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RESEARCH ARTICLE

Toward Autonomous Vehicles and Machinery in Mill Yards of the Forest Industry: Technologies and Proposals for Autonomous Vehicle Operations

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ABSTRACT The use of autonomous systems at wood processing sites of forest industries can significantly increase safety, productivity and efficiency by reducing the number of monotonous and dangerous tasks conducted by human labor utilizing heavy machinery. However, autonomous machine operation in mill yards is challenging because of the dynamic and complex working environment and partly unstructured processes. The inherent complexity of wood handling and storage tasks requires significant human expertise. Rapid advancements in sensor technologies and machine learning techniques, along with increases in available computational power have enabled progress in automated operation frameworks and algorithms development, which opens the door to the introduction of novel autonomous systems into this environment. With the aim of gaining a better understanding of current issues and facilitating optimal strategies for the deployment of high-level autonomous systems in mill yard environments, this study: (1) utilizes a systematic literature review to map current autonomous technologies and algorithms suitable for adoption by the forest industry in automation of vehicles working in mill yards; (2) summarizes and discusses the potential feasibility of the considered sensors, systems and adoption strategies, and considers implementation challenges for high-level autonomous machinery in mill yard environments; and (3) proposes a system framework that integrates multiple technologies to enable autonomous navigation and material handling in mill yards. The study is the first of its kind as a comprehensive study on autonomous vehicles and machinery in mill yard environments. Our novel framework aids in the identification of follow-up research areas and thus promotes the adoption and use of complex autonomous systems in industrial environments.

INDEX TERMS Automation, autonomous vehicles, autonomous heavy machinery, forestry, terminals, mill yards, systematic literature review (SLR).

I. INTRODUCTION

Continued growth in the world economy in a context of climate change is stimulating high demand for renewable raw materials such as wood [1], as can be seen in the production of industrial roundwood and sawn goods, which reached a new record high in 2018 with increases on the previous year of 5% and 2%, respectively [2]. To meet this demand, suppliers are constantly trying to increase production volumes, leading to a need to hire more workers. Globally, the

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current estimated number of workers in the forestry sector is 30–45 million people [3]. Many of these workers have little or no training, which leads to an unnecessarily high rate of work-related accidents in the forest industry compared with other similar industries. Some estimates suggest that work-related accidents in forestry and the forest industry exceed 170,000 accidents a year [4] and the EU-27 report published in 2020 stated that the forest industry has one of the highest work-related accident rates found in the primary sector [5].

Mechanization has been a typical industry solution to decrease the number of accidents [6], increase productivity and efficiency [7], and safeguard humans from high-speed asset handling operations [8]. While mechanization results in fewer disabling accidents, it often comes at a cost of an increase in cumulative trauma disorders (repetitive stress injuries) among machine operators due to the complicated tasks and machine sizes they are required to operate, which demand constant vigilance [6]. Additionally, as modern machines become better and faster, operators are expected to be more productive and work more intensively. However, despite the increasingly challenging nature of the modern workplace, developing countries and nations with low birthrates are facing pressure to consider raising the retirement age [9]. Although higher retirement ages for men and women are associated with lower mortality, diabetes risk and depression [10], changes in the retirement age, on the other hand, can result in huge social inequalities, pushing some workers to stay in the labor market despite their poor health, which can lead to more accidents [11]. Furthermore, with modern machines becoming more complicated, required training time has increased considerably [7].

The changing social and technical environment is leading to a growing labor shortage in the forest industry, which will have serious effects on the industry's ability to meet increasing demand for forest industry products [12]. In this context of increasing demand and growing labor shortages, automation can offer potential solutions enabling employers to reduce the need for monotonous and dangerous tasks, thus lessening the danger of workplace accidents while improving productivity. Additionally, automation can address the issue of long working hours doing tasks that require high alertness, as well as reduce the need for long training times, and help in transformation of industry-related operational models [13], increasing the attractiveness of the industry. The forest industry and mill yards can be considered valid locations for the adoption of automation technology because current working conditions are physically demanding and involve repetitive tasks and activities requiring constant alertness. This working environment can lead to cumulative trauma and push people to early retirement. Vehicle automation in mill yards could help the workforce increase productivity as well as improve cost and energy efficiency while reducing stress and the risk of injury.

In light of safety-related issues and the working environment, our study investigates the possibility of automating vehicle operations in wood terminals and mill yard areas. Our results are based on currently available technologies. Several studies on autonomous forest machines (i.e., forest harvesters and forwarders) as well as work on teleoperation and robotics in forest operations have been presented (e.g. [7], [16], [17], [18], [19], [20], [21]) and an in-depth review of forest robotics can be found in [22]. Moreover, the idea of self-driving timber trucks on highways, i.e., public roads, has been introduced in recent years [23]. Nevertheless, to the best of our knowledge, there are no comprehensive studies on vehicle automation in mill yards of forest industries.

The main research question of this study is: *What current autonomous systems are feasible for use with vehicles operating in mill yards and terminals of forest industries?* In more detail, this study aims to ascertain technologies suitable for mill yard automation and suggests practical solutions from other industries that can be adopted by vehicles and machines currently operating in wood terminals and mill yards. The functionality of the considered technologies in the discussed environment must be fully considered throughout the process as the working environment differs greatly from urban, construction, mining, agriculture, or even the forest environment. As a research method, the study utilizes literature review and mapping work. Then, a novel system framework for autonomous vehicle operations in mill yards is suggested based on the findings. The framework integrates various technologies to enable autonomous navigation and material handling. The study helps determine areas of future research that will make it possible to introduce autonomous systems in the mill yards of the forest industry.

The remainder of this paper is structured as follows. Section II provides background information and highlights the research motivation. Section III presents the selected research methodologies. Section IV contains the findings of this study. Section V presents a summary and discussion of

FIGURE 1. Examples of wood handling vehicles: From left to right: Volvo L90E wheel loader shaping a pile of wood chips, RTD3126 TW Log Stacker, manufactured by SKS Toijala Works Oy handling a bundle of industrial roundwood logs, and Mantsinen 300 material handler unloading train wagons.

the study results. Section VI introduces a novel framework based on the study findings. Limitations and threats to the validity of the study are discussed in Section VII. Finally, Section VIII summarizes our conclusions and proposes future research directions.

II. RESEARCH MOTIVATION AND BACKGROUND

The topic under research is automation in the forest industry context, more particularly, operations in outdoor environments or mill yards that utilize vehicles and machinery to handle industrial roundwood for use as input raw material. Worldwide industrial roundwood cuttings in 2019 were around 2.0 billion m^3 (under bark), with the production of sawn goods and wood-based panels being 488 and 357 million m^3, respectively [14]. In the same period, the worldwide production of wood pulp, and paperboard was 190 and 404 million tons, respectively [14]. Many different vehicles are used to handle the material flow of industrial roundwood and wood chips, i.e., when carrying out unloading, stacking to storage, loading, and transportation operations. Such material handling machines include log stackers, wheel loaders, bulldozers, and timber and chip trucks (examples are given in Fig. 1) and the scale of this fleet alone shows the huge potential for automation in mill areas and across multiple operational sites when optimization is done at fleet level [24], [25].

Within this specific context (operations size and environment), our study examines practical automatization and technology transfer possibilities from other industries. The material in the mill yard operations under consideration is mostly common industrial roundwood and wood chips. The layout, transportation sequences used, and volumes handled by the terminals differ considerably, e.g., port activities (wood deliveries by water) and other services are provided by some terminals, some mill yards have railways coming directly into the yard areas, and other sites rely 100% on truck delivery. This process is presented in a simplified format in Fig. 2. The focus area of the study is from the point where the raw material arrives in the yard area to the input point into the factory wood processing units. The research in this study excluded supply chain aspects related to, e.g., road and rail logistics into the mill yards. Additionally, wood processing operations inside the mills, for example, debarking and chipping, are not covered. Generally speaking, the most pertinent operations for this research are material receipt, material measurement, material unloading to storage or straight to the mill process, and material transit from storage to the mill. Navigation, material manipulation, and control and management activities connected to automated processes are common tasks at wood terminals, which are then followed by mill-related wood operations and handling processes.

In the dynamic environment of mill yard operations, machines and vehicles work in quite close proximity, and in some cases, workers and site visitors may be moving around the operation area, which increases the need to constantly consider 360 degrees around the work area and complicates safety issues, especially when planning changes to work processes [15]. Furthermore, the yards have different road types (structured, unstructured, paved, unpaved) and are usually outdoors, and consequently affected by changing weather conditions (rain, snow, fog, drought, high heat). These conditions impose constraints on production site management and provide motivation for increased automation and work process simplification.

When considering the operational area of the yard's vehicles and machinery, it is worth noting that some vehicles and machines in these closed mills / terminal areas might move around for just some tens of meters, whereas others may move up to several kilometers (going around obstacles, buildings, and wood stockpiles) while executing different work tasks. In this sort of environment, drivers and operators can suffer work fatigue as they can be constantly repeating (familiar) driving routes and operation actions. At the same time, as operators know they are working in closed fence-protected areas, they may be surprised by unexpected encounters with outside personnel and/or vehicles, which can increase the likelihood of accidents.

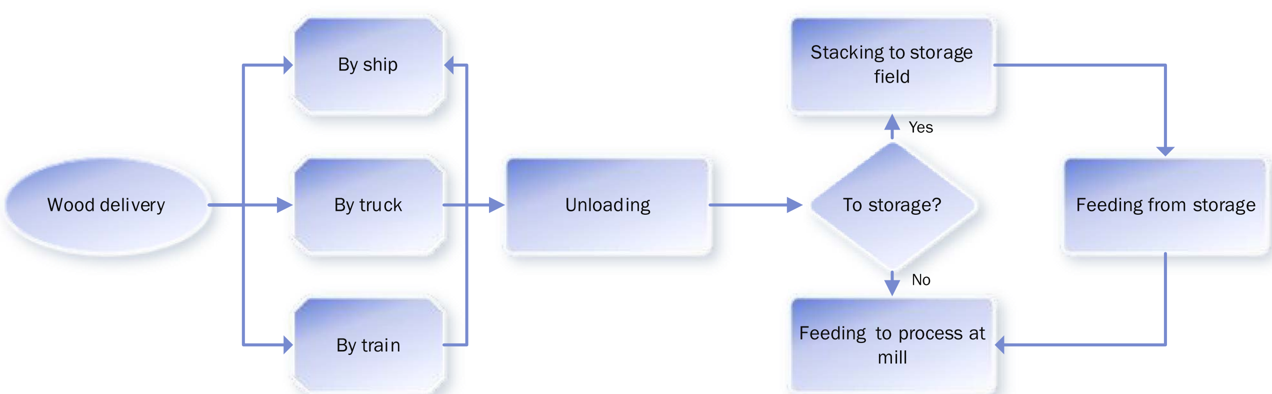

FIGURE 2. Simplified wood flow visualization for wood delivery and feeding to process of mill.

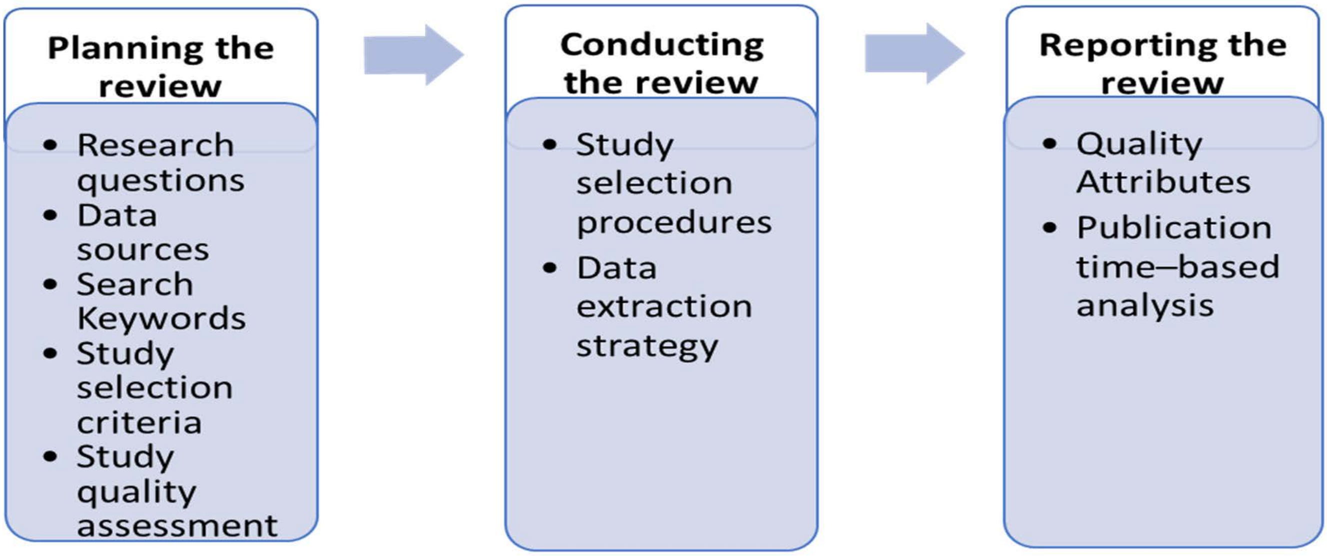

FIGURE 3. Adapted version of systematic literature review (SLR) based on Kitchenham & Charters [23].

III. RESEARCH METHODOLOGY

As mentioned previously the main research question of this study is: *What current autonomous systems are feasible for use with vehicles operating in the mill yards and terminals of forest industries?* Specifically, the study examines the current practical solutions introduced in the academic literature to ascertain technologies from other fields suitable for the automation of heavy machinery and different types of vehicles and machines that are used in mill yard and wood terminal areas (Fig. 1). In more detail, the study investigates autonomous navigation and material handling systems that can be adopted by vehicles operating in the mill yard environment. Furthermore, the study also looks at the types of sensors utilized by those systems. To answer the main research question, the work is supported by the following sub-questions:

1. What current practical autonomous navigation and material handling solutions in the literature are suitable for the mill yard environment?
2. What sorts of sensors are utilized in these systems?

The study utilizes a systematic literature review (SLR) to delve into the literature for the purpose of extracting data and examining technology transfer possibilities from other industries. The SLR is a well-recognized and extensively used literature assessment approach that evaluates research associated with a particular study area. An SLR differs from a standard literature review in that it is systematically designed and implemented. Additionally, an SLR has a higher level of validity through its systematic process of locating, evaluating, and summarizing all existing evidence on a specific study question [26]. Our literature review is based on the guidelines of Kitchenham and Charters [27] and is enhanced by the suggestions given by Akbar *et al.* in [28]. Furthermore, we investigated the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) [29] and utilized them to develop the studies' quality evaluation questions. The SLR method used is depicted in Fig. 3 and described further in the following sections.

A. PLANNING THE REVIEW

1) RESEARCH QUESTIONS

The research questions are given above.

2) DATA SOURCES

As mentioned earlier, our research focuses on academic literature, which is a literature form commonly found in scientific reference databases such as the Web of Science (WOS). WOS is one of the most widely used databases for tracking high-quality research [30]. The database includes over 21,100 high-quality indexed academic journals with almost 75 million records [31], [32], [33]. Furthermore, other databases are also indexed in the WOS database, such as IEEE Xplore digital library database, CABI Databases, KCI - Korean Journal Database, Scientific Electronic Library Online (SciELO) database, and many others, together with most of the journals indexed in SpringerLink [34], [35]. Hence, the WOS core collection database was selected as the main data source for this study.

3) SEARCH KEYWORDS

Different literature reviews and mapping studies on topics such as automation, sensor technologies, autonomous vehicles and forest machinery were first studied [22], [36], [37], [38], [39], [40], [41], [42], [43], [44] to gain an overview of the field. Based on the findings, a set of keywords were extracted as a starting point for our search strings. This procedure resulted in a series of topic-related keywords relevant to the topics under research: Group A – autonomous vehicles, navigation and environment mapping related keywords; Group B – words related to sensor technologies; Group C – keywords related to vehicles used in the forest industry and other related industries; and

TABLE 1. Keywords' groups extracted from different studies.

Group A	Group B	Group C	Group D
Self-driving	Sensor*	Vehicle*	Forestry &Forest
Autonomous	Technolog*	Car	Mining
Driverless	Survey	Truck*	Agriculture
Connected Autonomous	Review	Delimber*	Construction
Automat*		Yarder*	Industr*
Automation		Forwarder*	
Mapping		Log Loader*	
Navigation		Robot*	
Simultaneous localization and mapping		Tractor*	
Obstacle detection		Machinery	
Environment sensing		Machin*	
SLAM		Excavator	

Group D – keywords related to the forest and related industries. The keyword groups are given in Table 1.

From the first round of searches, two things became very apparent. First, a few terms were identified as irrelevant or unconnected to the research objectives. Studying the most important keywords in each of the studies, we were able to compile a list of keywords to be excluded from later searches. These excluded keywords are: underwater, flying, cyber-attacks, 3D printed, aerial, repair, air, indoor, underground, water, "air vehicle∗", humanoid, "fire-detection", UAV, and "Biologic∗". Second, it was noted that many search phrases connected to automation or autonomous vehicles are far too broad and vague to be used as topics, since the number of results is too large to be examined, and a short overview of the resulting publications showed that they are primarily unrelated to the specific area of automation considered in this research. To limit all further queries, different search term combinations were carefully built using the Boolean "OR", "AND" and "NOT" operators to concatenate and formulate the complete search strings. In total, 17 search strings (Table 2) were formulated. The searches were then limited only to the publications' titles, and only in some cases was the topic included when the search results were considered insufficient. Then, an online search was conducted using the set of keyword combinations on the Web of Science core collection database. The time period for publications for inclusion in the study was set between 2000 to 2021 to focus on recent automation technology research. A table showing the different search combinations is given in Table 2.

4) STUDY SELECTION CRITERIA

To focus on technologies that are adaptable to the mill yard environment, a set of inclusion and exclusion criteria were established:

- The system should rely on a set of sensors to support navigation in different weather and lighting conditions.
- The system should be able to work on either structured roads or unstructured roads.
- The system should be able to conduct real-time mapping, perception, localization, or control.
- Real-life system robustness validation experiments were conducted, or the system was at least tested on a large dataset.
- The system can operate in an outdoor environment.
- The system can be converted and adopted by the forest industry in terms of efficiency.
- Only peer-reviewed English language journal articles and conference proceedings papers were considered.
- Only papers published between January 2000 to December 2021 were considered.
- All duplicate articles were excluded.

5) STUDY QUALITY ASSESSMENT CHECKLISTS AND PROCEDURES

During the final stage of selecting the articles, a quality evaluation assessment was conducted. Four quality evaluation (QE) questions were developed in accordance with the PRISMA statement for appraising quality criteria (Table 3). The first QE question (QE1) was set to guarantee the relevance of a study to the research topic. QE2 ensured that the system discussed in a certain study utilizes different sensors to support navigation and material handling in different light and weather conditions. QE3 was designed to investigate whether the system discussed in a specific study is feasible in mill yard environments. The final question, QE4, ensured the robustness of the system presented in the reviewed studies and confirmed that the system can be presented as a practically functional solution. An article was selected if it met all the criteria in the quality evaluation questions.

B. CONDUCTING THE REVIEW

1) STUDY SELECTION PROCEDURES

This research utilizes the tollgate method developed by Afzal *et al.* [45] to filter the list of initial search results. The method uses three different filtering stages in order to locate the most relevant and useful content for a study question. The steps and results of the tollgate approach are shown in Fig. 4.

The selection process started by executing an online search on the selected database using our 17 developed search strings (Table 2), which generated 1882 articles in total. All duplicates and non-English studies were then removed, and the article titles, abstracts, and conclusions were scanned to verify their scope against the research objectives and topic. These two steps resulted in 326 articles for the last scanning stage, where the full text of every study was read and the previously mentioned study quality evaluation questions (QE1–4) were applied, resulting in a reduction of the number of studies for consideration to 28 studies. The number of articles excluded based on each of the 4 used quality evaluation questions is

TABLE 2. List or search stings combinations & tollgate selection process results.

Keyword Combinations	First Stage	Second Stage	Final Stage
("Self-driving" OR "Autonomous" **OR** "connected Autonomous" **OR** "Driverless" OR "automat*") **AND** (Sensor*) **AND** (Vehicle **OR** Vehicles **OR** Car **OR** Cars **OR** Tractor* **OR** Truck* **OR** Delimber* **OR** Yarder* **OR** Forwarder* **OR** “Log Loader*” **OR** Excavator) NOT (Underwater **OR** flying **OR** cyber-attacks **OR** “3D printed” **OR** aerial **OR** repair **OR** AIR **OR** indoor)	375	54	11
("Self-driving" **OR** "Autonomous" **OR** "connected Autonomous") **AND** (Automation) **AND** (Vehicle **OR** Vehicles **OR** Car **OR** Cars **OR** Tractor* **OR** Truck* **OR** Delimber* **OR** Yarder* **OR** Forwarder* **OR** Log Loader* **OR** Excavator)	27	1	0
("Self-driving" **OR** "Autonomous") **AND** (vehicle* **OR** Robot* **OR** Car **OR** cars) **AND** (“Environment sensing” **OR** “Navigation” **OR** “obstacle detection”) **AND** {(industr*) **in topic**}	59	14	3
("Self-driving" **OR** "Autonomous") **AND** (vehicle* **OR** Robot* **OR** Car **OR** cars) **AND** ("SLAM" **OR** "Simultaneous localization and mapping")	86	13	1
("Self-driving" **OR** "Autonomous") **AND** (vehicle* **OR** Robot* **OR** Car **OR** cars) **AND** (Mapping)	390	94	6
("Self-driving" **OR** "Autonomous") **AND** (vehicle* **OR** Robot* **OR** Car **OR** cars) **AND** ("Sensor*") **NOT** (aerial **OR** underwater **OR** underground **OR** water **OR** "air vehicle*" **OR** humanoid **OR** "fire-detection" **OR** "UAV" **OR** indoor **OR** railway **OR** "Biologic*")	404	44	0
{Automation **AND** (Industr*) **in title**} **AND** {(Vehicle **OR** Vehicles **OR** Car **OR** Cars **OR** Tractor* **OR** Truck* **OR** Delimber* **OR** Yarder* **OR** Forwarder* **OR** “Log Loader*” **OR** Excavator) **in topic**}	23	4	0
(Automation) **AND** (Forestry **OR** Forest)	12	2	0
(Automation) **AND** (Machinery)	22	2	1
(Automation) **AND** (Material* **AND** handl*)	11	2	0
(Automation) **AND** (mapping)	59	2	0
(Automation) **AND** (Sensor*) **AND** {(Vehicle **OR** Vehicles **OR** Car **OR** Cars **OR** Tractor* **OR** Truck* **OR** Delimber* **OR** Yarder* **OR** Forwarder* **OR** "Log Loader*" **OR** Excavator) **in topic**}	12	4	1
(Automation) **AND** (Survey) **AND** {("Self-driving" **OR** "Autonomous" **OR** "connected Autonomous" **OR** "Driverless") **in topic**}	4	1	0
("Self-driving" **OR** "Autonomous" **OR** "connected Autonomous" **OR** "Driverless") **AND** (mining **OR** construction **OR** agriculture **OR** Forest*) **AND** (Vehicle **OR** Vehicles **OR** Car **OR** Cars **OR** Tractor* **OR** Truck* **OR** Delimber* **OR** Yarder* **OR** Forwarder* **OR** "Log Loader*" **OR** Excavator) **NOT** (underground)	67	22	2
Automation **AND** (Vehicle **OR** Vehicles **OR** Car **OR** Cars **OR** Tractor* **OR** Truck* **OR** Delimber* **OR** Yarder* **OR** Forwarder* **OR** "Log Loader*" **OR** Excavator)	206	20	0
"Simultaneous localization and mapping" **AND** “Review”	10	10	1
(Tractor* **OR** Delimber* **OR** Yarder* **OR** Forwarder* **OR** “Log Loader*” **OR** Excavator) **AND** ("automat*")	115	37	2
Total	1882	326	28

FIGURE 4. Steps and results of the filtering process.

TABLE 3. Study quality evaluation (QE) questions.

QE Question	Checklist Questions
QE1	Does the selected study report on autonomous, or material handling systems for vehicles or heavy machinery?
QE2	Does the system discussed in the paper rely on different sensors?
QE3	Can the system discussed in the paper be adopted and function in the mill yard context?
QE4	Has the system discussed in the paper been validated by experimental / simulation work?

TABLE 4. Number of excluded studies during the third filtering stage based on the QE Criteria.

Exclusion criteria applied during the third stage	Number of excluded studies
The paper is not reporting on autonomous, or material handling systems for vehicles or heavy machinery	71
The system reported in the paper relies on one type of sensors	51
The system is not functional for the mill yard environment in terms of efficiency, suitability, or adoptability	138
No real-life system robustness validation experiments were conducted, or the system was tested on a small dataset.	38

shown in Table 4. All the scan stages were conducted by the first author and then thoroughly reviewed by the second author. A table showing the tollgate process results based on every search string is given in Table 2.

2) DATA EXTRACTION STRATEGY

For data extraction, the papers selected were compared to the research subject, and the studies were thoroughly analyzed to extract data to answer the research questions set. The extraction stage was conducted by the first author by applying the inclusion and exclusion criteria. The second author thoroughly inspected the retrieved data. In order to rule out interpersonal bias, the first author supervisor (second author) participated, inspected, and reviewed all the steps of the studies selection and data extraction process. Furthermore, all findings, conclusions, and hypotheses made in the paper were reviewed by industrial and academic experts in the field of forestry and autonomous vehicles. The results of the revision showed significant agreement between all parties.

C. REPORTING THE REVIEW

1) QUALITY ATTRIBUTES OF THE SELECTED PAPERS

The quality evaluation (QE) criteria were used to assess the significance and value of each of the publications for the literature review in hand. All selected papers met the four QE criteria in the questions in Table 3 and thus were considered suitable for further analysis.

2) PUBLICATION TIME–BASED ANALYSIS OF THE SELECTED STUDIES

The papers scanned were published between January 2000 to December 2021. Our work aims to present a state-of-the-art overview of sensors and autonomous vehicle systems that can be adopted by machinery working in mill yards. The selection of the time frame was based on preliminary research which found that the main studies on sensors and automation before January 2000 were outdated and their findings unsuitable for adoption by the present-day forest industry. It should be noted that all the studies that passed to the analysis stage of the literature review were published between January 2012 and December 2021, i.e., in the latter half of the examined time period.

IV. RESULTS

As a result of the search and selection process, 28 publications (out of 1882) passed to the analysis stage of our study. The number of publications found is lower than expected, but not worryingly low. The reason for the low size of the literature base seems to be the challenging working environment of the mill yards, and as a result, there are currently few suitable solutions that can be adopted by vehicles operating in this environment. Furthermore, the search focused on practical solutions with high proven efficiency demonstrated through validation experiments, which also contributed to the low selection rate. The papers resulting from the selection process came from 22 different proceedings and journals, as shown in Table 5. The selected papers' findings were divided into four categories. These four categories are the main components of any autonomous vehicle system. The first category is sensors in autonomous vehicles. The second category is localization, which contains three methods: global navigation satellite systems (GNSS), simultaneous localization and mapping (SLAM), and a priori map-based localization. The third category is perception, which compromises two factors: object detection and classification, and road and obstacles detection. Finally, the fourth category is control and task execution. The papers contributing to each category are listed in Table 6.

It can be noticed from Table 6 that a paper can contribute to several categories since some studies present a full autonomous system, thus contributing to each category. The contribution mapping showed that of the studies selected, 21.4% contributed to the sensor in autonomous vehicles category, while 32.1% contributed to the localization category. Additionally, the majority of the studies contributed to the perception category, with a 57.1% contribution rate, and only 7.1% of the studies contributed to the control and task execution category, which is the least represented category.

TABLE 5. Database used and its associated proceeding and journals.

Database	Publications
Web Of Science	IEEE Access
	Engineering
	Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering
	International Journal of Advanced Robotic Systems
	IEEE International Conference on Control System, Computing and Engineering
	Proceedings of the ION
	Expert Systems with Applications
	Advanced Computing Strategies for Engineering, EG-ICE 2018
	Journal of Intelligent & Robotic Systems
	Proceedings of the 5th International Conference on Vehicle Technology and Intelligent Transport Systems
	Applied Sciences
	IEEE Intelligent Transportation Systems Magazine
	Transactions of the ASABE
	IEEE Intelligent Transportation Systems Conference
	Sensors
	IEEE International Conference on Electro Information Technology
	IEEE Transactions on Vehicular Technology
	International Conference on Information Technology: New Generations
	International Conference of Electrical and Electronic Technologies for Automotive
	Journal of Intelligent & Fuzzy Systems
	IEEE/RSJ International Conference on Intelligent Robots and Systems
	Irish Signals and Systems Conference

TABLE 6. Context and number of selected studies per category.

Category	Subcategory	Selected study	Total number of papers
Sensors in autonomous vehicles		[46],[47],[48],[49],[50], [51]	6
Localization			9
	Global navigation satellite systems	[18], [53]	
	Simultaneous localization and mapping	[52], [54], [55],[56]	
	A priori map-based localization	[57], [58], [50]	
Perception			16
	Object detection and classification	[60], [47], [48], [63]	
	Road and obstacle detection	[64], [65], [66], [68] [69], [70], [71], [72], [73],[47],[55],[49]	
Control & task execution		[74],[75]	2

V. DISCUSSION AND SUMMARY

As a summary, we review the relevant technologies for each of the previously mentioned categories based on the data extracted from the selected studies. The section discusses the kinds of sensor types each system utilizes and the suitability of each technology for the mill yard environment.

A. SENSORS IN AUTONOMOUS VEHICLES

Sensors are a crucial component for all autonomous vehicles as the data they provide to perceive the environment surrounding the vehicle is essential for path planning and control decision-making processes. Research in the field of autonomous navigation and object detection has made great progress in recent years, mainly because of the decreasing cost of sensor components, advancements made in artificial intelligence (AI), and the significant increase in available computational power [46].

For an autonomous vehicle to be able to make decisions in real-time, the sensors used must provide locational and perceptive information about the environment. To achieve these tasks, two types of sensors are used: 1) exteroceptive sensors, and 2) proprioceptive sensors. Exteroceptive sensors

TABLE 7. Comparison of exteroceptive sensors.

Sensor	Impacted by Illumination	Impacted by Weather	Depth	Color	Accuracy	Range	Cost
LIDAR	-	✓	✓	-	High	Medium (<200 m)	High
Radar	-	-	✓	-	Medium	High	Medium
Camera	✓	✓	✓	✓	Low	Medium (<100 m)	Low
Ultrasonic	-	-	✓	-	Low	Short	Low

are responsible for providing information about the environment surrounding the vehicle. Commonly used exteroceptive sensors are light detection and ranging (LIDAR) sensors, radar sensors, cameras, and ultrasonic sensors. Proprioceptive sensors, on the other hand, are responsible for providing information about the vehicle's internal data, such as location, orientation, and acceleration. Examples of these sensors are global positioning and navigating systems (GNSS), inertial measurement units (IMU), and encoders [46]. More details about sensor technologies and their working principles are given in [46].

No sensors are perfect for all situations, and all sensors have their technology-based advantages, limitations, and disadvantages. Table 7 presents a comparison of common exteroceptive sensors based on key characteristics. For example, cameras are affected by lighting conditions and weather variation, but on the other hand, cameras have high resolution and are a primary sensor for tasks like color perception, semantic segmentation, and object detection. LIDAR sensors can provide accurate range and shape measurements compared to other sensors (such as radars and cameras) but can be affected by snow and rain. Radar sensors have low resolution and detection accuracy, but they have the merit of accurate target velocity measurements and are not easily affected by adverse weather conditions.

Ultrasonic sensors are the cheapest of all sensors used in autonomous vehicles and the most accurate for close-range applications. They are minimally affected by severe weather conditions but can be heavily influenced by changes in

environmental conditions such as heat or humidity [47], [48], [49], [50]. In view of the different characteristics of the sensors, a target's velocity, type, and location cannot be ascertained accurately using a single sensor alone. To solve this problem, autonomous vehicle systems utilize and fuse data from different sets of sensors to enhance the accuracy of the system [51]. Several sensor fusion techniques can be used for this purpose, for example, state estimators, Kalman filters, and machine learning-based methods. More details are given in [51].

B. LOCALIZATION AND MAPPING

Localization is the task of defining the vehicle's position relative to the environment, which is crucial information for navigation [52]. Machines working in mill yards operate in a dynamic and unstructured environment that contains different road types (structured, unstructured, and off-road). An autonomous system functioning in such an environment should be able to localize itself in real-time with centimeter-level accuracy to safely navigate, handle material, and avoid obstacles. Different sets of sensor combinations and algorithms have been proposed to solve the localization problem. The following sections review the most common approaches that have potential for operating in mill yard environments.

1) GLOBAL NAVIGATION SATELLITE SYSTEMS

A simple solution for the localization problem can be achieved using a high-precision positioning system. There are different types of GNSS systems, for example, GPS, GLONASS, Galileo, and BeiDou. These systems can give a vehicle estimate position at all times, but with low accuracy. The estimated position given by these systems can be off by more than 15 m from the true location in some cases [53]. However, GNSS accuracy can be improved by utilizing a real-time kinematic (RTK) solution. For example, [18] presented an autonomous path tracking system for a forwarder navigating in a forest environment. The system uses a real-time kinematic GPS (RTK-GPS) system with three receivers and a gyro to localize the vehicle into the path. A similar approach can be seen in [53], where a Leica Jigsaw Positioning System (JPS) was used to localize autonomous vehicles in open mining pits. Both systems give good positioning estimates with centimeters level accuracy, and if coupled with other supporting positioning systems such as inertial navigation systems (INS) to compensate for the imprecision of GNSS satellite signals, they could serve as a valid positioning system for the mill yard environment.

2) SIMULTANEOUS LOCALIZATION AND MAPPING

Simultaneous localization and mapping (SLAM) is the simultaneous creation of an online map and localization on the map. When using SLAM, no prior knowledge of the surroundings is necessary, which makes it one of the most effective ways to solve the localization problem, especially in indoor environments [52]. Several approaches have been presented for outdoor environments like mill yards.

In [54], the authors propose a graph SLAM-based algorithm for mapping large-scale and complex environments. The map is structured using odometry, IMU, GPS and 3D LIDAR, and the map can then be used for navigation and localization by autonomous vehicles. The approach can be considered useful for the environment discussed in this study as the mapping system can work in challenging environments, including loop closures separated by long distances. The system was evaluated and tested by mapping three different environments, and it delivered precise mapping and loop closure results. Work by Kim *et al.* [55] specifically focuses on navigating the challenging environment conditions found on construction sites. These sites are highly dynamic and as such are remarkably similar to the mill yard environment. The authors proposed SLAM-based navigation methods using multiple 2D LIDARs, infrared and sonar sensors, and a camera. The robot was successfully able to navigate the indoor and outdoor environment in a construction site. It was noted, however, that the outdoor environment was much more challenging due to the uneven ground and changing soil types. A system specifically developed for off-road mapping and localization is described in [56]. The system can produce accurate terrain mapping while navigating in an off-road environment. To this end, the system utilizes several cameras with 2D LIDAR, IMU, radar, and internal vehicle information fused through an extended Kalman filter (EKF).

3) A PRIORI MAP-BASED LOCALIZATION

A priori map-based localization approaches are based on the concept of matching. Localization is accomplished by comparing online readings to information on a precise pre-built map and determining the location of the best feasible match. An initial pose estimation, from a GPS, for example, is frequently employed [57], [58] at the start of the matching process

Several methods can be used for creating maps, as well as preferred modalities. For instance, [58] showed that using a GPS + radar + camera + digital maps and a map matching technique known as iterative closest point (ICP) can increase vehicle localization accuracy. Other map matching techniques can also be considered. A mapping and localization method by fusing 3D LIDAR, odometer, IMU, and GPS data using normal distribution transform (NDT) matching is suggested in [57]. The proposed method gave accurate localization and mapping results. Such techniques can also be used in mill yards, where a high-density (HD) map can be processed from 3D scanning of the yard. Vehicles working in the yard can then use this map and the ICP or NDT algorithm to efficiently localize themselves at all times. Other map-based localization approaches that require low computation power are presented in [50], where a camera and a 2D LIDAR are used to produce a 2D local map for real-time route generation. The suggested algorithm removes the height value found in 3D maps to decrease the amount of processed data, which leads to faster processing time, but lower accuracy compared to 3D maps-based localization.

C. PERCEPTION AND MATERIAL RECOGNITION

The primary goal of perception for autonomous vehicles is to perceive the surrounding environment and extract information that is necessary for safe navigation and material handling. In the literature studied, cameras and LIDARs are the most commonly used sensors to solve the perception problem [59]. The remainder of this section is divided into key perception tasks such as object detection, road detection, and obstacle detection, which are vital tasks when considering automation for vehicles and heavy machinery operating in mill yards.

1) OBJECT DETECTION AND CLASSIFICATION

Detecting the position and size of items of interest is referred to as object detection [60]. Static items, such as walls, buildings, and material, and dynamic objects, such as other machines or vehicles and people, are all sources of concern to vehicles operating in mill yards.

In the studies selected for examination, state-of-the-art methods for identifying objects and their geometry all rely on deep convolutional neural networks (DCNN). For example, in [47], the authors propose a multisensory system for autonomous driving that uses a fast and efficient DCNN known as YOLO-V3 [61] for real-time object detection and classification. Another approach is shown in [48], where data from cameras, sonar sensors and 3D LIDAR are fused to achieve reliable object detection in a 3D space. The system integrates two state-of-the-art DCNNs to achieve this goal: YOLO-V3 and Mask RCNN [62]. The proposed solution differs from other approaches in that an end-to-end learning strategy is not needed. However, the solution requires that high geometric data is obtained from onboard sensors. The result was a reliable generalized obstacle detection and object classification solution that removes the need to annotate new training data to overfit a certain environment. A solution specifically designed for bad weather and bad lighting condition is proposed in [63]. The system fuses color camera images with infrared camera images to establish a dual-modal optical sensor to attain better detection robustness of low-observable targets (LOT). The proposed dual-modal deep neural network was found to have better recognition results compared with single pattern recognition methods but requires higher computation power.

2) ROAD AND OBSTACLE DETECTION

Effective detection of the drivable surface and obstacles is crucial to enable autonomous vehicles and machinery to operate safely in their environment. This requirement poses significant challenges as mill yards have different road types (structured and unstructured, with and without paving). This section gives an overview of existing approaches for detecting obstacles and drivable areas that can be adopted by mill vehicles and machinery.

In [64], an industrial size vehicle working in the forest environment was automated using a vision sensor + ultrasonic sensors + a magnetic compass with a hierarchical fuzzy logic controller. The ultrasonic sensors were used to detect obstacles, while the cameras were utilized to construct coast maps. The vehicle was able to successfully navigate several forest trails ranging in length from 229 to 430 m. The authors of [65] propose a mine road detection solution based on a 3D LIDAR and double meshing method. The proposed method has good detection results even though mine roads are not flat and have very large slopes, which can be the case in some mill yards. The authors in [66] present a new road (structured and unstructured) and obstacle detection method known as co-point mapping. The method relies on a novel fusion technique between the data of a camera and a laser sensor. The method can be generalized to different environments as it does not need strong prior hypotheses or labeled data. High robustness and efficiency were demonstrated by the system when tested on the KITTI database, which is a widely used autonomous driving benchmarking platform [67]. The co-point mapping algorithm can be considered as having potential for detection of drivable areas in mill yards, where both structured and unstructured roads are also found.

In [68], a camera and 3D LIDAR are used to detect road boundaries and the drivable area. The system calculates the height difference between the road surface and the curb to detect the road drivable area. Such an approach would be suitable for the detection of the drivable area in mill yards that have relatively flat surfaces. In [69], the authors suggest a system for navigation in real-world urban scenarios. The system uses 2D LIDARs and cameras and is capable of autonomous navigation on structured and unstructured roads. It can also deal with various challenging situations (e.g., strong shadow, pavement distress, dirt, puddles, rain or snow, and different lighting situations). This system differs from others in that the optimal drivable area detection occurs without using positioning sensors such as GPS/GIS. The system is also capable of detecting different traffic signs and road shoulders [70]. A solution for road and obstacle detection is presented in [71] that utilizes cameras and radar fusion under an adaptive self-learning method. The system can detect drivable areas and obstacles, especially in an off-road scenario, without the need for manual supervision for training. In [72], the authors utilized a combination of 3D LIDAR + 2D LIDAR + radars + camera to develop an obstacle detection system. The system uses 3D LIDAR and two radars to cover the areas surrounding the vehicle and uses the 2D LIDAR data as a safety layer to validate the data coming from the radars. The camera data provide a dense representation of the area in front of the vehicle and a low level of semantic understanding. System testing showed accurate results in detecting obstacles around the vehicle without the need for high computational power. Vehicles and machinery operating in mill yards can feasibly utilize the same approach, especially the use of 2D LIDAR for validation and safety assessment. A system for detecting other vehicles in the front driving area where a monocular vision sensor and 3D LIDAR are used is described in [73]. The suggested system had a 96.3% successful detect rate and a 39 ms detection time for every single frame, which is sufficient for real-time safe navigation. Other drivable areas and obstacle, detection solutions based on DCNN are presented in [47]. The systems use 3D LIDAR + cameras + radar fused together through a fully convolutional network (encoder-decoder-based) (FCNx) and extended Kalman filter (EKF). The system focuses on segmenting the road into two categories, free spaces (drivable areas) and not drivable areas, rather than small fine segments as mostly used in the literature. The system then utilizes YOLO-V3 DCNN for real-time obstacle detection. Kim *et al.* [55] present an obstacle detection method for an autonomous mobile robot working in a construction site. The method utilizes 2D LIDARs, infrared, and sonar sensors with a camera to detect and avoid obstacles in the environment. Yi *et al.* [49] used a camera, 2D LIDAR, radar, and a KF to develop an accurate object detection and tracking system that focuses on the target location, velocity, and type. The combined use of different sensors gives the system an edge over single sensor systems and more robustness in different weather conditions, which also adds an additional safety layer to the operations.

D. CONTROL AND TASK EXECUTION

After detecting the pose, location, and type of the materials, the machine needs to proceed to task execution. In the case of asset and machinery interaction like loading and unloading operations, the task can be highly demanding to execute with high accuracy and professional human driver-like behavior. The basis of the problem relates to the strong nonlinearities of the kinematics and dynamics of heavy machinery, which challenges mathematical modeling [74]. Three types of control approaches are commonly used in the literature: 1) nonlinear model-based approaches, which can give high precision and accuracy but rely on an accurate mathematical model of the system, which is very difficult to obtain; 2) model-free approaches such as PID (Proportional Integral Derivative) controllers, which do not use the same complicated mathematical models but require tiresome parameter tuning for every machine individually and their performance deteriorates over time, and; 3) data-driven methods such as reinforcement learning (RL), which can effectively generate and track a trajectory without the need for an accurate mathematical model or tedious tuning of different parameters [74], [75].

Due to the high complexity of mathematical models for heavy machinery, reinforcement learning is considered the most relevant method for control of the trajectory planning and motion of such machines. RL enables the machine to learn by interacting with the environment in a trial-and-error technique [75].

Many studies have provided evidence on the suitability of reinforcement learning for controlling heavy machinery motion [74], [75]. Egli and Hutter [74] presented an example where a reinforcement learning method is utilized to control a hydraulic arm that requires minimum machine parameter knowledge. The system can be trained in a simulator and then directly deployed to the machine after training. The method was tested on a heavy hydraulic excavator and demonstrated sufficient performance for practical application. A similar approach for automating an excavator using RL has also been presented by Kurinov *et al.* [75].

VI. PROPOSED SYSTEM

Research towards autonomous vehicles and autonomous heavy machinery has been active for a long time, but, in practice, only a handful of solutions are seen as feasible. Developing autonomous forestry equipment suitable for operations in mill yards will require the combined efforts of researchers and machine equipment manufacturers and investment in testing ideas and developing prototypes.

Considering the nature of operations in mill yard environments, and after analyzing the research papers selected, a high-level (conceptual) autonomous vehicle framework for mill yards combining different methods and approaches was developed. The structure of the suggested system is given in Fig 5. The system relies on three main components: localization, perception, and control, to achieve autonomous navigation and material handling in the mill yards of forest industries. The suggested localization, perception, and control methods alongside the challenges facing systems operating in the mill yard environment are discussed in the following sections.

A. LOCALIZATION

We propose that an a priori map-based localization method such as presented in [50] or [57] coupled with high precision positioning systems like real-time kinematic GPS [18] be used. The real-time kinematic GPS estimation is used as a validation and safety method for the autonomous localization function. A priori map-based localization offers greater accuracy than SLAM-based methods [60] and can be considered more suitable for mill yards as the layout of the roads inside such fenced areas rarely changes.

B. PERCEPTION

Using a predefined dataset of materials, obstacles and different road types to use in the designed structure (i.e., stereo images, edge detection, laser scanning), the vehicle can automatically perceive the environment using DCNN approaches [47], [48]. Even if obstacles and materials are in different shapes or locations, the system can still tell them apart. When constructing a complex structure made up of various

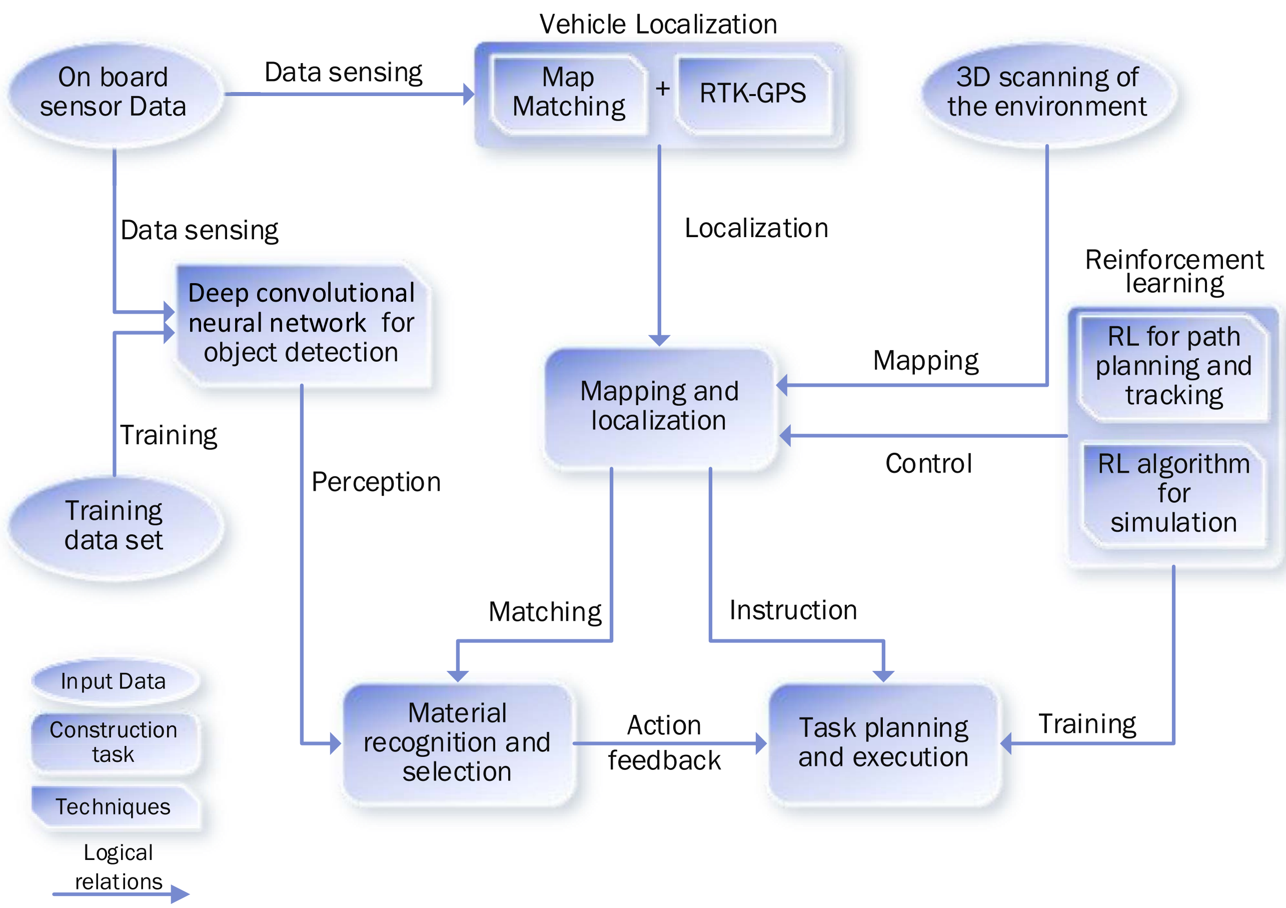

FIGURE 5. **Conceptual framework for Autonomous vehicles operating in the mill yards.**

materials, objects, obstacles and roads, the matching process can provide state and action feedback to the vehicles so that they can generate an execution plan to obtain the necessary materials or avoid obstacles.

C. CONTROL

Vehicles working in mill yards should be able to fulfill numerous tasks, for example, going across potholes, balancing on uneven surfaces, avoiding obstacles, and handling materials. The controllers monitoring these actions in real-time need a lot of extra effort to be properly programmed, since the problem to be solved involves extensive analytical manipulation of the dynamics and kinematics of the vehicles and loads being handled. Reinforcement learning algorithms [74], [75] appear to be a suitable fit for more complex heavy machinery applications that require real-time environment feedback with minimal error and robust localization control. The state of the vehicle and task can be described using environment information extracted from previous steps. Then, using a predefined RL reward policy, algorithms can be developed to inform the machine or vehicle of the requested motion and to control its execution.

D. CHALLENGES AND RECOMMENDATIONS

The context of autonomous vehicles and machinery operating in mill yard environments means that complex robotic systems operate in an unpredictable environment. As a result, there are numerous challenges which researchers and machine manufacturers must keep in mind when developing autonomous machines for this sort of environment. This section reviews the high-level challenges of developing autonomous vehicles for the mill yard environment.

1) NAVIGATION

The main challenge with navigation is detecting the drivable area, especially as the road surfaces in mill yards can change from large flat areas and flat structured roads to bumpy, uneven roads (off-road), which can affect low height obstacle detection. In an off-road situation, the road may have different heights, colors, or textures from the surrounding area, which allows machine learning and computer vision techniques to distinguish the drivable area. On the other hand, these differences may not be present. Also, in winter, the whole road and yard can be covered by a snow layer. A solution for such a problem is to always rely on a 3D localization option and a priori map-based localization approaches as the layout of the roads in the yards, buildings and material stacking locations does not change frequently. This approach would ensure sufficient localization and drivable area preknowledge and include the possibility of manually defining different static/trusted zones, such as predefined main roads, inside the mill yard premises.

2) SEVERE WEATHER CONDITION

Detecting obstacles and materials in bad weather such as snow, fog, and rain can be challenging. Although some studies have offered scalable solutions for such problems [63], [69], additional tests and validation work are still needed to ensure the reliability and robustness of these approaches. To solve the problem of challenging weather conditions, a multi-sensor configuration consisting of a system based on LIDAR, radar and camera technology is needed to offer safe and reliable obstacle detection and collision avoidance [60]. This multi-sensor setup, of course, has an effect on the cost of adopting the technology and puts pressure on the software development process to resolve conflicting measurements and identify false positives/negatives depending on the reliability of the sensor type relative to the weather conditions.

3) MATERIAL RECOGNITION

Recognizing the types, poses, and geometries of materials is of extreme importance to enable safe material handling. Deep Learning and Convolutional Neural Networks (CNNs) and Fully Convolutional Networks (FCNs) have achieved state-of-the-art results in object recognition and classification [47], [48]. For CNNs to work efficiently in mill yards, a training dataset must be developed by the industry specifically for the intended environment. With fewer material types and objects to be recognized, more diverse training data can be offered for the Neural Network (NN) to achieve high recognition results in challenging situations. The reality with wood material is that logs that look very similar to one another to the camera can be very different in density, quality, and moisture content, which affects the log properties greatly.

4) MATERIAL HANDLING

The most challenging task is automating the interaction between the machine tool and the environment as material properties (i.e., timber assortment, density, growth rate, moisture content, and surface roughness) and dimensions (i.e., top diameter and length of logs) change rapidly. Deep learning techniques such as RL could be a solution, but the amount of time and data needed to achieve sufficient training could be huge [76]. However, vehicles and heavy machinery working in mill yards will not require the same amount of data to build a reliable and robust system as all-road autonomous vehicles, since they operate in a more controlled environment with fewer possible scenarios to be trained for. Another important aspect of model training is the need to take into account the variety of training data required to avoid overfitting and to estimate the computational power needed for model deployment on the vehicles when designing the system [76].

In addition, it could be the reality that some mill yard operations may need to be somehow simplified, and the materials processed homogenized to enable process operations using automated machinery. Also, it is highly possible that any technological and business operations development may have effects on the status quo of a company's business culture [77], which has to be taken into account, too. On the technical side, for instance, the length of softwood pulpwood poles is known to vary considerably. In Finland, this variation is typically from 2.7 to 5.0 meters. It can be assumed that for autonomous machinery, it would be more efficient and also safer to handle timber with a fixed length or at least with less variance in length. This may apply especially to, e.g., automated wood bundle lifting stability and force directions, and sizes forecasting in dynamic lift and movement events (cf., Fig. 1). Moreover, equipping each autonomous material handling machine utilizing a crane with a scale measurement system can improve process and quantity management in mill yards. Overall, it can most likely be assumed that some processes would need cross supply chain related shared development and collaboration efforts [78], good trust between collaborating partners [79], and new forms/ways of formalizing front-end innovation processes [80] for effective automatization of the whole wood supply chain, not just yard area operations.

VII. THREATS TO VALIDITY

The first author of this study gathered the majority of the data. The data-gathering could include a small risk to the validity of the study's findings via non-intentional data bias. To minimize this sort of data bias threat, the co-authors observed, validated, and examined the collation, selection, inclusion, and exclusion of the publications and data extraction.

Furthermore, as this is the first study to specifically focus on development towards autonomous vehicles in the mill yard environment, the criteria set to evaluate whether a system is feasible in the environment were developed by the authors in light of their understanding of the environment. This could count as a threat to the validity of the results of this study as different perspectives can lead to different evaluation criteria. To minimize this threat, the environment was studied extensively by the authors before the criteria were set. Additionally, an expert from the forest industry reviewed the criteria to insure their suitability for mill yard operations and the mill yard environment.

VIII. CONCLUSION

The forest industry has the potential to benefit greatly from mill yard machinery automation. This study utilized a systematic literature review (SLR) approach to summarize and discuss current technologies and techniques presented in the academic literature that can be converted to the forest industry mill yard machinery context and can advance the development and utilization of autonomous heavy machinery operations on the sites of forest industries. This review conducted a bibliographic search in the Web of Science (WOS) database. Using various inclusion and exclusion criteria, 28 studies were selected for detailed review out of 1882 studies. The contributions of the studies were divided into four main categories: sensors in autonomous vehicles, localization, perception, and control and task execution.

On the basis of the information gained, a conceptual framework is presented capable of completing the entire navigation and material handling process with minimal human interaction. We suggest using an a priori map-based localization approach with a high precision GNSS system for localization and mapping, a deep convolutional neural network, and a training dataset developed specifically for mill yard environments to detect, identify and reconstruct objects in the environment. The framework focuses on the use of appropriate sensors and training the operational machines to understand their environment, identify the required tasks, and allocate operations to material handling. The framework employs simulation and training stages to ensure the vehicle's motion and task execution are carried out as intended. Simultaneously, the use of reinforcement learning to teach the vehicles to learn like humans is proposed so that the machines can learn from previous errors and the results of previous simulation iterations.

Incorporating the above-mentioned techniques will bring the forest industry one step closer to fully automated precision vehicles for mill yards, which will increase yields while relieving humans of tedious labor. However, there are some significant challenges in putting the proposed framework into action. First, the complexity of the environment may cause noise in the vehicle system, which can have a significant impact on its efficiency and accuracy. Second, additional testing and improvements are needed to ensure that the algorithm's calculation capacity is sufficient to execute complex tasks and that the vehicle can operate in different weather conditions. Third, determining that the amount of training data and simulation is sufficient for the material recognition and task execution process to function smoothly when unexpected differences and scenarios occur is a challenging task. Moreover, some complex work phases (e.g., log lifting) may have to be operated by a human operator using remote-control and the rest of the work tasks carried out autonomously.

Generally, more research is needed to introduce autonomous machinery in the mill yard environment, and multiple stakeholders, sustainability aspects and digitalization-related challenges [81] have to be taken into consideration when proceeding with these development efforts. In future research, we suggest expanding the search to include other databases and gray literature to ascertain further suitable technological solutions. Carrying out interviews with experts from both the forest industry and forest machinery manufacturers to evaluate the efficacy of the proposed solutions would provide valuable insights.

Our future work will include evaluating the efficacy of the proposed framework utilizing an autonomous robot platform with a robotic arm. A method for mapping and reconstructing a real-world mill yard is also under design and planning. Tests are being planned to focus on task execution and material handling using reinforcement learning. Additionally, fleet-level training and cross-site data exchange for enhanced fine-tuning and optimization of these operations are to be examined.

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