AROWA: An autonomous robot framework for Warehouse 4.0 health and safety inspection operations

Fotios K. Konstantinidis[1], Vasiliki Balaska[1],
Symeon Symeonidis[2], Spyridon G. Mouroutsos[2], and Antonios Gasteratos[1]

Abstract— **Over the previous two decades, a tremendous impact has been created on each stage of the production value chain, through digitization of the traditional industrial processes and procedures. Since warehouses are at the heart of distributed supply chain networks, it is critical to leverage modern automation tools and through-engineering solutions to increase their efficiency and continuously meet the demanding standards. Towards this end, we describe the design of a health and safety (H&S) inspection robot capable of autonomously detecting hazard events without human intervention in warehouses. It makes use of computer vision (CV) techniques, edge computing (EC) and artificial intelligence (AI) to identify critical occurrences that have a detrimental impact on H&S. while counting available resources using inventory tracking methodologies. Furthermore, action-based modules are activated in response to the recognised event, informing warehouse workers about it and notifying other systems, operators and stakeholders, where appropriate, as foreseen by the protocol. Lastly, the conceptual architecture of the proposed autonomous robot is presented, which classifies the needed vision-based and action-based modules.**

I. Introduction

The fourth industrial revolution is rapidly being occurred via the digitalisation of the manufacturing processes, the use of distributed processing, and the vertical/horizontal integration of the entire supply chain. Through this initiative, the interest of researchers turned to the industrial manufacturing field, yielding innovation and advancements, which can easily be applied in other industries or supportive stages such as storing and recycling [1]. In the warehouses, the digitalisation of the processes offers a fully automated ecosystem, where machines and humans harmonically coexist, improving the quality of services and the efficiency of production lines, while at the same time they keep the costs and the failures at low levels [2]. Nonetheless, the human element is still essential and, as a sequence, health & safety them is mandatory in the new era.

Occupation health & safety (OHS) inspection practises remaining a major concern in warehouses [3], where humans are still part of the processes despite the automation provided by Warehouse 4.0 [4]. To ensure the safety of the workers, OHS officers are responsible for monitoring and controlling workplace risks and hazards through scheduled inspections [5]. Nevertheless, events such as blocked paths or lack of personal protective equipment (PPE) that expose the workers to hazards are not recognized in real-time and can lead to harmful incidents [6]. With the aim to apply industry 4.0 (I4.0) technologies in this sector, we propose an autonomous robot-based inspection platform that surveys the warehouse across all shifts, thus affecting the impact of possible hazards to workers and enterprises [7].

Within warehouses, the incoming and outgoing flow of materials create a dynamic environment containing handling equipment, racks and personnel resources. The (H&S) risks of the workforce need therefore to be heightened, making it important to diminish the hazards [8]. The most common warehouse safety hazards are slips, stumbles, and falls, accounting for 31% of reported accidents because of objects being left in walkways or spillages [9]. Another leading cause of incidents is incorrect manual handling (21%), as long as workers are not properly kitted out or tasks are performed by untrained personnel. Besides, other issues such as fault evacuation instruction, lack of H&S signs or fault racking have also been reported, which increases the accidents within the warehouse facilities [9].

To foster a safe and healthy environment, advanced technologies, vision-based sensors and intelligent control functionalities are fused to synthesize the proposed robot-based inspection platform. The robotic system is capable of surveying the entire warehouse premises and navigating through humans and objects without obstacle restrictions [10]. During autonomous navigation, a camera captures the activities occurring within the surroundings. The frames are processed in separated event-based modules using CV techniques to extract features and detect critical events. Based on the identified event, action elements are activated that informs workers about the incident and reports the occasion to other systems. Following the described sequence of actions, the proposed system can identify fire [11] and flood events [12], capturing their location to generate alerts for workers and OHS officers. Furthermore, the lack of predefined H&S signs and blocked paths [13] are recognised, as well as the fullness of racks or dangerous boxes placements [14]. Lastly, machine vision algorithms are utilised to identify the proper use of the PPE based on their current activities [6]. The aforementioned components ensure that the proposed vision-based robotic vehicle automates the H&S inspection procedures and inform stakeholders about incidents in real-time. The contributions of this paper are summarized as follows:

[1]Fotios K. Konstantinidis, Vasiliki Balaska and Antonios Gasteratos are with the Department of Production and Management Engineering, Democritus University of Thrace, 12 Vas. Sophias, GR-671 32, Xanthi, Greece {fokonsta, vbalaska and agaster} @ pme.duth.gr

[2]Symeon Symeonidis and Spyridon G. Mouroutsos is with the Department of Electrical and Computer Engineering, Democritus University of Thrace, Kimmeria, GR-671 00, Xanthi, Greece {ssymeoni and sgmour}@ ee.duth.gr

- The introduction of an autonomous H&S inspection robot, detecting incidents in real-time within warehouse.
- The proposed robot utilizes image-based sensors and artificial intelligence to identify eight distinct hazards.
- The robot's architecture is designed to be easily integrated with smart and warehouse management systems.

The rest of this paper is structured as follows. In Section II, we present the description of the warehouse processes. Section III contains information about the H&S procedures in Warehouse 4.0, while Section IV and Section V describes in detail the vision-based and action-based modules of the proposed robot. In the following section VI, the system's architecture is presented. Lastly, in Section VII, we draw conclusions and present suggestions for future work.

II. Warehouse

Warehouses are viewed as assets by a range of enterprises along the global supply chain, and their operational success has an effect on the overall efficiency of logistics. A warehouse is structured as goods entry, storage, and distribution management. Inefficient space management, damaged goods, ineffective operations and underutilized material handling equipment are all disadvantages of traditional warehouses [15]. The explosion of I4.0 contributed to the Smart warehouse's development, automating traditional warehouse procedures. Generally, Warehouse 4.0 attempts to improve service quality, productivity, and efficiency, lowering costs and eliminating failures, while the existence of Automated Guided Vehicle (AGV) on the novel stock houses is remarkable. The fundamental operation of AGV is the creation of an efficient path through the products' tracking (or the products shelves), to collect or distribute them [16], [17]. Besides, advanced robotics for picking operations stands as an essential technology within the warehouse since it automates the procedures. Hence, a Smart Warehouse Management System (WMS) supports the smart warehouse idea [18]. Smart warehouse monitoring and control systems also embrace Internet of Things (IoT) [19] and Augmented Reality (AR) technologies, the latter aiding to a seamless human-machine interaction (HMI) [20]. Smart warehouse automation, based on these technologies, provides cost-effective services, robust retrieval and storage, and reduced delay and errors. Contemporary studies have proposed and explored various types of smart warehouses, highlighting critical problems and presenting several solutions to address these challenges [8].

III. Health & Safety

In modern societies, safety rules and disciplinary measures Should be implemented in workplaces, with the aim to reduce the number of accidents occurring. As manufacturing technologies advanced and factories enhanced their productivity through the use of human resources, standards were developed to outline the fundamental H&S regulations that businesses should adhere to, guide employer obligations and report methods [21]. Within warehouses, the OHS officer's responsibilities include risk assessment and signal placement, providing employees with information about hazards, ensuring that all personnel are equipped with PPE, mitigating the consequences of a possible accident, as well as preventing exposure to hazardous substances [22]. Although workers are subjected to rigorous standards and laws, they are still at risk of being injured due to unforeseen circumstances. Some of the most common warehouse safety hazards are as follows: (i) slips, trips, and falls, (ii) manual and mechanical handling, (iii) traffic safety (iv) work at height (v) racking and (vi) fire safety [9]. On the other hand, the fourth industrial revolution impacts on the H&S of the workers in terms of regulations, standards and hazards [4], [23]. In this field, researchers have begun to study new occupational H&S issues that may occur as a result of I4.0 adoption into manufacturing sector [5] while improvements in intelligent devices such as smart protective clothing [24] and smart PPEs alert workers about harmful circumstances; thus mitigating risks. However, although robots are used for safety alerts in other cases [25], we have not identified any robotic assistant, apt to navigate autonomously within a warehouse, so as to identify risks and dangerous events without human support.

IV. Robot-based vision-based modules

In this section, we present a detailed description of the vision-based recognition modules utilized in the proposed autonomous H&S robot.

A. Autonomous Navigation

Autonomous navigation is based on the exploration of the surroundings, the localization and the determination of paths by mobile robots and vehicles. Hence, navigation comprises three main operations, namely (i) localization (ii) path planning and (iii) map building interpretation. The existence of a vision system on vehicles contributes to their autonomous locomotion [26]. Even so, no comprehensive autonomous navigation system based solely on vision and suitable for dynamic indoor scenes has yet to be fully built [27]. The widespread use of AGV in the production environment necessitates the use of a reliable management system, which is still explored by many researchers and businesses. Modern warehouse automation systems provide greater flexibility and the capacity to comprehend and interact with the environment at a higher level [2]. The robotized systems can recognize places and entities, to classify them into semantic regions, resulting in the creation of semantic metric (2D or 3D) maps [28]. In particular, current techniques for tackling the aforementioned challenges have been implemented in both indoor and outdoor environments, achieving a robust semantic mapping. The autonomous navigation process is improved through them [29], [30]. Furthermore, the AGV and Warehouse Management Systems (WMS) are integrated, enabling information synchronization and speedy skill deployment across the supply chain [2]. Hence, we claim in this conceptual research that semantic maps of smart warehouses can be useful in WMS. Finally, the AGV visual-based navigation requires an efficient recognition inventory,

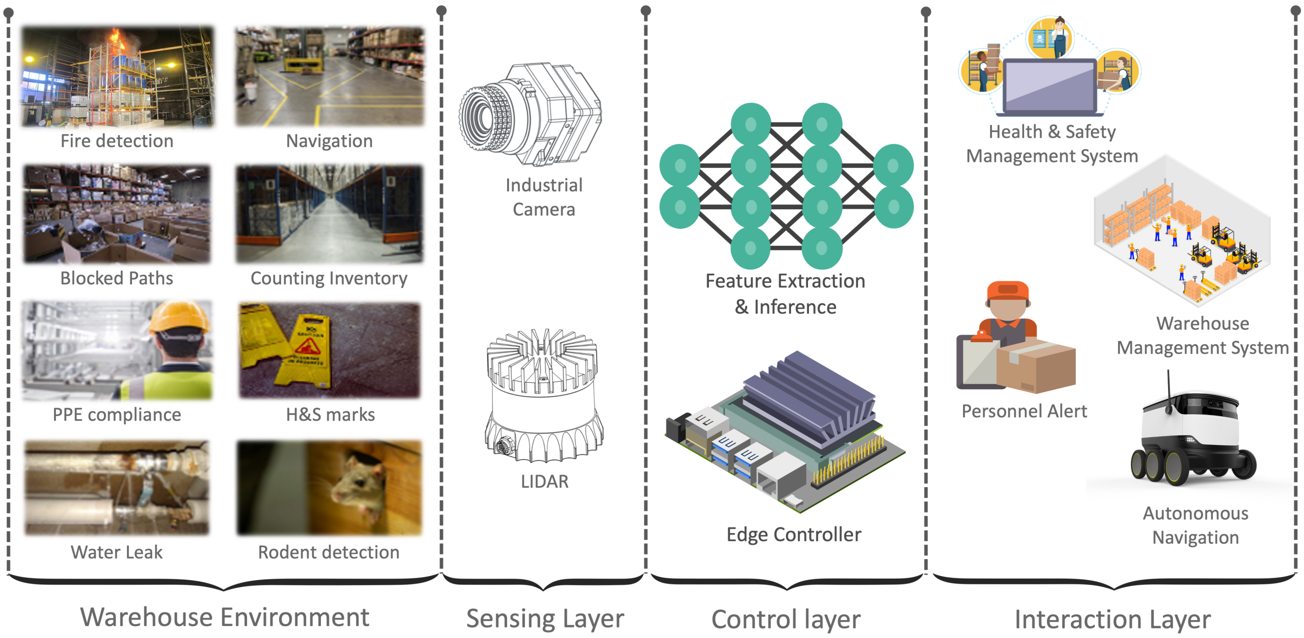

Fig. 1: Flowchart of the autonomous health & safety inspection robot

warehouse shelves/racks, line marking in the warehouse to achieve a safe and robust motion.

B. Fire Detection

Early image fire detection has lately played a critical part in decreasing fire losses by notifying people. Using convolutional neural networks (CNNs) and image fire detection techniques, researchers have recently merged their efforts to obtain exceptional performance in visual search. Light CNN architectures have been proposed for fire detection [11]. This model is fine-tuned to balance the efficiency and accuracy considering the nature of the target situation and fire data. In addition, spatiotemporal CNN has been proposed for smoke detection and real-time detection [31]. Finally, a comparative study about the proposed algorithm's accuracy of fire detection based on object detection showed that CNN-based fire detection techniques are more precise than other algorithms [32].

C. Blocked Paths

Object recognition and detection are very important challenges for contemporary robotic vision science, especially with the rapid development of deep learning techniques. A very important application of modern methods is the detection and tracking of warehouse inventories, to achieve counting them or robot navigation within it. A well-known deep architecture is You Only Look Once (YOLO), which was used to detect people, objects and other visual entities with impressive results [33]. Also, by replacing the standard area proposal step with a cohesive neural network dubbed the Area Proposal Network, Faster R-CNN [34] enhanced the detection speed of Fast R-CNN. An extension of the above architecture is presented in [35], where some additional provisions are adapted for the classification per pixel. Mask R-CNN has been applied in accurate autonomous driving applications on urban roads, exhibiting high performance [13]. Similarly, in a more cohesive indoor environment (such as a warehouse) the above techniques could be adopted to recognize different entities and create an efficient path planning by avoiding obstacles.

D. PPE identification

The proper use of PPE as defined in safety regulations limits the risk of accidents and dangers when performing operations. Vision-based technology is a common way to identify PPEs in workers, as the so-far proposed systems recognize their identity and map the required equipment based on their activities. The researcher developed a classifier based on fully YOLOv3 network to identify the regular PPEs (hardhat, shirt, glove, belt, pant, shoe) in construction workers. The finetune is based on a pre-trained model on Imagenet for PPE, while the Facenet developed by Google is utilised to recognise the identity of the workers [6]. In another study, YOLOv4 and YOLOv4-Tiny were used to train similar classifiers to tackle the PPE identification challenge [36]. Experiments proved that the YOLOv4-Tiny is better suited for integration into a smart system than the YOLOv4, ensuring low latency in the object detection tasks.

E. Inventory counting

Warehouse inventory counting constitutes one of the most important tasks in warehouse management by achieving increased functionality, maintainability and efficiency. The main purpose of the warehouse inventory is to ensure the accuracy of the stock quantity by accurately measuring the quantity of goods, to provide accurate information for various decisions. The existence of a dynamic repository containing the stored products contributes to monitoring the quantity of available stocks. Autonomous and reliable inventory recording based on machine learning methods can improve the WMS. Hence, drones have been proposed recently for inventory counting [14]. In particular, camera module is mounted on a drone scan quick response (QR) codes. Also, they can provide solutions in a WMS automatization by the semantic segmentation of the entire scene through CNN and then the measurement of the entities' quantities (number) per category through a simpleminded machine-learning algorithm [37].

F. Health & Safety marks identification

Integrating visual information throughout the visual field of the workers is necessary for maintaining situational awareness when walking, working or driving. Within the industrial environment, H&S signs and marks are frequently employed in industrial settings to provide warnings about hazards and safety information. To the best of our knowledge, no vision-based inference models have been built to identify them, but Chou et al. [38] proposed new processing algorithms for detecting and recognising gesture images. Removing the elbow and forearm from collected images spins an askew gesture to the proper position during the detection phase, the methodology may be used for H&S signs identification.

G. Water leak identification

Standard features that are relatively invariant to light, camera angle or the backdrop scene are included in flood detection methodologies. Based on that, a pre-processing pipeline (water edge detection, picture inpainting, and contrast correction) is used before training a Region-Based CNN, to improve inference efficiency [39]. It is necessary to register these pictures using the Scale Invariant Flow Algorithm (SIFT), observing the water recedes and defining the flooded region. In another study [12] an image classification and flood area segmentation method is developed to accomplish this objective. A pre-trained deep neural architecture, viz. VGG-16, and a combination of local binary patterns and histograms of oriented gradients were utilized as features. The extracted features were trained in different classifiers (logistic regression, k-nearest neighbours, and decision tree classifiers), suggesting that logistic regression with VGG-16 achieves better performance, while Fully CNN offers the highest segmentation metrics in contrast with superpixel-based methods.

H. Rodents identification

In locations where non-target species are prevalent and trap detection rates for target species are poor, remote sensing cameras are an effective and efficient alternative to live trapping approaches in the study of [40]. A practical framework for evaluating the correlates of invasive rodent activity with low impact on target and non-target species is provided by the capacity to create relative activity levels with high certainty rapidly.

V. Action-based Modules

Detailed descriptions of the action-based modules, that are enabled by the aforementioned vision-based modules are listed in this section.

A. Autonomous locomotion

Initially, in the proposed system, an RGB or RGB-D camera rig is mounted on the autonomous vehicles, that move in the warehouse. Based on visual sensors, AGVs map the area recognizing objects and lines marking through semantic mapping algorithms. Even 3D modeling of areas and inventories is their vital task to achieve our proposed concept, the collaboration with multiple cloud-based AGVs creates a flexible production and handling system in smart factories using private 5G communication technology. Also, the collaboration provides the autonomous movement of the AGV based on the fusion of inertial measurement units and image data from unmarked scenes, as successfully piloted in the manufacturing base's production line [2].

B. Evacuation instruction

During the detection of a fire by the proposed autonomous robot, the location of the fire and the surrounding context may be used to tailor optimized instructions to warehouse workers, thereby increasing the evacuation efficiency. Especially, the generated instructions include a proposed evacuation path that takes into account the alternative route that will be analyzed in Subsec. V-C as well as a safe destination that was determined using optimization methods [41]. Moreover, the proposed robot can bear the right aparatus to facilitate evacuation [25].

C. Alternative paths

As previously stated, visual sensors and a lidar are essential components of the proposed system. The robotic agent's safe mobility will be aided by the integration of entity recognition algorithms and the export of stock size. In certain circumstances, boxes are stored in the warehouse (rather than on designated shelves) while being transported, making access difficult. Furthermore, an unlucky incidence of merchandise falling off the shelves would cause complications in the robot and human mobility space. Our suggested system, on the other hand, will be able to recognize goods and their sizes, avoiding them during robot navigation.

D. Worker's alert

Warehouse workers are exposed to hazards, putting them at risk for a variety of occupational diseases and injuries among others. In order to minimize exposure to the aforementioned situations, our proposed robot is capable to identify the proper use of PPE by warehouse workers. In case of wearing fault PPEs, an alarm will be generated to inform the warehouse worker or H&S officer about the incident. This module increases the integration capabilities of the proposed robot enabling interaction with other I4.0-ready smart H&S systems, which is a critical requirement to enable the vertical integration within the Warehouse 4.0 [42].

E. Inventory management

Due to the rapid development of AI, the traditional inventory counting methods are gradually being replaced by modern ones. In particular, changing the way inventories are recorded, through the evolution of machine learning methods in modern logistics, improves industrial efficiency, reduces costs and promotes long-term business development. Thus the proposed system is possible to contribute to the recording of stocks. The inventories' counting will be achieved through the development and implementation of methods for object recognition from visual data. Furthermore, the proposed automated method of counting eliminates potential human errors, and the process is completed in a relatively short time.

F. Maintenance alerts

The continuous maintenance of the warehouse infrastructure is a critical requirement for the ongoing operations that ensure the effective control of the work processes. Thus the proposed robot uses the vision-based modules, described in Sec. IV, to identify the critical events (fire, fluid, rodents and missing H&S signs) and enable alerts for the maintenance staff. For example, the occurrence of water leaks will generate an warning, informing the hydraulics engineer about the exact location of the event. Similar instructions will be generated in case of rodent identification or missing H&S signs within the warehouse. The integration with the WMS will provide a centralised repository of required actions, where managers can prioritise them based on the available staff and criticality of the events.

VI. Autonomous Health & Safety inspection robot conceptual architecture

In this section, the architecture of the autonomous H&S inspection robot is analysed and presented in Fig. 1. The proposed system uses vision-based data to understand the environment, machine vision techniques to extract features and machine- or deep-learning approaches to inference, guiding the vehicles and generating alarms for the stakeholders.

A. Physical environment

Various events and actions take place in warehouses, impacting on the overall efficiency of the warehouse operations. The warehouse's physical environment includes machines, handling equipment, racks and personnel resources, while events such as fire, flood and blocked paths among others are occurred. As the majority of these events can be captured using vision-based sensors or sensing techniques, the proposed robot utilises only machine vision technology.

B. Perception layer

Vision-based sensors are used to capture information about the surrounding environment of the warehouse. The proposed robot uses an industrial camera (RGB or RGB-D) with a large field of view intending to create a warehouse's semantic map and to recognize some bulky entities-inventories. Apart from that, three-dimensional dynamic real-time imaging is accomplished through the use of a 3D lidar sensor, which restores the shape and size of warehouse objects, feeding the control layer for autonomous navigation.

C. Control layer

This layer is the most critical component of the proposed autonomous H&S inspection robot. The control layer is responsible for the decision-making mechanism that inference the collected image frames and generates alerts or messages for other management systems. Especially, the mechanism identifies events such as fire, water leaks, rodents and PPEs while H&S signs, blocked paths and warehouse capacity through CNN-based modules are captured. Besides that, the navigation control application of the proposed robot is managed by this layer combining lidar-based data with SLAM methodology for map construction and path planning.

D. Interaction layer

All services and interactions with other systems are included in this layer. Incidents such as missing H&S marks, water leaks, rodents' existence that are correlated with the compliance of the health regulation and the maintenance of the warehouse are mainly reported to the corresponding management system. Another integration can be achieved with smart workers' devices and inform them about non-proper use of PPEs or unauthorised access. Furthermore, the existence and location of the fire shall be reported to enable and program evacuation instructions. Moreover, the robot bears a beacon and provides recorded voice instructions to attract the evacuees through a safe path towards the exit of the warehouse. Finally, in addition to the generation of control navigation signals for the mobile platform's movement, the recording of stocks can be obtained and reported to the warehouse management system.

VII. Conclusion & Future Direction

The goal of this paper is to propose an autonomous health & safety inspection robot capable of identifying risks within warehouses, in accordance to Warehouse 4.0 principals. The research concludes the required modules to meet the H&S requirements, while the machine vision technology enhanced with artificial intelligence is capable of recognizing events without human interaction. While the majority of the events (fire, flood, blocked paths and PPE detection) and functions (navigation, inventory counting) have been investigated in previous years and described in Section IV, there is a research gap in health & safety signs and rodents vision-based identification methodologies. Through the robot, the vision-based modules are linked with the action-based modules that a) inform warehouse workers about incidents such as the lack of PPE, evacuation instructions, fire or flood occurrence, b) update the inventory management system about the stored quantities, c) notify the warehouse maintenance manager to conform events such as insecticide, pipe fixing or H&S marks replacement, as well as d) robot's autonomous guidance. Future work will focus on developing of machine vision system capable of recognizing the bulk of the aforementioned occurrences, while the technical design of the autonomous robot will be explored.

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