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EARTHMOVING EQUIPMENT AUTOMATION: A REVIEW OF TECHNICAL ADVANCES AND FUTURE OUTLOOK

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SUMMARY: *In the construction industry, the earthmoving sector is among the pioneers in adopting new sensing and information technologies to reduce operation costs, improve productivity, and enhance automation and safety. Fleet tracking and management systems, automated machine guidance and control, and proximity detection devices for accident warning are some examples of emerging products for earthmoving equipment. In addition to the commercial solutions, the research community actively develops and evaluates new systems in this area. This paper aims to critically review the related advances in this field. A three-phase literature review was carried out to investigate the innovations in industrial and academic research communities. Advances in six major industrial companies and a total of 102 related academic papers have been reviewed and discussed. Based on the application area and the function, current research works are divided into four categories: equipment tracking and fleet management, safety management, equipment pose estimation and machine control technology, and remote control and autonomous operation. The underlying technologies and methods used in these systems are discussed in detail. Finally, future research opportunities, based on the identified shortcomings and gaps in knowledge, are highlighted. In particular, the remote control and autonomous operation of earthmoving equipment are identified as the most underdeveloped and complicated areas, and the missing modules and research directions in these fields are discussed.*

KEYWORDS: *earthmoving equipment, sensing technology, information systems, productivity, automation*

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1 INTRODUCTION

In the 20th century, advances in the field of earthmoving equipment focused on developing new, specialized forms of equipment and on incrementally improving their power, flexibility, and efficiency (Tatum et al. 2006). In the 21st century, innovation efforts continue to create incremental improvements in the equipment systems; these improvements include increased engine efficiency, reduced greenhouse gas emission, improved electro-hydraulic control, and others. In addition to improvements to the mechanical and electronic systems of the machines, the last two decades have seen advances in new add-on sensing and information systems. These systems have contributed to improved productivity, safety, operation, maintenance, and management of earthmoving equipment (Edwards and Holt 2009; Tatum et al. 2006). Fig. 1 provides a schematic view of the evolution of motorized earthmoving equipment, which presents the gradual use of automated systems and artificial intelligence aimed at cognitive robotic operation of these equipment.

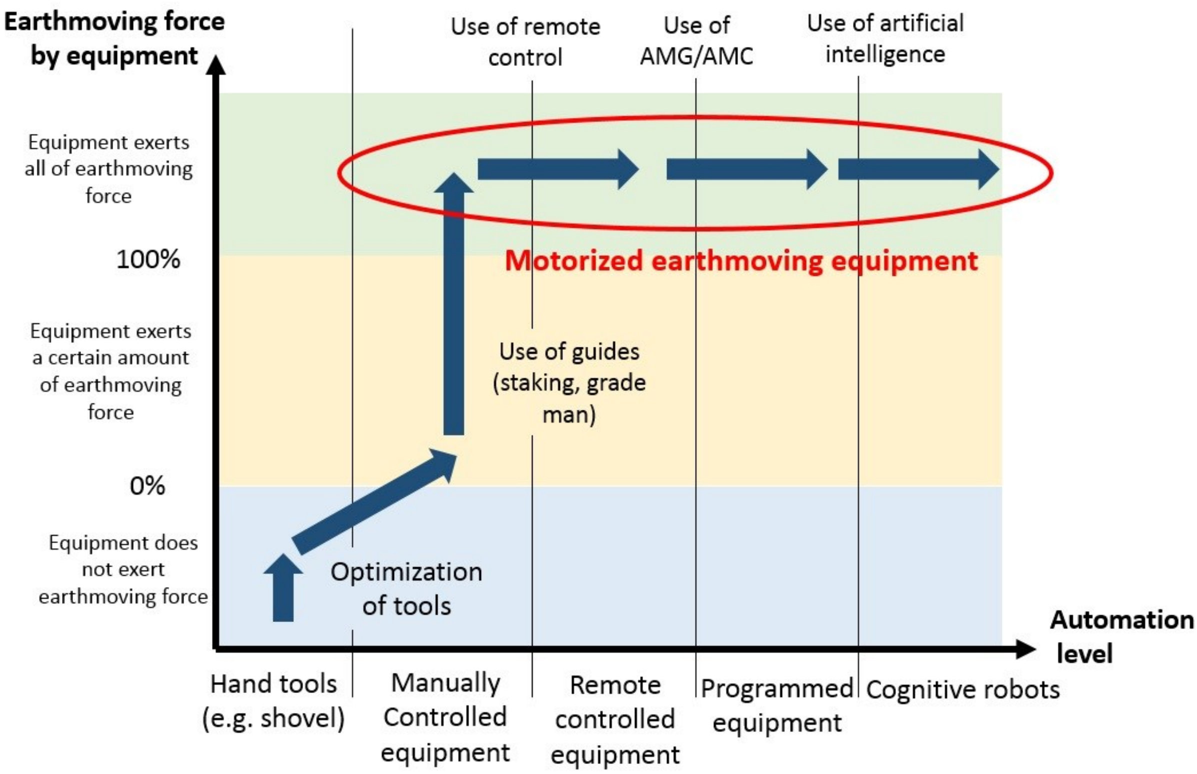

Figure 1. Evolution of the earthmoving operations (based on the concept presented by Van Gassel and Maas 2008)

Although some of the sensing and information systems are developed by the original equipment manufacturers, most of them are independently developed by commercial entities to be installed later on the machine, as an Original Equipment Manufacturer (OEM) arrangement or standalone product. This is an active sector of the earthmoving equipment industry and the rate of innovations in this area possibly exceeds that for the conventional systems of the equipment. In addition to commercial systems developers, the research community actively develops and tests new systems in this field. As a result, research studies sometimes include reviews of innovations in sensing and information systems. Most of the recent technical reviews, however, only focus on a specific topic related to the earthmoving equipment automation and do not provide a comprehensive picture of the state of research and development in this broad area. For example, research efforts investigated the advances in real-time locating systems (RTLSs) (Li et al. 2016), technology applications in construction safety (Seo et al. 2015; Skibniewski 2014), vision-based monitoring systems (Yang et al. 2015; Teizer 2015), and challenges of developing tele-operated and autonomous earthmoving machines (Dadhich et al. 2016a). Amongst all, there is a research project which provided a multifaceted review about construction equipment management. Edwards and

Holt (2009) investigated the state of construction plant and equipment management research in the eight themes of maintenance, downtime/productivity, optimization, robotics/automation, health and safety, operators/operator competence, machine control, and miscellaneous. This literature review, however, investigated the broad topic of construction plant and equipment management, and some sensing and information systems (such as tracking and monitoring systems) were missing. In addition, numerous cutting-edge systems, namely in the fields of vision-based sensing (Yang et al. 2015; Rezazadeh Azar 2015), semi- and fully autonomous operation (Dadhich et al. 2016a), and application of smartphones (Akhavian and Behzadan 2015), have been developed in the last seven years. These systems should also be included in a review.

Therefore, this paper provides an inclusive and critical review of the sensing and information systems for earthmoving equipment, discusses relevant works from research and commercial communities, and evaluates their potential and limitations. Such a comprehensive review is beneficial for both the academic and industry research communities. Based on the literature review, the state of the art research and developments were categorized into four areas and each is discussed separately. Finally, the future paths are presented.

It should be mentioned that there are other active research areas in the field of construction equipment management, such as planning and optimization, simulation, emission, maintenance, and cost and value estimation. However, these areas are outside the scope of this review and are not discussed.

2 RESEARCH METHOD

Since this research focuses on advances in the field of earthmoving automation, the recent developments in both industry and academic research community were studied. The literature review was carried out in three phases: First, it investigated the recent products and automation solutions offered by the major equipment manufacturers, including Caterpillar, Komatsu, and Liebherr, and the technology providers, such as Trimble, Topcon, and Leica. Second, six world-class academic journals within the area of construction engineering and automation were selected, including Automation in Construction, Journal of Computing in Civil Engineering, Advanced Engineering Informatics, Journal of Construction Engineering and Management, Information Technology in Construction, and Journal of Computer-Aided Civil and Infrastructure Engineering, because they are widely accepted as high-impact resources by the research community (Li et al. 2016). Then a comprehensive search in the "title/abstract/keyword" for "earthmoving equipment" was conducted through the search engine of each of these journals. The abstracts of the retrieved papers were carefully studied to decide whether the paper relates to "earthmoving equipment automation". Finally, all the selected papers were searched in the Google scholar to trace their subsequent citations. This way, the recent related efforts in other journals and conferences, especially in the field of robotics and computer science, were reviewed as well. In the second step, 73 related papers were found and reviewed, and 29 research papers were identified and included in the third stage of the research. These papers cover a wide range of innovations in the field of earthmoving equipment automation, but they could be classified into the four main areas:

- Equipment tracking and fleet management
- Safety management
- Equipment pose estimation and machine control technology
- Remote control and autonomous operation

3 EQUIPMENT TRACKING AND FLEET MANAGEMENT

Real-time localization and tracking of earthmoving equipment is beneficial for many purposes in construction and mining domains. For example, it facilitates integrated fleet management and helps to actively allocate resources to work zones in large jobsites. Moreover, the spatiotemporal data could be used to interpret the equipment actions and therefore estimate their productivity.

Integrated fleet information management is among the growing solutions in the heavy construction and mining sectors. Many of the large equipment manufacturers and construction information technology companies provide integrated fleet management systems. These systems utilize a series of built-in sensors and onboard diagnostic systems to provide a wide range of data about the condition and output of the fleet. Table 1 provides a summary of the popular fleet management systems and their features. Most of these systems use a global navigation system (GPS/GLONASS) to locate the machine and employ an on-board diagnostics system for health monitoring and maintenance planning of the fleet. As presented in this table, all these competitor systems provide quite similar data.

Table 1. Examples of commercial fleet management products

System	Company	Features
Product Link	Caterpillar (2016)	Localization, fuel consumption, working and idle times, web-based application, condition monitoring
Vision Link	Trimble (2016)	Localization, fuel consumption, working and idle times, web-based application, condition monitoring
Komtrax	Komatsu (2016)	Localization, fuel consumption, working and idle times, web-based application, condition monitoring, payload and dump count
LiDAT	Liebherr (2016)	Localization, fuel consumption, working and idle times, service intervals
Sitelink3D Enterprise	Topcon	Real-time tracking, visualization, volume and haul reporting, working and idle times, as-built overview

These systems are mostly used to track the fuel consumption, working and idle hours, and location (mainly for security) of the equipment. Despite providing useful data, these systems have shortcomings, and the research community is attempting to address them. First, locational data are not thoroughly analyzed using a reasoning or pattern recognition algorithm, and they are mainly used for positioning and geo-fencing (security) purposes. Second, equipment times are mainly divided into working and idle states, which do not provide a detailed picture of the operations. For example, the working state is not classified into detailed actions (e.g. moving, loading, swinging), and the operations are not analyzed to determine whether or not they add value. Of the above systems, Komtrax can provide more detailed information about working states (e.g., travel time and digging hours) which depends on several integrated sensors in the machine. Finally, all these systems use a number of built-in sensors that are only available in new equipment or that can be retrofitted on newer electronically controlled equipment, most of which is less than 10 years old. However, many active machines do not have those sensors or technology.

Most of the existing fleet management systems usually lack an in-depth analysis of the spatiotemporal data. Therefore, many research works address real-time tracking and productivity estimation of the equipment, using different real-time locating systems (RTLSs), which are described below. The level of accuracy, advantages, and limitations of these RTLS were investigated in a recent study (Li et al. 2016).

3.1 Radio-based technologies

Radio-based localization systems can be divided into global and local positioning systems. GPS-based systems are the dominant technology in this area for many reasons, such as the relatively low cost, reliability, and availability of technology (both hardware and software). Research efforts in the late 1990s and early 2000s investigated methods to collect and enhance the quality of data, and research in the later 2000s developed systems to interpret the collected data and recognize the operations. The next stream of research projects utilized local radio-based technologies, namely RFID and UWB, to locate and track fleet equipment. Each technology has benefits and shortcomings. On one hand, the RFID-based systems have a low setup cost, but the system can register an event only if a tagged machine gets within the (relatively close) range of an RFID reader. On the other hand, UWB systems provide consistent and fairly accurate spatiotemporal data of the tagged equipment, but also only within a limited range.

Moreover, some research projects used multimodal sensors, such as weight and angle sensors, together with a positioning system to address the lack of productivity estimation data for payloads. Table 2 provides a summary of the related research topics, applied technology, and their contribution in a chronological order.

As presented in Table 2, two trends have emerged in research work since 2012: First, projects applied a reasoning and/or pattern recognition algorithm to analyze the spatiotemporal data and to locate the work zone, namely loading and dumping zones (see Fig. 2). This feature enhances the functionality of the system compared to the older versions, in which the user had to define the work zones. Application of other data, such the payload and pose of the machine, also helped improve pattern recognition (Ibrahim and Moselhi 2014; Akhavian and Behzadan 2013). Second, most of the recent research efforts highlighted the lack of in-depth knowledge-based application of the captured data for modeling and controlling the cyclic operations; therefore, some research projects used the captured data to update and run near real-time simulations to detect deviations and take corrective measures (Pradhananga and Teizer 2015; Montaser and Moselhi 2014; Akhavian and Behzadan 2013).

Table 2. Radio-based equipment tracking and productivity estimation research works

Year	Research work	Sensing technology	Scope
2004	Navon et al.	GPS	Analysed operations of equipment based on their movement in work zones
2005	Hildreth et al.	GPS	Improved the detail level of spatiotemporal data for operation analysis
2007	Lu et al.	GPS and dead reckoning	Used GPS with dead reckoning to supplant GPS when GPS signals are unavailable or unreliable in dense urban environments
2007	Worrall and Nebot	GPS	Developed a method to broadcast the GPS position of the mining fleet via a wireless network
2008	Teizer et al.	UWB	Evaluated the accuracy of UWB position estimation and investigated feasibility of using this sensing technology in construction
2012	Akhavian and Behzadan,	Angle sensors	Used pose and locational data to update a discrete event simulation model of the operation
2012	Montaser and Moselhi	RFID	Used RFID tags to keep track of entrances and exits of hauling equipment to estimate the cycle times
2012	Montaser et al.	GPS	Used GPS data together with Google Earth to update a near real-time simulation model, estimate productivity of the hauling operations, and discover deviations
2012	Song and Eldin	GPS	Used locational data to update simulation and schedule the forthcoming operations
2013	Akhavian and Behzadan	UWB, weight, load cells, and angle sensors	Employed a set of sensors to collect data, then used reasoning and a pattern recognition algorithm (k-means clustering) to recognize loading cycles, estimate productivity, and generate an automated simulation model
2013	Montaser and Moselhi	RFID and control sensor	Used RFID tags to detect the proximity of a truck and loading unit to recognize loading events, and also employed a control sensor to detect dumping event. These data were used to estimate cycle times
2013	Pradhananga and Teizer	GPS	Used low-cost GPS, performed error analysis, and applied spatiotemporal analysis to detect work zones, cyclic activities, and proximity of equipment
2014	Ibrahim and Moselhi	GPS, weight, pressure, and angle sensor	Used a set of sensors for productivity estimation and then measured the deviation from the simulation results
2014	Montaser and Moselhi	GPS	Used GPS data and a GIS web-based system to update a near real-time simulation model and estimate productivity
2014	Vahdatikhaki and Hammad	GPS, UWB	Used the spatiotemporal data provided by the installed RTLS (including GPS and UWB) on a dump truck and an excavator for detailed analysis of their working states and create near real-time simulation
2015	Pradhananga and Teizer	GPS	Used spatiotemporal data from equipment and continuous spatial changes to the site layout during the project for cell-based simulation of the earthmoving operations
2016	Alshibani and Moselhi	GPS	Used GPS data and a GIS system to obtain limited samples of GPS data to track and control earthmoving equipment

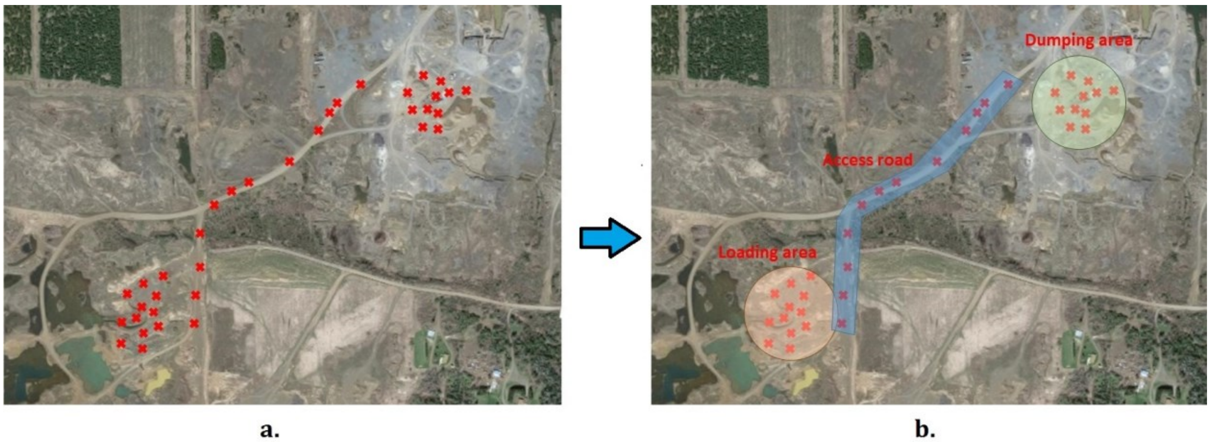

Figure 2. Recognition of work zones using spatiotemporal data

The emergence of smartphones has also provided a new opportunity for intelligent monitoring of earthmoving operations. Not only are the devices themselves equipped with a range of sensors (including GPS, accelerometer, and three-axis gyroscope), they are also standalone computing units with a wide range of communication tools, such as cellular network, Wi-Fi, and Bluetooth. Thus, the feasibility of using these devices for monitoring was examined. For example, built-in accelerometers recorded the vibrations in different working and idle states of an operating excavator, then a signal analysis method was applied to distinguish the equipment's different working states and thus estimate its operation efficiency (Ahn et al. 2013). Akhavian and Behzadan (2015) used supervised machine learning algorithms to classify features from the raw data captured by the GPS, gyroscope, and the accelerometer embedded in a smartphone installed on a front-end loader. This setup could estimate cycle times, which could then be used for the simulation of the operation.

Based on the results of academic research and widespread application of commercial systems, radio-based technology, namely GPS, provides reliable and robust solutions for equipment tracking and monitoring. These solutions, however, have some limitations. First, they are intrusive, because every single piece of equipment must be tagged, which could become problematic while using rental equipment or a sub-contractor. Second, as cited in the literature, spatiotemporal data might not be sufficient for activity recognition, and multimodal sensing system would thus be required.

3.2 Computer vision-based technologies

Computer vision algorithms are among the latest technologies employed to monitor earthmoving operations and are heavily investigated for this purpose (Yang et al. 2015). The pipelines for vision-based monitoring usually consist of three main modules: detection, tracking, and action recognition. A few research works used another approach in which they extracted visual features to interpret a task without detection and tracking (Golparvar-Fard et al. 2013).

Each of the three modules usually uses several algorithms, and construction researchers evaluated and modified state-of-the-art methods in each field to provide a reliable algorithm for equipment monitoring. In addition to passive imaging techniques, methods were developed to process point cloud images captured by a laser scanner in an effort to recognize operating equipment (Wang and Cho 2015). Table 3 presents the timeline and the topics of these research projects.

As presented in Table 3, majority of the research works emerged in the last six years and there are some main motivations for that. First, development of these vision-based systems depends on strong object recognition and tracking algorithms, which majority of them were introduced by the computer vision researchers in the last 10 to 15 years. Second, all of these vision systems employ computationally-intensive algorithms and emergence of low-cost computing platforms, namely parallel computing on graphical processing units, made near or full real-time processes possible.

Despite promising progress, several factors including harsh visual noise, occlusion, limited coverage, poor performance at low lighting conditions (e.g. night and fog), and rather low reliability (relatively high false negative and false alarm rates) were cited as the main limitations of these algorithms for practical application. In addition, the developed classifiers are only able to detect a few types of equipment, such as excavator and dump truck, and recognize only one or two type of actions (Bügler et al. 2016; Rezazadeh Azar et al. 2013; Golparvar-Fard et al. 2013; Gong and Caldas 2011), which make them impractical in dynamic construction environments.

Table 3. Vision-based equipment monitoring research works

Year	Research work	Area	Scope
2007	Zou and Kim	Tracking and action recognition	Used hue, saturation, and value color space to track an excavator in a plain background and distinguish its idle and active times
2011	Brilakis et al.	Tracking	Tracked the entities in the videos captured by two calibrated cameras, then matched the object in both views and employed triangulation of two cameras' views to estimate the 3D coordinates of the target
2011	Chi and Caldas	Object recognition	Used a background subtraction method to isolate moving objects in construction videos with static backgrounds, and then classified them using Bayes or neural network classifiers
2011	Gong and Caldas	Tracking and action recognition	Evaluated different tracking methods, including Codebook, Gaussian mixture, and Bayesian background, for tracking entities in construction videos Applied an object recognition and a tracking method to analyze time utilization, production cycle, and abnormal production scenarios of a loader
2011	Jog et al.	Object recognition	Used Semantic Texton Forests to detect truck faces
2011	Park et al.	Tracking	Compared different categories of 2D vision tracking methods, including contour-based, kernel-based, and point-based methods, to find the most appropriate choice for 3D vision tracking.
2012	Park and Brilakis	Object recognition and tracking	Used background subtraction, Haar-like features, and color information to detect equipment and then employed a tracking algorithm to reduce the false detections
2012	Rezazadeh Azar and McCabe (a)	Object recognition	Developed a cascade method, using Histogram of Oriented Gradients (HOG) and Haar features object detection algorithms, for timely detection of dump trucks in construction images and videos
2012	Rezazadeh Azar and McCabe (b)	Object recognition	Developed a part-based and reasoning framework to detect excavators in construction videos
2012	Park et al.	Tracking	Used a 2D tracking method to obtain 2D pixel coordinates of the target's centroid in two calibrated camera views. Then applied epipolar geometry (using intrinsic and extrinsic parameters) to triangulate the centroids from multiple views and retrieved 3D location
2013	Memarzadeh et al.	Object recognition	Developed an equipment recognition framework using HOG and hue–saturation colors
2013	Golparvar-Fard et al.	Action recognition	Used spatiotemporal HOG features and a multi-class Support Vector Machine (SVM) to train classifiers, which then are used for action recognition of earthmoving equipment
2013	Rezazadeh Azar et al.	Tracking and action recognition	Developed a hybrid tracking algorithm to track dump trucks in congested scenes; also used a linear SVM classifier to recognize loading cycles
2014	Tajeen and Zhu	Object recognition	Developed a dataset for the recognition of excavator, loader, dozer, roller and backhoe; compared the performance of two popular object recognition methods in detection of earthmoving equipment
2014	Yang et al.	Object recognition	Developed an inverse "V" model to detect a hydraulic excavator in real-time videos
2015	Rezazadeh Azar	Object recognition	Used dynamic optical zooming and AprilTag marker recognition to identify individual equipment in real-time videos
2015	Teizer	Object recognition and tracking	Reviewed relevant detection and tracking methods and their application in construction
2015	Wang and Cho	Object recognition	Used regular videos to detect and track targets, then utilized a laser scanner to capture a 3D point cloud image of the scene, finally applied a surface modelling to generate a concave hull of the detected equipment
2016	Soltani et al.	Object recognition	Developed and automated a method for creating and annotating synthetic images of construction equipment to reduce the time for supervised training of object recognition classifiers
2016	Zhu et al.	Tracking	Developed a vision tracking algorithm using particle filters to address the occlusion problem in construction sites
2016	Yuan et al.	Object recognition and tracking	Recognition and tracking of excavators using stereo vision based on hybrid kinematic shape and key node features
2016	Bügler et al.	Action recognition and volume estimation	Developed an integrated vision system using photogrammetry and video analysis system to estimate the volume of the removed soil by excavators and dump trucks

4 SAFETY MANAGEMENT

Earthwork jobsites are dynamic environment, where there is extensive number of interactions between equipment, workers, and materials. This level of interaction and proximities requires high-level of situational-awareness and a considerable portion of fatalities and critical injuries in the United States construction sector were related to construction equipment and contact collisions (Vahdatikhaki and Hammad 2015; Teizer et al. 2010a; Teizer et al. 2010b). In particular, nonvisible areas for the equipment operators, called blind spots, are accident-prone zones and the collision risk is critical for those who work in the blind spots of the operating equipment (ENR 2015; Hinze and Teizer 2011). Therefore, several systems were developed to improve the safety of operations that involve heavy equipment (Skibniewski 2014). In addition to the sensing technologies used for tracking and productivity estimation, other sensing methods such as radar, ultrasonic (Choe et al. 2014), and magnetic field (Li et al. 2012) systems were evaluated for collision prevention.

GPS was among the early technologies investigated to provide accident warnings. For example, GPS and wireless communication were employed to improve the situational awareness of the operators (Oloufa et al. 2003). In another research project, a system, named SightSafety, was developed using a combination of GPS, smart sensors, and wireless networks to alert management and employees about potential dangers (Riaz et al. 2006). GPS-based systems, however, tended to produce excessive false alarms; thus the Kalman filter was combined with the nearest-neighbor method to reduce the false alarm rate (Wang and Razavi 2015). Moreover, a wireless communication network was used to communicate the GPS data of the equipment to each other as a proximity warning in open-pit mines (Sabniveesu et al. 2015). Lastly, a GPS-based framework was developed to visualize the near miss interactions between workers-on-foot and construction equipment in form of heat map on the building information model of the project (Golovina et al. 2016).

Radio frequency (RF) remote sensing was another radio-based technology investigated in this domain. In an experimental setting, RFID readers were installed on the heavy equipment and RFID tags were attached on some guardrails, heavy equipment, and hardhats of some workers, and the recorded proximities were sent to a central processing unit (Chae and Yoshida 2010). In another research setup, workers were tagged (using personal protection units (PPU)) and the installed antennas on the equipment (equipment protection units (EPU)) detected dangerous proximities and informed the operator and worker using a set of visual and audio alerts (Marks and Teizer 2013; Teizer et al. 2010a). A later study compared the performance of a Bluetooth system (available on smartphones) in proximity detection to that of RFID and Magnetic field systems (Park et al. 2016). Moreover, UWB technology was used to estimate dynamic equipment workspaces of operating equipment for collision avoidance (Vahdatikhaki and Hammad 2015).

Imaging methods were also tested for accident warning. For example, range-imaging cameras were used to generate a 3D model of the work environment and detect nearby objects (Son et al. 2010). In addition to their use in object detection, laser scanners can also provide a quick point cloud of the surrounding environment, which can then be processed to measure and create a 3D blind spot diagram for each piece of equipment (Ray and Teizer 2013; Marks et al. 2013; Teizer et al. 2010b).

Regular cameras also showed promising performance in detecting dangerous proximities. For example, vision-based object recognition and tracking algorithms were used to locate and track earthmoving machinery, and then safety rules were applied to detect safety violations (Chi and Caldas 2012a). They also developed a preliminary error impact analysis framework to model object detection and tracking errors caused by image-based devices and methods, and to analyze the consequence of such errors on safety assessment (Chi and Caldas 2012b).
In addition, Kim et al. (2015) developed a vision-based safety monitoring system that uses background subtraction (based on the Gaussian mixture model) to isolate and detect equipment and workers, and then tracks them using a Kalman filter. Finally, it employs fuzzy set theory and fuzzy inference to analyze the safety expert reasoning and assess the safety of the tracked entities. Despite these encouraging advances, the use of vision-based methods in the earthmoving industry is still far from practicality because of technical limitations such as reliability (e.g. occlusion, and type I and II errors), accuracy, and applicability (Seo et al. 2015).

5 EQUIPMENT POSE ESTIMATION AND AUTOMATED MACHINE GUIDANCE TECHNOLOGY

Automated machine guidance (AMG) and automated machine control (AMC) products are relatively new in the heavy civil engineering sector. These systems use accurate sensing technologies to provide real-time, accurate pose information about the end-effector so that machine operators can carry out processes more quickly and with higher precision. The pose data of the equipment are usually emulated and visualized with respect to the design levels. Perkinson et al. (2010) conducted a survey among some US heavy construction contractors and found that 60% of them use GPS for site layout and 50% use GPS for vehicle guidance and/or control purposes. These systems showed considerable improvement in the productivity of heavy construction operations (see Table 4). The reported productivity improvement rates, however, were not consistent in these studies and factors, such as project conditions and materials (Rezazadeh Azar et al. 2015a; Vennapusa et al. 2015), would affect the productivity gains.

Table 4. Comparison of studies about the benefits of using AMG/AMC

Study	**Methodology**	**Results**
Han et al. (2006)	Discrete event simulation	Two different GPS-based earthmoving scenarios were analyzed; the productivity improvement rates over the conventional system were 21.74% in short haul and 5.67% in long haul distance
Han et al. (2008)	Discrete event simulation	Productivity improvement depends on site conditions. Two models were analyzed with 34.36% and 16.38% productivity improvement rates for the GPS-based system
Shehata et al. (2012)	Discrete event simulation	Time saving of 18.57% and productivity improvement of 41.47% were found for the GPS-based operation
Rezazadeh Azar et al. (2015a)	Field study	Productivity improved by 6% to 34% for bulldozers (depending on jobsite and soil conditions) and 19% to 23% for excavators
Vennapusa et al. 2015	Survey responses from various AMG users	Productivity improvement can vary significantly due to various factors, such as project conditions, materials, application, equipment used, employed positioning technologies, and operator experience.

The capabilities of AMG products vary widely, from one-dimensional depth estimation to full 3D monitoring of the equipment pose. These systems utilize a variety of sensing technologies, depending on the type of equipment and the output data. Fig. 3 shows the most common types of AMG systems for earthmoving equipment. The solution for graders and scrapers is basically the same as that for bulldozers; they are equipped with one or two real-time kinematic (RTK) GPS antennas to monitor the pose of the end-effector. A roller can also be tracked with GPS and additional sensors can measure parameters that provide indirect measurement of the compaction level (Xu and Chang 2016).

In parallel with industry researchers, academic construction researchers have investigated RTK GPS for machine guidance as well. For example, research experiments were carried out to assess the performance of RTK GPS for machine control applications, and to filter noises and improve accuracy (Peyret et al. 2000). Later, a Kalman estimator was used to fuse the output of a cylinder encoder, radar, fibre-optic gyro, and data from an RTK GPS to provide accurate localization of a compactor. This dead-reckoning navigation system could compensate for the signal losses problem possible in GPS (Bouvet et al. 2001). Moreover, electronic joint encoders were utilized to estimate the angles of an excavator's arm and two laser receivers were added to the system to localize the machine in a site coordinate system. This prototype could achieve the accuracy of 5.1 cm (Bernold 2002; Huang and Bernold 1997).

AMG systems are not only useful to improve productivity and accuracy, but also could help reduce accidental strikes of buried infrastructure. A system was developed to emulate the movement of an excavator in a virtual environment that measures the proximity of the end-effector to the utilities buried in the excavator's vicinity (Talmaki and Kamat 2014). The effectiveness of this system, however, depends on the quality of the infrastructure's GIS data; therefore, methods were developed to assess the uncertainty of the underground infrastructure geospatial data (Li et al. 2015).

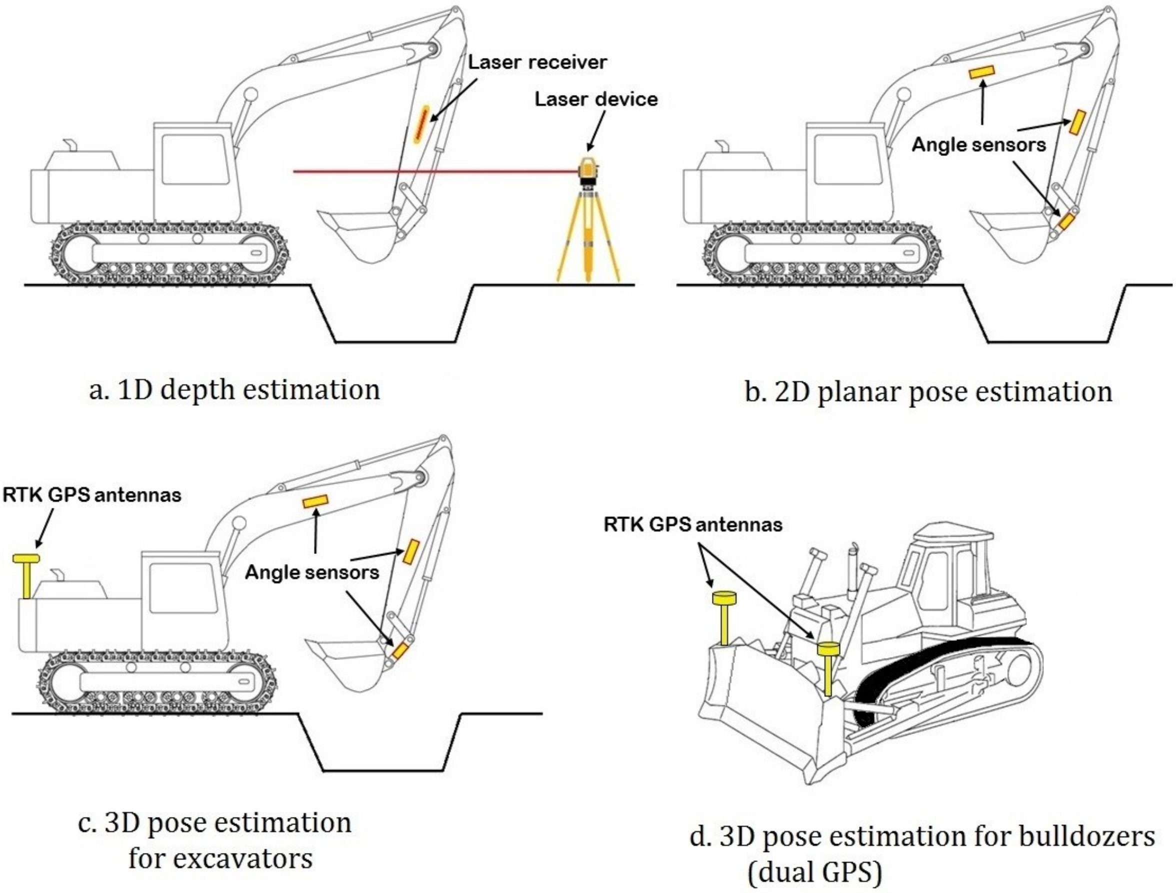

Figure 3. Common AMG systems for earthmoving equipment

Another stream of research in this field attempted to address the high cost of these products by using less expensive sensing technologies, mostly for the excavators. UWB was selected as a potential RTLS; however, its accuracy was not sufficient for AMG applications. Thus, an optimization-based correction was carried out, which improved the initial locational and pose estimations (Vahdatikhaki et al. 2015). Vision-based methods were also used to track the pose of an excavator's arm in its plane, by tracking a set of fiducial markers attached to the arm. Despite its low cost, this system was not feasible because it could measure only 2D angles and it failed to track the bucket as it disappeared from the frame during excavation (Rezazadeh Azar et al. 2015b). Hence, the system was drastically modified by adding an on-board camera to the excavator to track the 3D pose of the machine by detecting benchmark markers installed on the ground; in addition, a special mechanism was added to rotate a marker and thereby estimate the pose of the bucket (Lundeen et al. 2016, Feng et al. 2015).

6 REMOTE CONTROL AND AUTONOMOUS OPERATION

Repetitive and linear tasks that are performed a large number of times are appropriate candidates for robotic applications. Most earthmoving operations, such as excavation and loading, are among the most repetitive activities in the heavy construction and mining sectors. Other reasons justify developing autonomous systems to operate heavy earthmoving equipment. First, operator crews of these machines are expensive and highly skilled laborers who require several years of training and experience, and there is a substantial need to expand or replace existing personnel in many countries that have growing construction and mining industries. For example, between 2014 and 2024, the growth rate for excavating and loading machine and dragline operators is expected to be 6.2% (U.S. Bureau of Labor Statistics 2015). Second, many natural resources companies have expanded their operations to remote and harsh-weather locations, such as northern latitudes and underground, which are not attractive for human operators. Third, tele-operated and autonomous equipment can be safely used in dangerous sites, such as disaster areas, without jeopardizing operators. In response, two research streams have tried to address these problems. The first group develops tele-operated systems, and the second research stream investigates autonomous operations.

A tele-operated system has two main modules: 1) a situational awareness module that consists of a set of sensing devices to provide real-time perception of environmental elements; and 2) a control system to accurately transmit commands to the equipment actuators. It was argued that regular videos cannot provide reliable environmental perception for the remote operators (Son and Kim 2012); thus, human-machine interfaces were developed to represent a three-dimensional view of the workspace. For example, a 3D interface was developed using a time-of-flight camera and charged-coupled device camera (Son and Kim 2012).
Control systems were also the subject of some studies. A remote-control system was developed using pneumatic rubber muscles to operate a backhoe's joystick (Sasaki and Kawashima 2008). Another research team designed a system that uses a series of motion sensors to capture the movements of a remote operator to control the movement of an excavator (Kim et al. 2009). These tele-operated activities, however, showed inferior productivity and precision compared to onboard operations.

Autonomous operation of a piece of equipment is much more complicated than tele-operation, because the system requires comprehensive technology to accurately localize its position; sense the surrounding environment, including static background and dynamic objects; sense the pose of the end effector; and then plan and react accordingly. The next challenge is to smoothly perform the required tasks without colliding with obstacles. For example, the shortest swing path for an excavator boom loading a dump truck may result in hitting the bed. Moreover, underground obstacles, such as rocks, could be harmful to the machine and need to be avoided.

Some of these issues were investigated by different researchers. One of the main requirements for an intelligent earthmoving system is 3D surface modeling, which can be created using mobile 3D laser scanners and a mathematical model. A complete 3D model of the work environment requires multiple scans from different angles, which are then automatically registered using sphere targets (Chae et al. 2011). A prototype robotic excavator has been developed; it uses 3D designs as a target and laser scanners and stereovision to sense the actual environment and reach the designed profiles (Yamamoto et al. 2009). Moreover, methods were studied to create task planner (Seo et al. 2011) and intelligent navigation strategies for an automated earthwork system. These navigation strategies were generated on the basis of a scanned environment (Kim et al. 2012). 3D graphical job planning tools and algorithms were also developed for supervisory control of the jobs performed by an autonomous compact wheel loader. This system displays updated job plans on a 3D model of the worksite, providing environmental perception for the remote operator (Halbach and Halme 2013). In addition to range imaging, a two-stage cascade matching method was proposed for 3D terrain reconstruction using a stereo camera system (Sung and Kim 2016).

The other research stream in autonomous operation focused on motion planning and control systems. In particular, robotic operation of the excavators and backhoes was heavily studied due their versatility and convenience. Dadhich et al. (2016a) classified the research efforts in this area into five main categories: modeling robotic mechanisms for control, automatic loading (Dadhich et al. 2016b), pile characterization (McKinnon and Marshall 2014), localization and navigation, and path planning. In particular, the last category, path planning, has attracted a considerable attention in recent years. For example, algorithms were proposed for optimal trajectories of excavator motions (Lee and Kim 2014; Kim et al. 2013). In addition, there were efforts to improve tracking accuracy for robotic excavators (Wang et al. 2016) and obstacle avoidance during operation (Bae et al. 2011; Son et al. 2010). To date, all the research efforts have investigated only a part of the multifaceted problem of autonomous operation, and fully automated operation has not been realized yet. Development of two main technologies, including simultaneous localization and mapping (SLAM) and integrated operation and data sharing of earthmoving fleet via a machine-to-machine (m2m) communication platform, are important requirements toward autonomous operation of earthmoving equipment in jobsites (Dadhich et al. 2016a).

7 FUTURE OF THE TECHNOLOGY

As described in the sections above, several research projects investigated methods to enhance automation of the operations in each of the four areas. There are, however, a number of development opportunities exist in each one of these fields. These gaps were identified based on the reported limitations and future opportunities in the reviewed works and are presented below.

7.1 Equipment tracking and fleet management

These systems are able to provide a large amount of various data, such as location, fuel consumption, and maintenance and engine parameters of the equipment. Therefore, there are opportunities to investigate and develop big data analysis technologies to process these large-scale data. First, machine learning algorithms could be used to undercover patterns and classify them for decision makers. Second, instead of sampling or creating templates, interactive visualization systems will use methods for pairing big data with visual analytics so the data could be displayed in a meaningful way.

In addition, these systems are the sensor module of a control system (marked by a red box in Fig. 4), which provide the key performance indicators to detect abnormal operations. They, however, do not usually provide possible cause(s) of inferior performance of the specific process. Thus, there is a need to develop artificial intelligence methods which are able to discover the possible causes of the abnormal operations (e.g. excessive idle times or long queues), this way it facilitates timely correction of the operations.

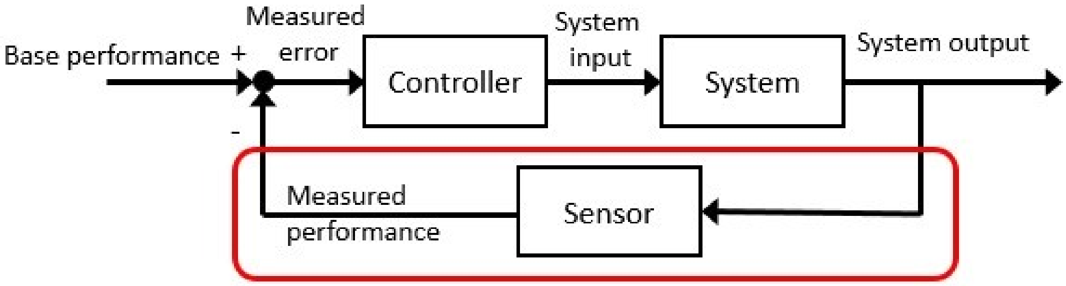

Figure 4. Sensor module in a control system

7.2 Safety management

Existing commercial accident warning systems mainly depend on radio-based devices to detect dangerous proximity, but this practice requires tagging of every worker. It would be useful to investigate passive technologies, such as laser scanning and vision-systems, to detect close proximities and obstacle recognition. Fig. 5 presents a schematic view of the future research directions based on the reported limitations. In particular, there is a promising research area for right-time accident warning instead of real-time approach (Teizer 2016). This approach emphasizes on the development of a strategic proactive accident prevention framework, as opposed to tactical responses.

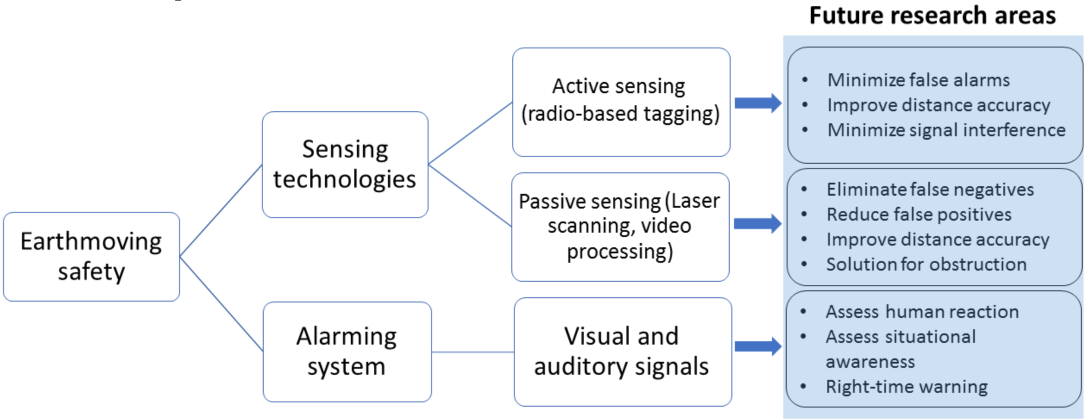

Figure 5. Future research directions in safety management of earthmoving equipment

7.3 Equipment pose estimation and machine control technology

Commercial machine control systems have proven to be effective for productivity improvement. These systems, however, rely on expensive RTLSs which limits their widespread use in industry. Therefore, there is a high potential for development cost-effective solutions, such as vision-based and smartphones, to increase the use of machine control systems in industry.

7.4 Remote control and autonomous operation

This is the most comprehensive and complicated area, because both remote control and autonomous operation of an earthmoving equipment in an uncontrolled jobsite condition requires a number of synchronized modules to run the process. As discussed before, some topics, including navigation, 3D environment modeling, motion planning, and optimal trajectory for the end-effector, have been the center point of most research studies, which provided valuable advances in the field (Dadhich et al. 2016a). However, there are several knowledge gaps in both remote control and autonomous operations. Future work towards fully tele-operated and autonomous operation requires development of various systems, and some of the most important areas to investigate are presented in Fig. 6 (Dadhich et al. 2016a).

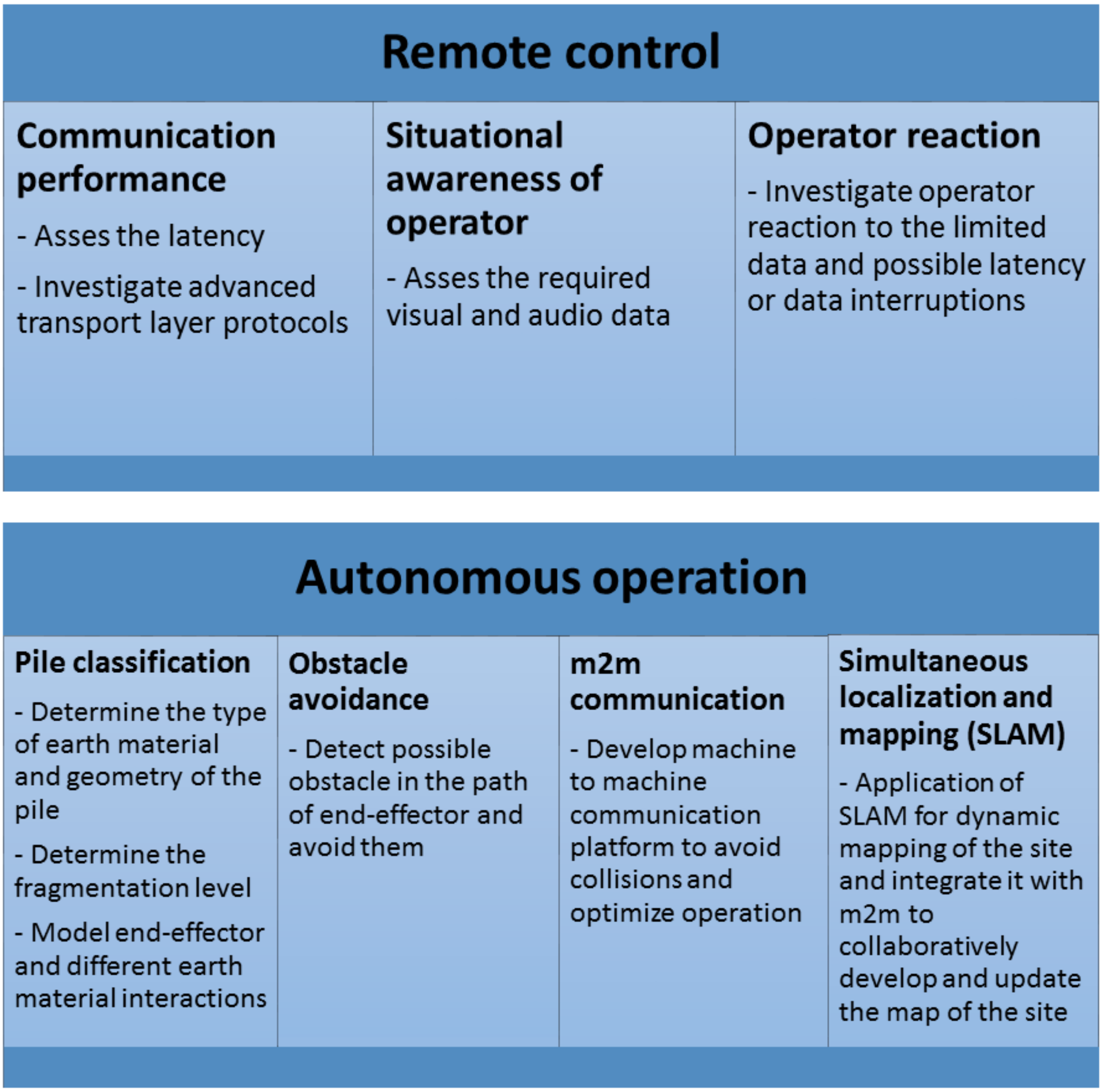

Figure 6. Major development areas for tele-operated and autonomous earthmoving operations

8 CONCLUSION

This paper discusses a detailed review of the recent developments in academic and industry sectors to enhance the automation level of the earthmoving equipment operation and control. This background study consisted of three main phases: review of recent industrial innovations in the field, comprehensive literature review in six major construction engineering and automation journals, and review of subsequent research articles in other academic resources. The identified innovations were classified into four groups and the applied methods, assumptions, and their limitations were discussed. Some of these solutions, including automated machine guidance and control and integrated fleet management systems, have gained a considerable popularity among earthmoving companies in recent years, because they proved to be effective in improving productivity and reducing the operation costs. The advances in other areas, such as robotic operations and advanced sensing technologies (e.g. computer vision) for tracking and safety, are still in experimental stage and yet have to prove their efficiency in practice. Finally, the limitations of the current state of development and innovative initiatives in each one of the four categories were identified and based on those findings, the outlook for the future research was proposed. Remote control and autonomous operation were identified as the most immature fields, and several areas, including machine learning, SLAM, and m2m, require further research and development to achieve higher level of automation.

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