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Review

Sensing, perception, decision, planning and action of autonomous excavators

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A B S T R A C T

A significant advancement in automated driving technology and the deployment of it have noticeably increased the safety of humans in transportation, industry, and the construction field in the last several decades. As a result, the automated driving technology of an autonomous excavator has become a hot topic among researchers. This study provides the findings of a systematic review of the literature on automated driving and working systems of autonomous excavators published in the last two decades. This paper divides the autonomous system into five groups, namely sensing, perception, decision, planning, and action, and presents research gaps that are not yet well studied for each group. Furthermore, the review of publications presented in this paper is conducted with the aim of highlighting key challenges and contributions of the previous and ongoing research work in this field. Finally, the paper is concluded and provides a direction for future work in this area.

1. Introduction

Many types of industrial machines that can be seen in mining, construction, forestry, agriculture, and further industries are called earth-moving machines. Earth-moving machines can mainly be divided into two parts: the main body (vehicle) and a robotic mechanism that is mounted on the main body [1,2]. A tool for excavation or loading tasks of material and a robotic arm controlled by use of a hydraulic system together make up a robotic mechanism. The tool can be changed to another depending on different tasks.

An example of earth-moving machines is an excavator [3]. An excavator is considered one of the main earth-moving machines. Excavators often work under dangerous and hazardous conditions like open-pit mines and toxic chemical mines, and the drivers of these machines are the weakest point of the whole process. Consequently, interest in autonomous excavators has increased significantly among manufacturers of earth-moving machines and researchers in the last two decades [4,5]. Use of autonomous excavators in a dangerous environment can guarantee a high level of safety and productivity. However, manufacturing and development of autonomous excavators are challenging tasks because of difficult working conditions [6–8].

Table 1 lists the operational functions of an automated driving system (ADS) as well as human driver role at various levels of vehicle automation [9]. Theoretically, an automated vehicle system can only be called “autonomous” if it can handle all dynamic driving tasks in any driving scenario. A vehicle is labeled an AV if it contains levels 3–5 automated systems, according to the US Department of Transportation’s Federal Automated Vehicles Policy [10]. However, in the literature, these levels of autonomy are not rigorously defined, and any level of autonomy is referred regarded be autonomous. Only the levels 3–5 automated systems will be referred to as AV and the references belong to these levels will be reviewed in this paper.

Many academics have done remarkable work on this topic to date, but there are only a few review papers on autonomous earth-moving devices [3]. On the other hand, there is no review paper about autonomous excavators that summarizes key challenges, main contributions of publications, and a future research direction. Therefore, this issue has inspired us to write a review paper. Hence, this paper concerns the automated driving and working of an autonomous excavator. This survey of publications aims to highlight primary contributions and findings of references corresponding to the sensing, perception, decision, planning, and action concepts of an autonomous excavator, as well as key challenges and future research directions.

The rest of the study is structured as follows. The preparation process

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for the survey of publications and the descriptive analysis are described in Section 2. Section 3 addresses concepts of sensing, perception, decision, planning, and action of an autonomous excavator. Section 4 presents key challenges and issues in this field, as well as a future study direction. At the end, Section 5 concludes the paper.

2. Methodology

2.1. Preparation for survey of publications

To perform a systematic literature review of existing publications that are available online and in English, an initial investigation was conducted on published articles from the following well-known source websites: Google Scholar, Scopus, Web of Science, and IEEE Xplore. Articles were searched and collected by use of key word combinations that include "autonomous," "excavator," "intelligent," "robotic," "driverless," "self-driving," "perception," "planning," "sensing," "action," "decision," "sensor," and "computer vision." The collection of articles covers articles that were published from 2000 to August 2021. The process until identifying primary publications for the systematic literature review can be divided into 4 steps, which are illustrated in Fig. 1.

In the first step, 278 articles were found from the source websites via key word combinations and downloaded. The dataset of the articles contains research articles, review papers, and master's and Ph.D. theses. Following that, duplicate articles were removed from the dataset, and the number of articles was decreased to 214 in the second step. After that, the concept of an automated driving and working system of an autonomous excavator was divided into five groups: sensing, perception, decision, planning, and action. However, there were some research works that are irrelevant to the groups. Those articles were ignored in step 3. Finally, the selection of primary articles was conducted regarding original novelties and solutions of challenges.

2.2. Descriptive analysis

Fig. 2 shows the percentages of primary research articles regarding the groups of sensing perception, decision, planning, and action. One thing that should be noted here is that some papers in the references' datasets are related to more than one group at the same time, and this was considered in the analysis. According to the pie chart, almost half of all research articles belong to only two groups (planning and action), while the rest of the articles belong to three groups (sensing, perception, and decision). Meanwhile, decision made up the lowest part with 8%.

Fig. 3 shows the percentage of the references' evaluation over the last two decades from 2000 until August 31, 2021. In recent years, as illustrated in Fig. 3, there has been a rise in the number of publications published on this subject matter. It is possible that our search parameters had an impact on the decreased number of publications in 2021, given our search only covered articles published through August 31, 2021.

As mentioned above, the primary research articles were categorized into five groups: sensing, perception, decision, planning, and action. Fig. 4 shows how these groups were developed. In sensing, perception, planning, and action, the number of studies has increased since 2016. The reason for this increment of the number of papers in the field of autonomous excavators is that machine learning algorithms have been implemented widely and successfully since the year 2016. According to the graph, however, no increase has been noticed in the decision group since that time period. In other words, the decision group has the least amount of development among the five groups.

3. Autonomous excavator

Sensing and perception, decision, planning, and action/control are the fundamental competences of an automated driving software system, with the connections between these skills and the vehicle's interactions with the environment represented in Fig. 5. Vehicle-to-Vehicle (V2V) communications can also be used to improve perception and/or planning by leveraging vehicle cooperation [11].

Functional block diagram for automated driving system is established depending on five concepts/groups including sensing, perception, decision, planning and action as shown in Fig. 6. Each concept includes several sub-concepts and depending on the diagram, the contributions and limitations of references belongs to these groups will be discussed below.

3.1. Sensing

In this section, a brief introduction of the sensing concept of autonomous excavators and original publications in this area will be presented. It is considered that sensing includes object detection (human and mobile tracking, equipment tracking, construction material detection, barrier detection, etc.), free space detection, and ego motion detection as shown in Fig. 6. Sensors such as Lidar, stereo cameras, cameras, accelerometers, and ultrasonic sensors play a key role in sensing and perception concepts of an autonomous excavator. It should be noted here that with the power of computer vision and artificial intelligence algorithms, safety and productivity have improved significantly by applying them to excavators in mining, construction, forestry, agriculture, and other industries [13–16].

Object detection is a machine vision problem that is being used in a variety of consumer applications, including surveillance and security systems, mobile text recognition, and disease diagnosis using MRI/CT scans. And object detection is also one of the most important components for autonomous driving. To ensure safe and reliable driving, autonomous excavators rely on sensing and perception of their surroundings. Object recognition algorithms are used by this perceptual system to precisely determine items in the excavator's surroundings, such as workers, construction machines, construction materials, barriers etc. Object detectors based on deep learning are critical for identifying and localizing these items in real time. For instance, one of the main problems for autonomous excavators is obstacle avoidance under working conditions. Obstacles can be divided into two groups in terms of their impact on excavators. The first group contains impediments on the ground. Examples are vehicles, workers, trees, and buildings. The second group contains underground impediments such as boulders, pipelines, roots of tree, etc. If this issue is tackled on time, it can help to avoid stopping an excavation process and improve productivity and maintenance. For this purpose, Hyongju et al. [15] investigated a problem of

Table 1
Automation levels of SAE J3016™.

Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Even when driver assistance functions are turned on, users are driving.			When autonomous driving features are enabled, users are not driving.		
Drivers are in charge of the assistance feature.			Drivers are required to drive if features request that they do so.	Users are not required to drive when using automated driving capabilities.	
Features are supported by drivers.			Automated driving features		
Localization Perception Planning Management	Localization Perception Planning Management	Localization Perception Planning Management	Control: lateral and longitudinal Localization Perception Planning	Control: lateral and longitudinal Localization Perception Planning	Control: lateral and longitudinal Localization Perception Planning

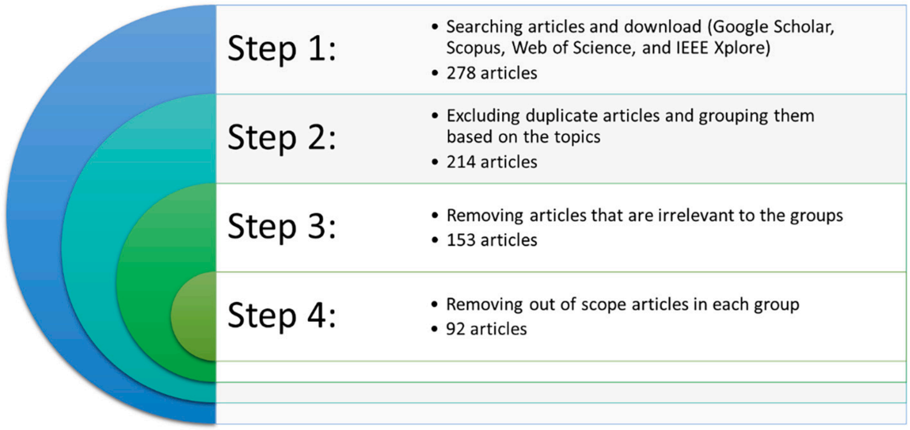

Fig. 1. Process of identification of primary articles.

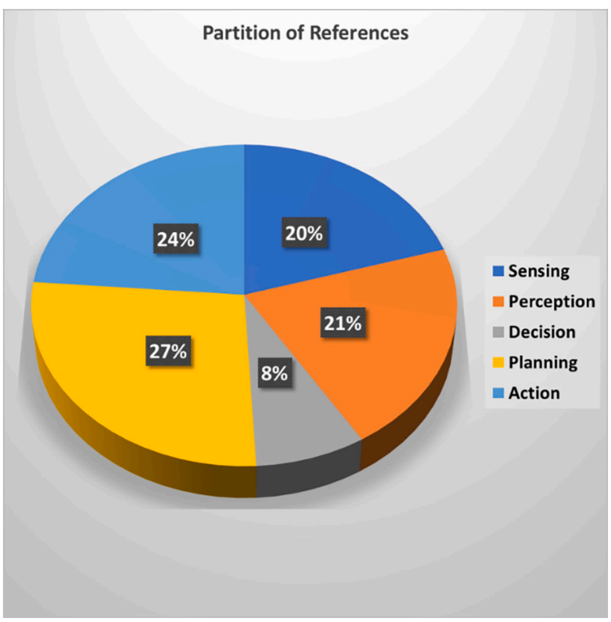

Fig. 2. Partition of the primary research articles regarding the groups.

obstacle avoidance in excavators by using a recurrent neural network. The result of this investigation showed that the excavator model is capable of doing its tasks without encountering any difficulties, such as malfunctioning, unexpected stoppage, and so forth. However, second group obstacles are not covered in this study.

Zhu et al. [16] have been proposed the use of video frames to recognize workers and mobile machinery, such as construction equipment, and to anticipate their motions using a Kalman filter. The proposed tracking filter only works with linear states, which is a limitation of this study. In reference [17], the unscented Kalman filter (UKF) was combined with joint probabilistic data association (JPDA) and the interactive multiple model filter (IMM) to create a multi-object tracking and management system. Oh et al. [18] have been introduced a safety system that uses 2D laser scanners and new safety indices to produce warnings to avoid collisions in the excavator. The usage of 2D laser scanners, on the other hand, limits the vertical location of detected items. Another limitation of this technology is that this sort of laser scanner only has a 270-degree field-of-view, necessitating the use of two scanners to get full 360-degree coverage. Due to the integration of their data, the fusion of two laser scanners makes the system expensive and sophisticated. In addition, prior research in the field of safety management has primarily focused on proximity detection and the use of current states of observed objects, which may be ineffective in capturing potential safety issues. For example, if a manipulator or vehicle remains immobile (i.e., does not move) or moves fast despite sufficient safe margins, proximity between construction equipment and employees may not be used to suggest potential harmful conditions. To analyze dangerous circumstances and potential threats in fully automated excavators, quantitative and predictive measures are essential. To address the aforementioned problem, Abdullah et al. [19,20] have developed 3D Lidar-based safety algorithms for autonomous excavators that can detect, track, and forecast item motion surrounding the excavator, and then assess the severity of collision hazards using a preset risk metric. But velocity and turn models have been assumed as a constant for the prediction of moving objects in the tracking filter.

Despite the fact that three-dimensional (3D) terrain reconstruction is critical for autonomous excavators, the problem is still far from solved due to the difficult construction environment of irregularly shaped and textureless ground. To eliminate this problem can be helpful in a variety of applications including path planning, navigation, and autonomous control. In terms of safety and productivity, reconstructed terrain is also beneficial. There are two basic approaches in classical terrain reconstruction techniques. The first is vision-based terrain reconstruction [21], and the second is terrain modeling using Light Detection and Ranging (LiDAR) [19]. LiDAR is a technology that scans the real world to create 3D discrete surface samples. LiDAR offers extremely precise distance measurements of the surface being scanned. LiDAR can capture wide-range measurements that vision sensors cannot because of its large field of view (FOV) [22]. However, there are some limitations of LiDAR-based terrain reconstruction. For example, because of the large size of the point cloud, creating 3D point clouds for 3D modeling is a time-consuming task. Furthermore, considerable power is required, and supplying such power to automated construction equipment connected to the LiDAR interface is difficult.

Vision sensors are frequently employed to overcome the drawbacks of LiDAR-based terrain reconstruction. The environment around a construction site can be captured more quickly using vision sensors. As a result, visual sensors respond to changes in the environment more quickly. Furthermore, due to the use of advanced computer vision technologies, vision-based terrain reconstruction takes less time to compute than LiDAR-based terrain reconstruction. As a result, vision-based landscape reconstruction can be used in 3D automated construction. Vision sensors use less power than LiDAR sensors in the reconstruction system, and they are also less expensive and lighter. This simplifies the building of a reconstruction system for automated construction equipment [23]. Nevertheless, utilizing a camera sensor to rebuild the 3D landscape of a construction site is also difficult. Textureless surfaces and repeating patterns, such as muddy patches and

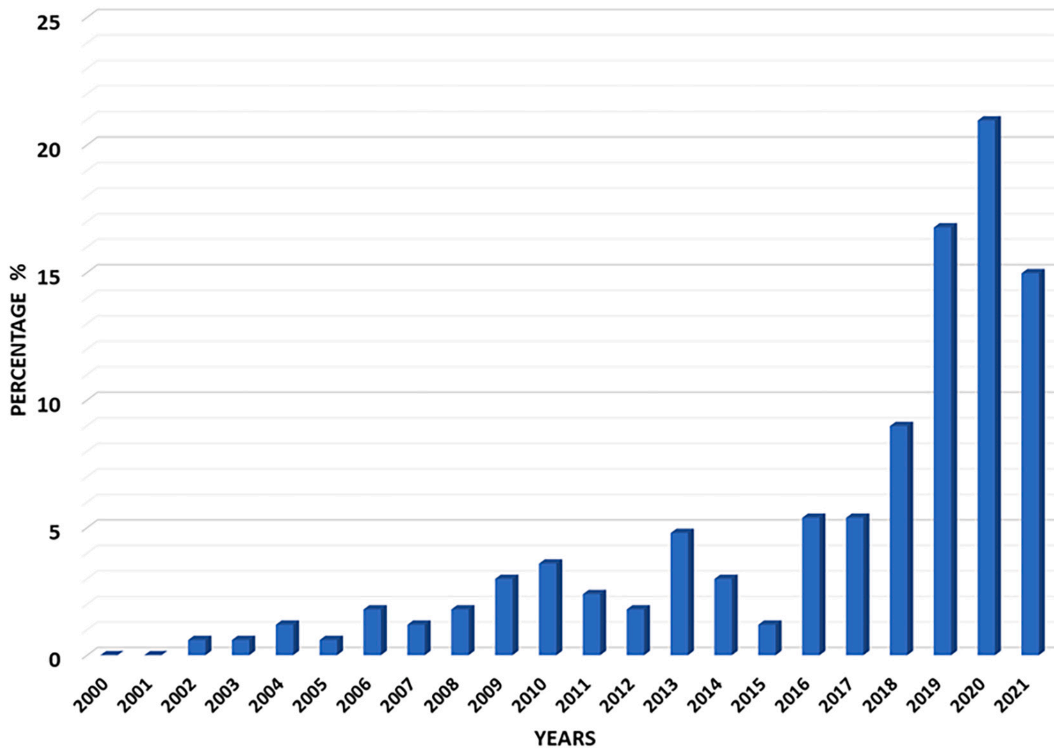

Fig. 3. Percentage of the references' evaluation over the last two decades.

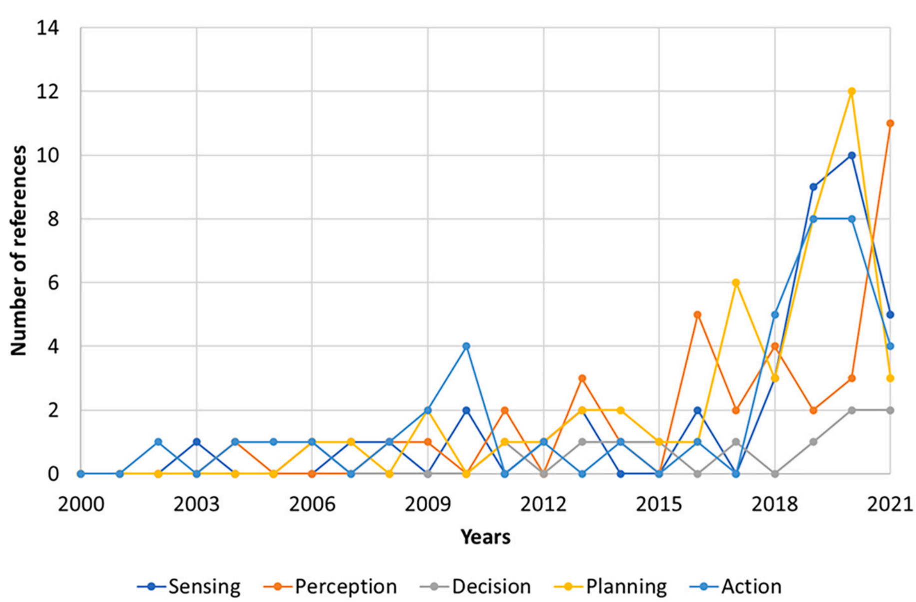

Fig. 4. Trend of evolution of references for sensing, perception, decision, planning, and action.

dirt roads, make up the ground of a building site. Furthermore, when images are acquired using excavator-mounted forward-looking cameras, the prevailing plane of the ground is extremely tilted. The frequently used feature-matching based algorithms implicitly assume that the ground surface is perpendicular to the image plane, making it challenging to recreate 3D terrain [24]. Another significant issue is the computation time. In order to overcome the difficulty of 3D reconstruction in these difficult situations, a multi-scale descriptor-based dense 3D terrain reconstruction method has been applied successfully for an excavator by use of a stereo camera by Changhun and Pan [23].

Predicting soil parameters while digging has the potential to be a highly effective method of adapting an excavator's digging trajectory to the specific soil conditions. During excavation operations such as ground leveling, digging, and sheet pilling, a unique approach for assessing soil parameters online was suggested [25,26]. The researchers have proposed the Newton Raphson method and compared the results with that of a graphical intersection-based method in their study. The result has proven that the Newton Raphson method is the best method for online soil parameter estimation for autonomous excavators and has an advantage of being 2000 times faster than the graphical intersection-based method. When the bucket of an excavator is used for cutting and pushing material forward, Rahman and Michael [27] focused on the

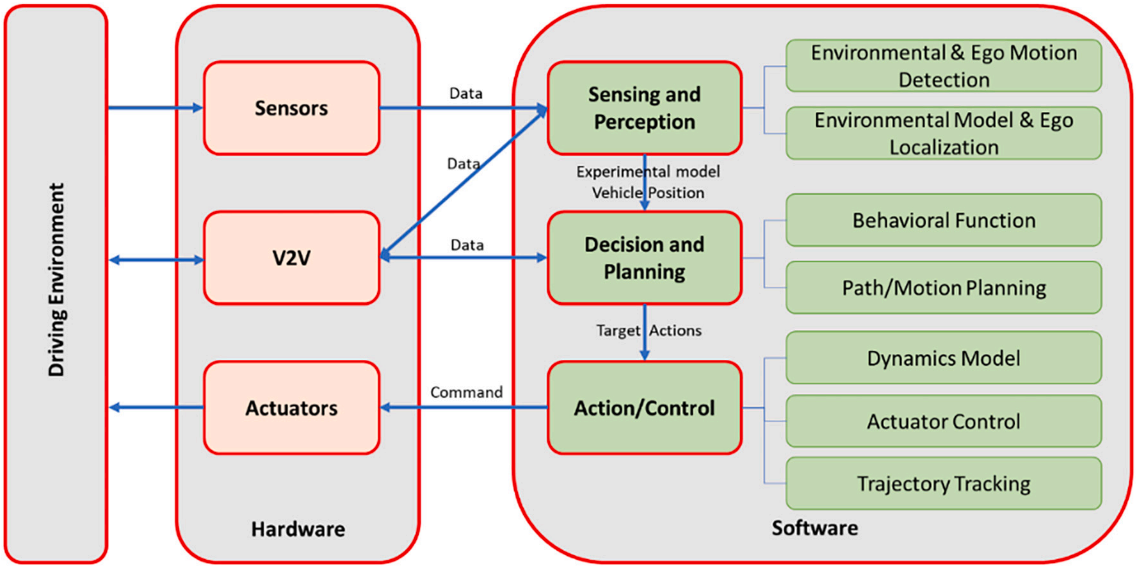

Fig. 5. Typical automated driving system.

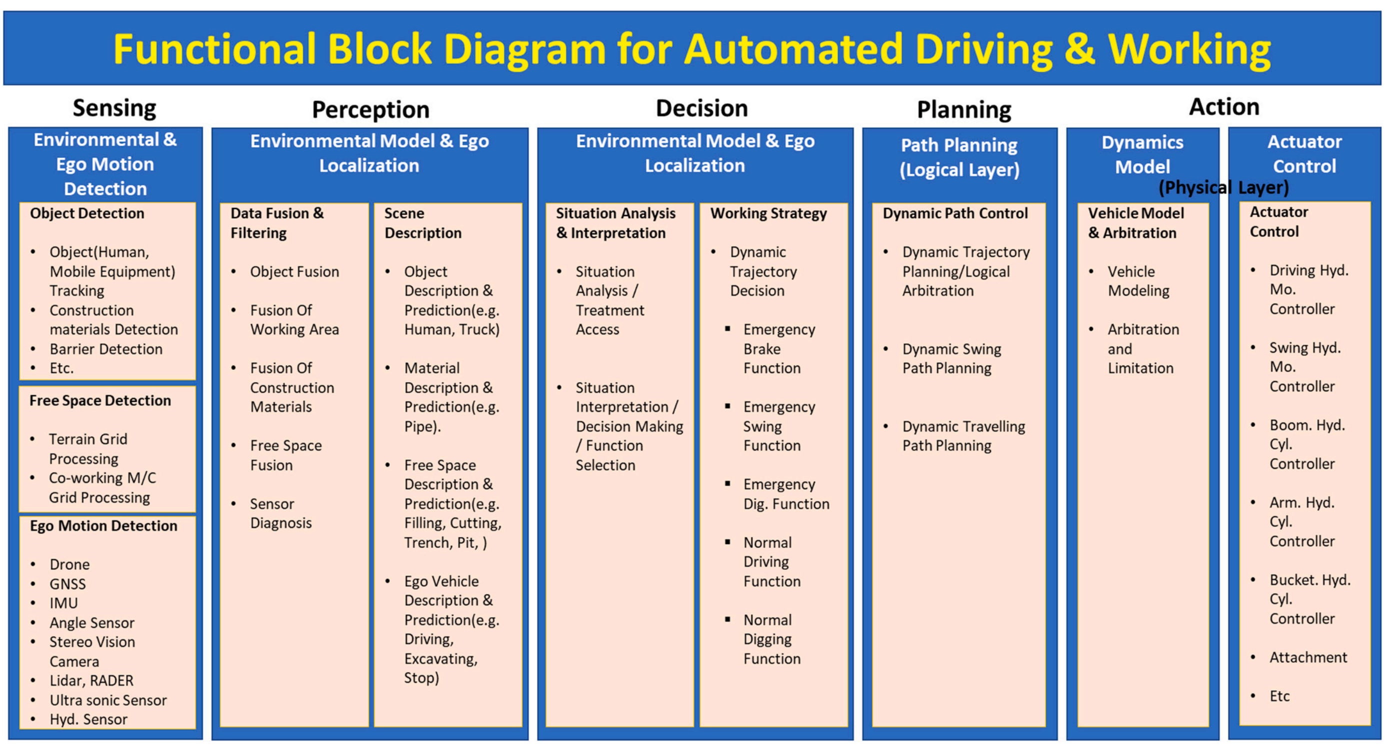

Fig. 6. Functional block diagram for automated driving and working for an autonomous excavator.

interaction period of the excavator and ground within a digging cycle in laboratory conditions in their study. They successfully implemented certain types of fault detection for excavator parts throughout time-varying operation. However, when there is a higher force on the tool or a higher operating speed, the power requirement and thus the possible energy dissipation rate linked to a fault may be more sensitive, raising the power requirement and thus the possible energy dissipation rate associated to a fault.

3.2. Perception

In this section, a brief introduction of the perception concept of autonomous excavators and original publications in this area will be presented. The perception process in autonomous excavators makes use of a combination of cameras and different types of sensors combined with cutting-edge software to analyze and realize the world surrounding the excavator in real time. As mentioned above, perception in autonomous excavators is essential in terms of safety and reliable operation since the obtained data from these processes can help for decision making to find out what is the next step of the excavator [28]. In contrast to sensing, perception has covered articles about data fusion and filtering (object fusion, fusion of working area, and fusion of construction materials) and scene description (description and prediction of an object and material) as shown in Fig. 6.

The ability to perceive the location and pose of the excavator's working device is required for the research of essential technologies such as trajectory planning and control. As a result, for autonomous excavation, the excavator's correct sense of position and pose information is critical. For that purpose, Yunhua et al. [29] have performed an investigation on perception and correction of position between a dump truck and an excavator's bucket during a loading operation. The suggested technique can accurately determine the relative location of the bucket and the dump truck based on simulated experiments and provide an appropriate rotation signal to the excavator. The research is critical for the development of self-driving excavators. However, there are some limitations of this research such as marking all dump trucks with color and, installation height of camera to the excavator should be the same with the height of the color mark on the dump trucks. These limitations can be problem in a large scale of construction projects.

An autonomous excavator system (AES) that can work under different environments has been presented for a material loading task [30]. Multimodal perception sensors such as cameras and Lidar are combined and implemented for object detection as well as material classification. The autonomous excavator system has performed successfully on standard and compact excavators in several sophisticated outdoor and indoor conditions, such as loading of material into dump trucks, rock capturing, and digging tasks. The proposed AES has been evaluated in ten different scenarios. In these cases, the system performs well. AES presently considers loading, dumping, rock removal, obstacle avoidance, water recognition, and base movement as common functions for completing effective material loading operations. Nevertheless, the suggested system has some flaws, including issues with perception, planning, and control modules. Furthermore, once these modules are integrated, some of the faults are exacerbated in terms of overall performance.

On the other hand, estimation of soil-tool intersection in real time is an essential way to develop an intelligent excavation system [31,32] because it can help to prevent a bucket of an excavator from breaking down. To tackle this issue, many articles have been published. For example, in order to improve the ability of autonomous excavators to have relevant information about materials while digging, a novel approach has been presented and proven by performing material classification of gravel and rock materials in reference [33]. The authors have used machine learning (ML) for binary material classification by using proprioceptive force data obtained from full-scale autonomous excavation trials. Although the proposed model works very well for material classification, these rates of these materials are not sufficient for a fully automated operating system because other types of excavation materials can be identified in actual mining and construction applications. Furthermore, Myung et al. [34] have contributed to the development of an intelligent excavation system by developing a mobile recognition system of a 3D work environment for different tasks. They have developed and optimized a scanner system of a 3D laser and software in their study. For a ground digging system of an autonomous excavator to evolve, sensors are crucial to measure the excavator manipulator's position for a control system. In terms of this issue, Jiaqi and Hwan-Sik [35] have suggested a novel approach for pose estimation of the manipulator based on computer vision techniques by use of an artificial neural network system. The data samples used for training in this study is acquired from the simulation, but realistic data samples are different with like having diverse background objects and scenes. These background noises of data samples can decrease estimation accuracy of the model.

To increase the scale of description and view of surrounding for excavators, a new method of integration of three sensors (2D-pulsed (TOF), 3D Lidar, and flash Lidar profilometer) has been deployed and experimented on, and a promising result have been acquired [36]. In addition, a sensing/perception system of an excavator can be made more robust by using a novel method that was developed by Xodong et al. [37]. They have also used multiple sensors in their study. They offered a pipeline for autonomous manipulation of items of interest using a robotic walking excavator using perception and grip position planning.

As mentioned above, vision sensors such as cameras, stereo cameras, LiDAR, profilometer etc. are an integral part of autonomous excavators in terms of sensing and perception concepts. Therefore, the references related to these concepts have been identified depending on objectives, used vision sensors, method and test scenario as depicted in Table 2.

3.3. Decision

Decision making for autonomous driving is required in dynamic and uncertain environments. Decision making is an ability of an autonomous vehicle that can handle a large number of functions in real time. To enable the autonomous excavators to work reliably and safely in complex construction tasks, several technical challenges from robotic excavators should be considered [50,51]. First, the perception of the autonomous excavation system is suspicious because of the noise and limitations of sensor range and occlusions in the working territory. Second, the movements of the autonomous excavator's surrounding participants must be forecasted in order to establish safe paths. The uncertainty of the existing states of the participants and concealed states regarding their intended destination make prediction particularly difficult. The ego vehicle's motion must be free of collisions, satisfy its kinematic and dynamic restrictions, and adhere to laws of construction, mining, forestry, etc.

To tackle the aforementioned issues of an autonomous excavator, a large amount of research has been conducted [52–54]. For instance, a method that totally automates the job of truck loading has been suggested in the article [55]. An excavator with this method can decide where it should be to dig in the target area and find the location of a dump truck to dump soil while avoiding obstacles, and it can work as quickly as a human. This fully autonomous excavator has been tested under different weather conditions such as rainy, dusty, snowy, frozen soil, wet soil. However, there are some issues that should be considered in this study. For example, noise sensor data can impact the truck recognition algorithm's planar segmentation, resulting in somewhat erroneous vehicle dimensions and pose measurements. Although a degree of imprecision in the truck's lateral position can be accepted, accurate measurement of the truck's height is necessary to avoid a potential collision between the truck's top and the bucket's bottom.

Jinxin and Liangjun [56] proposed a novel task planner (TaskNet) that is more efficient than a traditional imitation learning-based method for material loading task. The paper's main contribution is a unique neural network-based task planning formulation for excavation that takes advantage of the structure of the excavation task representation. The important concept is to transform the observation into latent space representation and then communicate the exact specification to the sub-level models in a sequential manner. To plan the excavation movement trajectories, comprehensive task primitives with specifications are eventually constructed. The task primitives that have been determined can also be used to execute policies online. The results of the experiment reveal that TaskNet can effectively learn task decomposition strategies through demonstration. But soil texture and hardness of terrain physical property which can influence potentially to the performance of the proposed model, is not considered in this study. Furthermore, Takumi et al. [57] have presented a novel trajectory tracking control method that is a combination of model predictive control and a servo mechanism for controlling of a digging operation in excavators. Their method can help the excavator to cope with unfamiliar reaction forces that occur when connecting with underground obstacles. The hydraulic excavator in their study simulates the behavior of a digging operation while the boom, arm, and bucket cylinder are all operated at the same time. The efficiency of the proposed strategy has been demonstrated using simulations in the presence and absence of the disturbance. A new design of a robot excavator has been modeled in terms of motion kinematics, and a digging process has been simulated by Dong et al. [58]. The findings of

Table 2
Summary of identified key references for sensing and perception groups. The "*" symbol indicates that the sensor is used. The "×" symbol indicates that the sensor is not used.

Ref.	Task	A	B	C	D	E	F	Method	Test scenario
[14]	Activity recognition	*	×	×	×	×	×	CNN	Test with video
[38]	Automated detection of workers and heavy equipment	*	×	×	×	×	×	IFaster R-CNN	Field test on a workstation
[39]	Ground objects detection based on unmanned aerial vehicle remote sensing	*	×	×	×	×	×	YOLOv3	Field test on a workstation
[13]	Vision-based detection, tracking and activity analysis of earthmoving equipment	*	×	×	×	×	×	CNN	Field test on a workstation
[40]	4D modeling of soil surface during excavation	×	×	×	×	*	×	Simulation	Simulation, Field test on a workstation
[41]	Large-scale object mapping, segmentation, and manipulation	*	*	×	×	×	×	RANSAC-based 3D plane fitting algorithm	Field test on a workstation
[42,43]	Pose verification for autonomous equipment interaction	×	*	×	×	×	×	Bayes' theory	Simulation, Field test on a workstation
[44]	Modular data communication	×	×	*	×	×	×	–	Simulation and field testing
[12]	Action recognition of earthmoving excavators	*	×	×	×	×	×	CNN-DLSTM	Field testing
[20]	Sensing Algorithms for Object Tracking and Predictive Safety	×	*	×	×	×	×	Unscented Kalman filter and joint probabilistic data association	Field testing
[45]	Material classification	×	×	×	*	×	×	ANN and KNN	Custom image dataset
[46]	Material loading	*	*	×	*	×	×	–	Field testing
[47]	3D terrain reconstruction of construction sites using	*	×	×	×	×	×	Multi-scale descriptors	Field testing
[35]	Vision-based estimation of excavator manipulator pose	*	×	×	×	×	×	ANN	Custom image dataset, Field testing
[48]	Skeleton estimation of excavator by detecting its parts	*	×	×	×	×	×	HOG algorithm	Custom image dataset
[36]	Generating a 4D model of a large-scale construction site from an excavator	×	*	×	×	*	×	Custom integrated solid-state 2D pulsed time-of-flight (TOF) laser profilometer and LiDAR	Field testing
[49]	A low-cost obstacle tracker for self-driving mobile robot navigation	×	×	×	×	×	*	Kalman filter and global nearest-neighbor (GNN)	Field testing

Note: A: camera, B: Lidar, C: GPS, D: Force sensor, E: Profilometer, F: Laser scanner.

this study can be a fundamental basis for autonomous excavators for pile construction in real working conditions.

3.4. Commonsense knowledge

Machine learning is centered on the goal of developing computers with cognitive abilities comparable to those of humans. Computers can be designed to absorb a lot of data about the real world if they work hard enough. Computers can learn because they act in line with knowledge that is encoded into them. Until computers are confronted with novel tasks, they can rely on pre-programmed knowledge. Computers must learn to make their own decisions in such situations. This is difficult for them because they lack something crucial that humans have: common sense, which is often intuitive [59]. Humans can use commonsense to tackle situations in which they have no past experience. Computers would be able to make intuitive and logical decisions similar to humans if they acquired commonsense knowledge (CSK) and could apply it to specific areas [60]. Even if a robot is equipped with current tools, recent research in autonomous cars [61] has revealed that it has problems reacting appropriately to things in its path. Therefore, Priya et al. [62] have performed investigation on enhancing Autonomous vehicles with commonsense and put two main goals: first is to developing a method that incorporates commonsense knowledge to allow autonomous cars to make human-like decisions, second is to apply this CSK-enabled technique to automated driving on a prototype testbed and provide appropriate recommendations. Nonetheless, there are several challenges in applying commonsense knowledge and commonsense reasoning to autonomous system and detailed explained in reference [59]. An important point should be noted here is that applying CSK to sensing and perception concepts of autonomous excavators can bring great advantages in developing of decision-making of fully autonomous system like autonomous cars [63]. Driving an excavator entail observing the environment and then making a driving decision based on those observations (steer, excavating, material loading, coast, etc.). All of these tasks must be automated in autonomous driving. Until now, the majority of autonomous driving technology has depended on machine learning approaches. Suitable technology should be utilized for the appropriate task, according to the argument. That example, while machine learning technology is useful for automatically seeing and analyzing an excavator's surroundings, commonsense reasoning is a better way to automate driving decisions. For instance, CSK's importance in NLP, vision, and robotics is underlined in many AI papers, such as those surveyed in [64]. Furthermore, Christopher et al. [65] have started deploying commonsense knowledge in the context of human-robot collaboration (HRC) for the first time. And then, they have moved a step farther in achieving task optimization for CSK-based HRC by using appropriate math modeling and algorithmic augmentation. To back up the proposed concept, they conducted simulation studies as well as laboratory experiments with a real robot [66]. One of the contributions of this study is that to enable task optimization, mathematical modeling for robot action planning and arm movement is being carried out.

3.5. Planning

It is crucial to investigate the task planning approach in robotic sectors because an autonomous excavator demonstrates features of both a service robot for excavation and loading tasks and a mobile robot for maneuvering. Task planning is concerned with the creation of a motion path and excavation area on a marked construction site that avoids missing any areas and colliding with recognized obstacles. A large amount of research has been carried out in the area of path planning for an autonomous excavator. For example, Jeonghwan et al. [67] have aimed to develop a task planning strategy for autonomous excavators for earthwork tasks. The characteristics of earthwork and environmental restrictions on the autonomous excavator have been used to build a complete coverage path planning (CCPP) method. The cost function of the algorithm takes into account the dump truck's accessibility as well as the working environment's external conditions. While the most of CCPP algorithms simply evaluate the moving distance and interior work environment, this allows for maximum collaboration with the dump truck to reflect practical solutions. The result (CCPP) algorithm can have a positive effect on the development of autonomous excavators, especially in collaborative and dynamic environments. However, CCPP systems are now being built using task studies and input from human experts in the given topic. Because of the number of inputs required from the operator, this might be a time-consuming process for some operations. There is also an issue about the task planning process' correctness and thoroughness. Dynamic planning is required to address these shortcomings.

One of the most pressing issues in the world of excavator research is how to automate the control of an excavator system. Excavator systems that operate without a human operator not only keep employees safe, but they also boost their efficiency. Therefore, in order to complete the work without the assistance of an operator, the trajectory must be meticulously planned. As a result, a large number of studies on the creation of the trajectory for the excavator have been published in scientific journals. For example, an advanced genetic algorithm has been suggested to find optimal proportional-integral-derivative PID controller parameters for trajectory control of autonomous excavators [68]. First, the authors have analyzed using the mechanism modeling method, the mathematical model of the excavator's kinematic and electro-hydraulic proportional control system. The identification experiment has established the actual model of the electro-hydraulic proportional system on this basis. The SGA's population, fitness function, crossover probability, and mutation probability have been all improved: the initial PID parameters have been calculated using the Ziegler-Nichols (*Z*-N) tuning method, and the initial population has been generated near it; the fitness function has been transformed to keep the population diverse; and the crossover and mutation probabilities have been adjusted automatically to avoid premature convergence. However, due to vibration and other causes, the tracking deviations are still high, according to the testing data. Therefore, vibration control and tracking error reduction should be addressed further. Furthermore, Takashi and Hiroshi [69] have done experiments on motion analysis of an excavator under working conditions such as excavating and loading in order to study autonomous control. They have used a hydraulic excavator equipped with multiple sensors for measuring and analyzing the angle of the upper rotating body, the lengths of the hydraulic cylinders of the boom, arm, and bucket, the upper and lower hydraulic pressure of each cylinder, and the quantity of movement of operating actuators when the excavator has been operated for loading and excavation tasks by several drivers under various working environment. Moreover, A navigation function of a construction site for reliable safe movement from one position to another one was proposed in reference [70]. The authors proved their result by use of an intelligent path planning algorithm, and the excavator can move from one pose to another safely. On a 2D grid map, the proposed intelligent path planning algorithm has been applied, which includes region growth for impediments as well as forward and backward movement. Although the proposed automated driving system performs well in the simulation it is difficult to say these proposed algorithm's performance will be the same in real world because the real vehicle's reaction to the driving commands is unknown.

As mentioned above digging and loading processes of excavators in mining and construction sites are very common and important. Making these processes fully autonomous is a challenging task for researchers in the present day. However, a big step forward has been taken already. For example, in order to tackle the challenges that an operator of large mining excavators can face during a digging process, an autonomous excavator has been developed based on digging patterns of an experienced operator [71]. Digging patterns have been collected by use of cameras as mining data, and bucket trajectories were classified in terms of the bucket's angle and location of the bucket in the digging pile. Moreover, an algorithm for generating the reference trajectory for an excavator arm working in a dynamic environment has been proposed using recurrent neural networks in reference [72]. A recurrent neural network is used to adapt the plant's dynamic, which includes the tracking controller, the arm, and the pile. The reference trajectory for the system is then calculated using a recurrent neural network which is combined with a Model Reference Adaptive Controller (MRAC). To optimize the dig weight, the generated trajectory is adjusted based on the pile variation. This approach is simple but effective because it just requires weight information for each excavator duty cycle. Simulations are used to verify the entire system's efficiency. The results show that the suggested technique performs well, with the dug weight being constant (nominal load) even while the pile changes shape over working time. But there are several assumptions in the reference such as: the pile is triangular in shape and lies above the ground; the volume of the bucket limits the digging weight in each time; following a digging cycle, the material on top of the pile will lie down and fill in the empty space, allowing the pile to maintain its triangle shape with a different slope; the trajectory in each period is represented by a set of parameters.

Accurate trajectory planning can be a foundation for execution of control of a trajectory of an excavator's arm. The excavation operation can be completed quickly and smoothly if the trajectory is well planned. Zhang et al. [73] have suggested optimal trajectory planning of an intelligent excavator. For the optimal trajectory planning of an intelligent excavator, they have employed the Sequential Quadratic Programming (SQP) approach. The trade-off between time and jerk is examined to achieve high efficiency and stationarity during the operation of the intelligent excavator. Interpolation in joint space has been done by use of cubic splines, and the best time-jerk trajectory has been found using the SQP with joint angular velocity, angular acceleration, and jerk as constraints. The excavator's optimal time-jerk trajectory planning has been realized after obtaining the optimal angle curves of each joint. The SQP method is more efficient in solving the optimal solution under the same weight, and the optimal excavating trajectory is smoother, with each joint reaching the target point with smaller angular velocity and acceleration change, avoiding the impact of each joint during operation and saving time. However, the existence of obstacles is not considered in this study. Therefore, some challenges might be occurred when the proposed method is executed in actual working environments.

3.6. *Action*

This section covers papers related to a dynamic model and actuator control for autonomous excavators. Beginning in the late twentieth century, many researchers around the world have been working on a robotic excavator with the eventual goal of digging trenches and material loading automatically without the need for human involvement. On the way to achieving this goal, Suzhou [74] has conducted an investigation on design of a joint arm control system for automated excavation. He has decided to employ a JCB 801 mini excavator that had been modified with electro-hydraulic servo valves, sensors, and a computer control system in order to enable experimental assessment and refining of controllers. The approach used is Proportional-Integral-Plus (PIP), which is based on the True Digital Control (TDC) design philosophy. Based on the Simplified Refined Instrumental Variable (SRIV) identification and estimation algorithm, to describe the extremely nonlinear dynamical behavior, data-based dynamic models have been created. The models demonstrate the relationship between input voltages and joint arm, boom, dipper, and bucket motions. And the author has focused on a joint arms PIP position control system based on the models' disclosed relationships, with the design applied on-line for dipper angle control. Although simulation results show feasibility of the suggested approach some physical aspects which can be faced and can degrade the control performance in real working condition such as the big load gravity effect and the drive demand changes direction at high frequency, are not considered.

In practice, the excavator's pilot hydraulic control system allows the

Table 3
Summary of key objectives of references. The "*" symbol indicates that the reference is related to the group. The "×" symbol indicates that the reference is not related to the group.

Ref.	Task	A	B	C	D	E	Method	Test scenario
[13,14,38,79]	Activity recognition and detection of workers and heavy equipment	*	*	×	×	×	CNN	Test with video, Field test on a workstation
[39]	Ground objects detection based on unmanned aerial vehicle remote sensing	*	×	×	×	×	YOLOv3	Field test on a workstation
[40]	4D modeling of soil surface during excavation	*	*	×	×	×	Simulation	Simulation, Field test on a workstation
[41]	Large-scale object mapping, segmentation, and manipulation	*	*	×	×	*	RANSAC-based 3D plane fitting algorithm	Field test on a workstation
[42,43]	Pose verification for autonomous equipment interaction	×	*	×	×	×	Bayes' theory	Simulation, Field test on a workstation
[44]	Modular data communication	*	*	×	×	×	TCR/IP	Simulation and field testing
[12]	Action recognition of earthmoving excavators	*	*	×	×	×	CNN-DLSTM	Field testing
[19,20]	Sensing Algorithms for Object Tracking and Predictive Safety	*	*	×	×	×	Unscented Kalman filter and joint probabilistic data association	Field testing, Matlab simulation
[45]	Material classification	*	*	×	×	×	ANN and KNN	Custom image dataset
[46]	Material loading	×	*	×	*	×	Automated excavator system	Field testing
[80]	Excavation path design	×	×	*	*	*		Simulation
[47]	3D terrain reconstruction of construction sites using	*	*	×	×	×	Multi-scale descriptors	Field testing
[35]	Vision-based estimation of excavator manipulator pose	*	×	×	×	×	ANN	Custom image dataset, Field testing
[48]	Skeleton estimation of excavator by detecting its parts	*	×	×	×	×	HOG algorithm	Custom image dataset
[36]	Generating a 4D model of a large-scale construction site from an excavator	*	*	×	×	×	Custom integrated solid-state 2D pulsed time-of-flight (TOF) laser profilometer and commercial mechanically spinning pulsed time-of-flight multi-echo Lidar	Field testing
[55]	Completely automates the truck loading task	*	*	*	*	*	–	Field testing
[53]	Trajectory Planning and Autodigging	×	×	*	*	×	Object-Oriented Graphics Rendering Engine and skeletal animation	3D entity simulation environment
[81]	A robust sliding controller	×	×	*	*	*	–	Simulation and field testing
[82]	Integrated tracking control algorithm for digging operations	×	×	*	*	*	NPI + CCP + FC	Simulation and field testing
[83]	Autonomous excavation of rocks	×	*	*	*	*	Unscented Kalman Filter	Testing in laboratory
[84]	Path Planning for an Excavator Arm	×	×	*	*	*	RNN	Simulation
[85]	Expert-Emulating Excavation Trajectory Planning	×	×	*	*	*	Multi-layer perceptron (MLP)	Simulation
[86]	Kinematics model and experiment system of telescopic excavator	×	×	*	*	×	D-H method and geometrical relationship method	Simulation and field testing
[87]	Task planner design for an automated excavation system	×	×	*	*	×	–	Simulation
[71]	Bucket trajectory classification of mining excavators	×	*	×	×	×	–	Field testing
[88]	Task planning strategy and path similarity analysis	×	*	×	×	×	A complete coverage path planning algorithm	Simulation
[89]	Optimization of trajectory durations based on flow rate scaling for a 4-DoF	×	×	*	*	×	–	Simulation
[90]	Trajectory control using an improved GA based PID controller	×	×	*	*	*	Improved genetic algorithm	Field testing
[91]	Compact reachability map for excavator motion planning	×	×	*	*	*	–	Simulation
[81]	Impedance control of a hydraulically actuated robotic excavator	×	×	×	*	*	Impedance control	Simulation and field testing
[92]	Prediction and optimal bucket-filling control for autonomous excavators	×	×	×	*	*	**Heteroscedastic Gaussian process**	Field testing
[93]	Control based on output power maximization	×	×	×	*	*	A Model-Free Extremum-Seeking	Field testing
[94]	Complex path tracking control	×	×	×	*	×	Reference adaptive control	–
[95]	FOPID control with parameter optimization	×	×	×	×	*	A fractional order proportional i[90]ntegral derivative	Testing in laboratory
[96]	Parallel end-to-end autonomous mining	*	*	*	*	*	An IoT-Oriented Approach	–
[77]	A robust control approach for hydraulic excavators	×	×	*	*	*	–	Field testing
[97]	Dynamically optimal trajectories for earthmoving excavators	×	×	*	*	*	–	Simulation and field testing
[98]		×	×	×	*	*	Koopman-DFL Lifting Linearization	Simulation

(continued on next page)

Table 3 (*continued*)

Ref.	Task	A	B	C	D	E	Method	Test scenario
[99]	Dynamic modeling of bucket-soil interactions Predicting the operator's intent in a dynamical environment	×	×	×	*	*	A task learning.	Scaled test plarform

Note: A: Sensing, B: Perception, C: Decision, D: Planning, D: Action.

operators to regulate the position and orientation of the bucket. Operators determine the discrepancy between the operation's needs and the actual condition of the bucket using observation and perceptual processes. Then, based on the fault, he or she makes judgments and manipulates the excavator to correct it. This is a closed-loop control mechanism that is activated by the feedback of the human perceptual visual system [75]. For developing the performance of a fully automatic control system, experienced operators' skills and how they control the excavator should be identified. The reference [76] has presented the development of an operator model for robotic excavation that is based on neural network theory. The results of the experiments suggest that this operator model is both successful and practicable.

Nonetheless, the motion control of an intelligent excavator manipulator is a particularly difficult task to accomplish in the development of an autonomous excavator system because of nonlinear dynamics of the manipulator, variability of mechanical structures of excavators, and disturbances. Numerous controllers for hydraulic manipulator systems have been suggested and explored in an attempt to resolve these issues. For example, Seunghyun et al. [77] has suggested a robust control system for the autonomation of an excavator. A robust controller is constructed using μ-synthesis to handle the nonlinearities and disturbances of a hydraulic excavator as uncertainties within the joint dynamics, ensuring robust stability and performance within the provided uncertainty bounds. They have also improved the overall performance of tracking the digging trajectory in the workspace by using a shared model reference for each joint. Experiments have been conducted on an industrial hydraulic excavator (21-ton class). As a result, they have improved the efficiency with which the digging trajectory is tracked throughout the work area. But they haven't specifically examined environmental disturbance forces in their study. In addition, the operation condition can change over time due to changes in pressure buildup time or mechanical fatigue in long-term operations.

Time delay control (TDC) and terminal sliding mode control (TSMC) have been coupled to provide a novel discrete model-free robust controller for robotic excavator motion control. With the TSMC's nonlinear intended error dynamics, a TDC without acceleration information has been suggested [78].

The all-primary articles' objectives, related to groups, used methods and test scenarios are listed in Table 3.

4. Key challenges and future work direction

Fully autonomous systems that can accomplish operation for excavators equally well as a human is still a long way off. Future studies on fully automated operation will have to solve a variety of issues, including the following:

→ Although a large number of studies have been conducted for material classification and material detection by using artificial intelligence algorithms and proprioceptive force sensing, a few materials are used in these studies [45]. These rates of these materials are not sufficient for a fully automated operating system because other types of excavation materials can be identified in actual mining and construction applications, such as intelligent excavation control adaption or optimization of blasting and crushing processes. Scaling the approach to detect new kinds of materials should be investigated in the future, which might potentially incorporate material features such as rock size distributions.

→ As mentioned in Section 3.1, obstacles can be divided into two groups like on the ground and underground in terms of their impact on excavators. Sufficient studies have been carried out for the first group while very few references can be found for underground obstacles detection for autonomous excavators. Future research should be taken in to account this issue which can contribute to the development of autonomous excavators.

→ The studies for detection of dump truck, estimation of pose of it and as well as estimation proper distance between an excavator and a dump truck have been conducted successfully for accurate material loading task. But a study about estimation of free volume of dump box of dump truck for loading material has not been done. Future study on this issue is urgently needed.

→ Pile shape and geometry characterization allows the machine to make cognitive decisions during the loading process. Existing technology, such as laser-based Lidar systems, are capable of meeting this need. In a continually changing environment, such as a blasting site, navigation systems and path planning should be performed with an exact map of the area. SLAM (simultaneous localization and mapping) technology can be utilized to produce the most up-to-date and accurate map of the site, which can then be disseminated to other equipment and site management software. Incorporating autonomous machines for operation, monitoring, and maintenance into site management technology will require more research and development.

→ Although autonomous excavators have been shown to be more accurate than human drivers in several tasks, there are still some things they cannot perform. When a task necessitates ongoing adaptation and includes numerous unexpected events, a human driver can still analyze and apply his knowledge to overcome the issue, whereas autonomous excavators would become stuck. To overcome such kind of challenges, applying a commonsense knowledge (CSK) concept to an autonomous excavator in decision making might be good solution. Furthermore, to apply this CSK-enabled technique to autonomous cars and robots has been done. But this technique is not studied well in the field of autonomous excavators. Successfully applying this technique might be big step towards fully autonomous excavator.

→ Robotics simulators are the most widely utilized simulators in the field of study. If it is assumed that autonomous excavators are a subset of robotics, this makes sense. However, not all robotic simulators are capable of providing the essential realism in these situations. As a result, the common practice is to use bespoke solutions built on top of established modeling and simulation platforms.

5. Conclusions

Although there has been a significant increase in the amount of research and literature on autonomous excavators in the last decade, there are still difficult challenges to overcome in this field. This paper has introduced the subject of automated driving and working systems of autonomous excavators by dividing five groups, namely: sensing, perception, decision, planning, and action, and then conducted a comprehensive literature review spanning a variety of research topics before identifying knowledge gaps for autonomous excavators.

Sensor fusion can improve the robustness of environmental perception systems, and additional research in this field is expected to completely utilize all the information offered by the sensors. Also, the new deep learning algorithms for detecting objects have gotten a lot better at what they do, but they haven't been made to work with sensor data from a wide range of sources yet.

While amazing capabilities have been proven in the field of planning algorithms, it is expected that real-time planning in dynamic contexts will continue to develop. Recent research in this area is trying to find ways to better combine the limits of robots' different kinds of motion and effective ways to keep track of what they know between planning cycles.

Machine-to-machine communication allows machines to coordinate their tasks. For example, on a construction site, an autonomous excavator and an autonomous dumper must connect with each other and employ coordinated path planning and navigation.

In recent years, significant theoretical progress has been made in the field of autonomous excavator control. Many of the breakthrough findings, however, have only been evaluated in a simulation or laboratory environment. It is very important to make sure that the autonomous system follows the rules for making decisions at a higher level.

Recognizing the rapid pace of autonomous excavators' research, the near future advancements that will overcome the cited hurdles and bring autonomous excavators to a higher prevalence in the construction and mining industries are eagerly anticipated.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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