805. doi:https://doi.org/10.1016/j.autcon.2016.05.009.

[4] Sanjiv Singh. State of the art in automation of earthmoving. *Journal of Aerospace Engineering*, 10(4): 179–188, 1997.

[5] Sanjiv Singh. State of the art in automation of earthmoving, 2002, Jun 2018.

[6] Boyd C. Paulson. Automation and robotics for construction. *Journal of Construction Engineering and Management*, 111(3):190–207, 1985. doi:10.1061/(ASCE)0733-9364(1985)111:3(190).

[7] Mirostaw J Skibniewski. Current status of construction automation and robotics in the united states of america. In *9th International Symposium on Automation and Robotics in Construction*, pages 17–24, 1992.

[8] National Highways. Connected autonmous plant roadmap to 2035. 2019. URL `https://assets.highwaysengland.co.uk/Innovation+Hub/CAP+roadmap.pdf`.

[9] Osama Moselhi and Adel Alshibani. Optimization of earthmoving operations in heavy civil engineering projects. *Journal of Construction Engineering and Management*, 135(10):948–954, 2009. doi:10.1061/(ASCE)0733-9364(2009)135:10(948).

[10] Vivswan Shitole, Joseph Louis, and Prasad Tadepalli. Optimizing earth moving operations via reinforcement learning. In *2019 Winter Simulation Conference (WSC)*, pages 2954–2965. IEEE, 2019.

[11] Naveed Anwar, Muhammad Amir Izhar, and Fawad Ahmed Najam. Construction monitoring and reporting using drones and unmanned aerial vehicles (uavs). In *The Tenth International Conference on Construction in the 21st Century (CITC-10)*, pages 2–4, 2018.

[12] Chao Wang and Yong K. Cho. Smart scanning and near real-time 3d surface modeling of dynamic construction equipment from a point cloud. *Automation in Construction*, 49:239–249, 2015. ISSN 0926-5805. doi:https://doi.org/10.1016/j.autcon.2014.06.003. 30th ISARC Special Issue.

[13] Health and Safety Executive. Workplace fatal injuries in great britain. 2021. URL `https://www.hse.gov.uk/statistics/pdf/fatalinjuries.pdf`.

[14] Sijie Zhang, Jochen Teizer, Jin-Kook Lee, Charles M. Eastman, and Manu Venugopal. Building information modeling (bim) and safety: Automatic safety checking of construction models and schedules. *Automation in Construction*, 29:183–195, 2013. ISSN 0926-5805. doi:https://doi.org/10.1016/j.autcon.2012.05.006.

[15] Jochen Teizer, Ben S. Allread, Clare E. Fullerton, and Jimmie Hinze. Autonomous pro-active real-time construction worker and equipment operator proximity safety alert system. *Automation in Construction*, 19(5):630–640, 2010. ISSN 0926-5805. doi:https://doi.org/10.1016/j.autcon.2010.02.009. Building Information Modeling and Collaborative Working Environments.

[16] Z. Li, C. Zhu, and C. Gold. *Digital Terrain Modeling: Principles and Methodology*. CRC Press, 2004. ISBN 9780203486740. URL `https://books.google.co.uk/books?id=JvEo41LqjtUC`.

[17] Abbas Rashidi, Mohamad Hoseyn Sigari, Marcel Maghiar, and David Citrin. An analogy between various machine-learning techniques for detecting construction materials in digital images. *KSCE Journal of Civil Engineering*, 20(4):1178–1188, May 2016. ISSN 1976-3808. doi:10.1007/s12205-015-0726-0.

[18] F. Bretar, M. Arab-Sedze, J. Champion, M. Pierrot-Deseilligny, E. Heggy, and S. Jacquemoud. An advanced photogrammetric method to measure surface roughness: Application to volcanic terrains in the piton de la fournaise, reunion island. *Remote Sensing of Environment*, 135:1–11, 2013. ISSN 0034-4257. doi:https://doi.org/10.1016/j.rse.2013.03.026.

[19] B. St-Onge, C. Vega, R. A. Fournier, and Y. Hu. Mapping canopy height using a combination of digital stereo-photogrammetry and lidar. *International Journal of Remote Sensing*, 29(11):3343–3364, 2008. doi:10.1080/01431160701469040.

[20] Michael Lim, David N. Petley, Nicholas J. Rosser, Robert J. Allison, Antony J. Long, and David Pybus. Combined digital photogrammetry and time-of-flight laser scanning for monitoring cliff evolution. *The Photogrammetric Record*, 20(110): 109–129, 2005. doi:https://doi.org/10.1111/j.1477-9730.2005.00315.x.

[21] Kun Qian, Zhaoyuan He, and Xinyu Zhang. 3d point cloud generation with millimeter-wave radar. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 4(4):1–23, 2020.

[22] Christos Papachristos and Anthony Tzes. The power-tethered uav-ugv team: A collaborative strategy for navigation in partially-mapped environments. In *22nd Mediterranean Conference on Control and Automation*, pages 1153–1158. IEEE, 2014.

[23] Koji A. O. Suzuki, Paulo Kemper Filho, and James R. Morrison. Automatic battery replacement system for uavs: Analysis and design. *Journal of Intelligent & Robotic Systems*, 65(1):563–586, Jan 2012. ISSN 1573-0409. doi:10.1007/s10846-011-9616-y.

[24] Fei Dai, Youyi Feng, and Ryan Hough. Photogrammetric error sources and impacts on modeling and surveying in construction engineering applications. *Visualization in Engineering*, 2(1):2, Apr 2014. ISSN 2213-7459. doi:10.1186/2213-7459-2-2.

[25] ISO/TC 127/SC 3. Iso/ts 15143: Earth-moving machinery and mobile road construction machinery — worksite data exchange — part 3: Telematics data. Standard, International Organization for Standardization, January 2020.

[26] Greg Welch, Gary Bishop, et al. An introduction to the kalman filter. Technical report, University of North Carolina at Chapel Hill, 1995.

[27] Guodong Rong, Byung Hyun Shin, Hadi Tabatabaee, Qiang Lu, Steve Lemke, Mārtiņš Možeiko, Eric Boise, Geehoon Uhm, Mark Gerow, Shalin Mehta, et al. Lgsvl simulator: A high fidelity simulator for autonomous driving. *arXiv preprint arXiv:2005.03778*, 2020.