22nd International Conference on Modelling and Applied Simulation
20th International Multidisciplinary Modeling & Simulation Multiconference

2724-0037 © 2023 The Authors.
doi: 10.46354/i3m.2023.mas.020

Autonomous System Digital Twin to test Machine Vision

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Abstract

Autonomous systems are playing crucial role in numerous industrial processes. However, while autonomous systems could offer numerous benefits in productivity and efficiency, their interaction with human operators introduces unique challenges. Autonomous vehicles equipped with combinations of sensors have immense potential in industrial environments, yet the integration and optimization of sensors like LIDAR and video cameras with machine vision pose complex challenges. This article highlights the role of simulation in development and testing of the sensor combination for autonomous vehicles to navigate safely in industrial settings, characterized by high levels of dust and noise as well as by presence of human operators.

Simulation emerges as a pivotal tool to replicate realistic environments, enabling comprehensive testing of the sensor combination's performance under diverse and challenging scenarios. Sensor fusion, a critical aspect of obstacle detection, receives validation and fine-tuning through repeatable simulations, enhancing the overall system efficiency.

By harnessing simulation's capabilities, developers could iteratively optimize sensor combinations, supporting the advancement of autonomous vehicles in industrial environments. The article describes a holistic approach that combines testing in synthetic environment with real-world validation, proposing the way for safer, more efficient, and reliable autonomous systems.

Keywords: Modeling and Simulation, Autonomous Systems, Machine Vision, Obstacle Detection, Image Recognition

1. Introduction

The utilization of autonomous vehicles has transformed industries, ushering in a new era of advanced automation and improved efficiency (Elbasheer, 2023; Braglia et al., 2019). As cutting-edge technologies continue to evolve, industries are increasingly embracing the potential of autonomous vehicles to revolutionize their operations. These vehicles, equipped with sophisticated sensor combinations and always improving artificial intelligence, are reshaping the industrial landscape, offering numerous applications and benefits.

From manufacturing plants and warehouses to mining operations and logistics centers, autonomous vehicles are finding their place as invaluable assets. Indeed, their ability to operate without human intervention, coupled with advanced perception and decision-making capabilities, allows them to navigate inside complex environments and execute tasks with high accuracy.

As industries focus on optimization of competitiveness by increasing efficiency and safety, the adoption of autonomous vehicles promises various advantages, such as to change workflows, improve resource allocation, and enhance overall productivity. At the same time, autonomous systems could be used to perform operations in dangerous environments, e.g. exposed to high temperature, toxic substances (Bruzzone et al., 2022b). However, the integration of autonomous vehicles in industrial environments also raises important questions about the human and machine collaboration, from point of view of both practical safety and of legal compliance. In order to address such a vast amount of constraints it is necessary that the whole development and engineering aim to create a high fidelity replica of a physical system, its digital twin (Longo et al., 2023; Bruzzone et al., 2022a).

Considering this, the authors focused their attention on the problem of work in environments, shared by human operators and autonomous systems, with particular attention to the safety aspects.

2. Object Detection

The starting point in solving of the problem of safe collaboration of humans and autonomous systems is ensuring awareness of presence, or else, that autonomous system is capable to recognize human operators and other fixed and moving obstacles and to react properly, and vice versa, that behavior of such systems is clear and predictable for the humans (Giovannetti et al., 2022).

There are several principal techniques for obstacle detection in autonomous vehicles, which are mainly based on LIDARs (Light Detection and Ranging), Radars (Radio Detection and Ranging), camera vision and ultrasonic proximity sensors. In particular, LIDAR uses laser beams to measure distances and create a map of its surroundings, which is typically 2D or 3D. It provides highly accurate and detailed data in form of cloud of points. LIDAR is reliable in various lighting conditions and is widely used in many autonomous vehicles. However, its main drawback is its high cost, which could limit its widespread adoption in some scenarios, especially related to industry in emerging economies.

Radar uses radio waves to detect obstacles and measure their distance and sometime speed and is effective in various weather conditions; at the same time, it could provide also long-range sensing capabilities. Radar is relatively cheaper than LIDAR, making it a popular choice in some autonomous vehicle systems. However, it offers lower spatial resolution compared to LIDAR, which might affect its ability to resolve small or closely spaced obstacles.

Video cameras are a cost-effective solution for obstacle detection; they capture images and could be used in combination with computer vision algorithms to identify and track objects in the environment. In some cases, it is possible to employ also a more expensive cameras with depth perception, to further improve variety of the data. While normal cameras are cheaper compared to LIDAR and radar, their performance could be affected by adverse weather conditions, low-light environments, and visual obstructions.

Finally, ultrasonic sensors use sound waves to detect objects and measure distances. They are commonly used for short-range obstacle detection, such as parking assistance in consumer vehicles. Ultrasonic sensors are relatively low-cost but have limitations in their range and accuracy compared to other sensing technologies. At the same time, this kind of sensors could be used in cases when an obstacle is out of field of view of other sensors, which is especially useful for collision avoidance.

In order to address limitation of any particular type of sensors, a sensor fusion could be used. Sensor fusion involves combining data from multiple sensors, such as LIDAR, radar, and cameras, to improve the overall perception of the surroundings. By integrating data from different sources, autonomous vehicles could leverage the strengths of each sensor while compensating for their individual weaknesses. Indeed, often the sensor fusion is essential to guarantee obstacle detection accuracy and reliability.

In overall, the choice of obstacle detection technique depends on the specific requirements and use cases of the autonomous vehicle. While LIDAR provides high accuracy, it comes at a higher cost. Radar and camera-based systems offer a balance between efficiency and cost, and ultrasonic sensors are the most budget-friendly option but have limited capabilities. As technology advances, the landscape of autonomous vehicle sensing is likely to evolve, potentially introducing new, more efficient, and cost-effective solutions.

3. Modeling and Simulation

Simulation offers numerous advantages, enabling efficient, cost-effective, and safe evaluation of the autonomous vehicle, including its sensor and control systems (Bruzzone et al., 2021b; Mazal et al., 2019). Indeed, simulation could be used to create virtual environments that replicate real-world scenarios, including various environmental conditions and layouts of workspace. This allows to test the sensor combination's performance in diverse and challenging situations, such as in presence of multiple movable obstacles and poor visibility conditions, all without putting physical systems and personnel at risk. Indeed, simulation could facilitate sensor fusion testing, where data from LIDAR, video cameras, and other sensors are combined to create a comprehensive perception of the environment, to fine-tune the sensor fusion algorithms to optimize obstacle detection and classification. At the same time, simulation enables the repetition of specific scenarios with precise control over variables, which is essential not only for debugging but to assess the performance of the sensor combination under various conditions; it allows developers to efficiently isolate and address issues. Similarly, simulation could be used to create edge cases and uncommon scenarios, such as emergencies, that might be improbable to encounter in real-world testing, hence, to improve efficiency of handling of such situations. At the same time, simulation provides a more cost-effective way to conduct extensive testing and experimentation with different sensor configurations without incurring the costs associated with physical testing, while allow for rapid iteration and quick testing of design changes. Last but not least, testing in simulated environments eliminates the risk of potential accidents during the development phase.

4. Proposed Sensor Configuration

In the proposed case study, the authors are particularly interested in the framework of heavy industry, such as steel and chemical plants. Considering the operation in an industrial plant with possible presence of high temperature, dust, as well as presence of human operators, the most efficient combination of sensors for obstacle detection in autonomous vehicles must be identified. Indeed, the combination should be robust, reliable, and capable of operating effectively in challenging and changing environmental conditions while ensuring the safety of human operators and of the autonomous system itself. Considering this, the authors choose combination of LIDAR and video cameras as the primary source of information, while ultrasonic sensors are used for the purpose of emergency stop in case of very close obstacle. By combining these sensors and fusing provided data, the autonomous vehicle could have a sufficiently complete perception of its environment, making it capable of detecting and avoiding obstacles, including human operators, in various industrial plant settings. The redundancy in sensor data ensures that even if one sensor fails, temporary or permanently, other sensors could still contribute to guarantee its safe operation. The integration of AI-based algorithms further enhances the vehicle's ability to make intelligent decisions, ensuring safe and efficient navigation in complex industrial environments (Cepolina et al., 2021).

In particular, combining LIDAR with video cameras equipped with object recognition and classification capabilities could provide several significant advantages by providing complementary data sources for obstacle detection (Derrouz et al., 2022). Indeed, LIDAR excels in accurately measuring distances and generating a 2D map of the obstacles, while cameras offer rich visual information about objects and humans; integrating these data streams by sensor fusion algorithms ensures accurate and robust obstacle detection, even in challenging conditions. Indeed, object recognition capabilities could identify and classify human workers, distinguishing them from other obstacles or other moving assets, which is crucial for ensuring the safety of human operators.

The system could implement specific safety protocols when approaching human workers, such as slowing down or stopping the vehicle to avoid collisions and potential accidents.

In industrial environments, the performance of individual sensors may vary based on boundary conditions, however, by fusing LIDAR and camera data together, the system could mitigate the impact of environmental factors. For example, if dust obscures the LIDAR's laser beams, the cameras could still provide visual input for object detection and classification; at the same time, cameras with depth perception also provide information regarding distance to obstacles. Overall, the combination of LIDAR with video cameras featuring object recognition and classification capabilities provides a powerful solution for obstacle detection and navigation in industrial plants.

Apart from detecting and recognizing objects, another important aspect is detection of their bounding boxes to further improve the situational awareness. Indeed, this information helps the autonomous vehicle understand the spatial position of obstacles, making it easier to plan safe navigation paths and execute appropriate avoidance maneuvers, especially in cases when distance measurement could be less reliable, e.g. due to presence of dust or strong irradiation. Hence, this approach allows the system to take extra caution and implement specific safety protocols when approaching humans. Finally, bounding box data could be used for improvement of the system itself as well as for resolution of possible accidents (Bruzzone et al., 2018). Indeed, the data helps in understanding the vehicle's interactions with various obstacles and could be used to enhance the system's performance through machine learning and continuous improvement.

Another aspect related to choice of sensors is related to the strategy of their usage. For example, it could be possible to address same problem of navigation by using expensive and reliable set of sensors with long expected work life, otherwise it is possible to install cheaper devices and replace them when broke. In the last case, technological advances make second approach more and more attractive, as employing advanced algorithms based on AI often allows to achieve good results even with relatively simple set of equipment.

5. Test Scenario

Considering characteristics and configurations of typical industrial plants, it is proposed a test scenario in which an autonomous system encounters a human operator on its path, while avoidance maneuvers could be dangerous or difficult to conduct. The action plan should involve a series of steps to avoid potential collisions while ensuring a safe and responsible response, at the same time, to guarantee that assigned tasks are completed. In this case, first of all, the sensors in the autonomous vehicle, should detect and recognize the presence of the human operator and other fixed obstacles in its path and near to it. Hence, object recognition algorithms should classify the human as a distinct entity to distinguish it from other obstacles. At the next step, the vehicle's control system should evaluate the potential outcomes of different actions, considering the current trajectory and speed of the vehicle, positions of the human operator and of the fixed obstacles; it should evaluate risks by identifying potential collision points and assess the severity of the consequences. Obviously, the autonomous vehicle must absolutely prioritize avoiding any collision and even physical contact with the human operator over collision with fixed obstacles. The AI system must decide on the safest and most responsible course of action to prevent harm to the human worker and reduce the risk of damage to the vehicle and fixed obstacles. Depending on the vehicle's speed and distance from the human operator and fixed obstacles, it may perform a safe emergency stop if there is enough distance to stop without causing harm. If stopping is not possible, the vehicle should perform an evasive maneuver to avoid the human operator while considering the fixed obstacles; however, in the proposed scenario it is decided that the maximum speed is limited in order to minimize probability of collision as well as to keep severity of possible consequences as low as possible. Once the risk of collision with personnel is mitigated, the system have to identify course of actions, required to proceed with the assigned task, including finding alternative ways to achieve desired result (Cepolina et al., 2022; Mazal et al., 2019; Stobola et al., 2014). In case if alternative route is classified as unsafe, the vehicle should use appropriate communication methods to signal its intent to the human operator, that could include visual indicators, audible signals, or even external displays conveying messages. At the same time, the vehicle's sensors should continuously monitor the human operator's actions and reactions to the vehicle's signals; if the human operator responds by moving out of the vehicle's path, the vehicle could proceed safely. In any case, the control system should continuously reevaluate the situation and adjust its actions based. If the human operator's movements become unpredictable or if new obstacles appear, the vehicle need to be capable to response accordingly.

In order to guarantee system improvement, the vehicle should log all relevant data related to the encounter for later analysis. Additionally, this data could be used in case of accidents and relative investigations.

In an industrial environment, it is crucial to employ effective and robust technologies to notify human operators about the presence and intentions of autonomous vehicles, which is essential to achieve the goal to enhance safety in shared workspaces. Using visual signals on the autonomous vehicle could be effective in notifying human operators. Indeed, lights and strobes, LED panels and display screens could indicate the vehicle's status and intentions. Despite high noise levels in some industrial settings, well-designed audible signals could still be effective, as the vehicle could emit distinct sounds for various actions; the frequency and intensity of the signals should be carefully chosen to be audible despite background noise. In some cases, it could be possible to communicate directly with wearable safety equipment of the plant operators (Bruzzone et al., 2021a).

6. Results

To assess the efficacy of the proposed approach, the authors engineered a synthetic 3D environment coupled with an external intelligent control system. To enhance simulation accuracy, the 3D virtual representation of the autonomous vehicle was created using 3D models of the prototype vehicle and of its systems and sub-systems, in a way to resemble the physical prototype from the perspective of graphical representation and of its interactions with the control system. Both the physical and virtual implementations provide the control system with an identical structure and amount of data, including information from LIDAR and other sensor as well as video feeds. Consequently, various combinations of sensors were efficiently evaluated during the initial stages of development of the physical prototype, hence, allowing the creation of effective obstacle detection and avoidance algorithms.

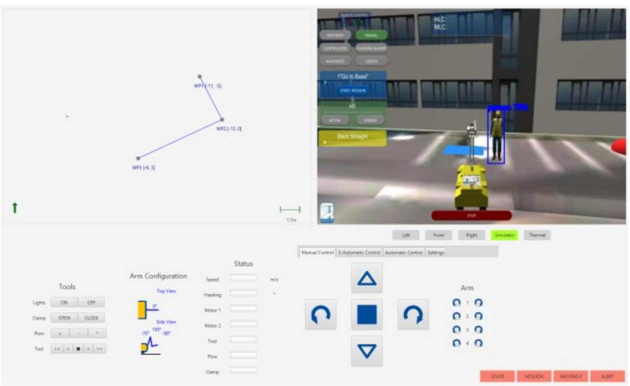

Figure 1. View from the control system

On the figure 1, it is shown a view from the control system. In this case, it is connected to the synthetic simulated environment, which provides the system with the sensor data, including information from sensors and video cameras. Indeed, it is shown successful automatic object detection and recognition done by the control system. In this particular case, a 3D model of a worker is successfully detected and recognized, including its bounding box.

Experimentation with both physical and virtual systems revealed that 3D environment provided sufficiently realistic picture for the image recognition system, with both physical and virtual persons being successfully detected.

For object detection, several algorithms with pre-trained Convolutional Neural Networks (CNN) were evaluated, such as SSD (Single-Shot Detector) and YOLO (You Only Look Once) (Diwan et al., 2023; Phadtare et al., 2021). Vice versa, there were employed different training datasets with mages and bounding boxes, such as VOC (Visual Object Classes) and COCO (Common Objects in Context), as presented in the following table

Table 1. Evaluated algorithms.

Algorithm	CNN	Training Dataset	Layers
SSD	Resnet50	VOC	50
SSD	VGG16	COCO	16
SSD	VGG16	VOC	16
YOLO	Mobilenet1.0	VOC	28
YOLO	Darknet53	VOC	53
YOLO	Darknet53	COCO	53

Hence, video feed from the 3D environment (or from the cameras on the physical system) is sent to the control system, which performs analysis, classifies objects, and identifies their bounding boxes; consequently, this information is used for vehicle control purposes.

During the experimentation, it was found that both VGG-based solutions were not capable to recognize virtual human operators as persons. Indeed, SSD-VGG16 network trained on VOC dataset had very high number of false positive detections when applied to the video from the synthetic environment, while that one trained on COCO dataset had lower number of false positive detection, but the number of true positives was insufficient as well. Quantitatively, both networks failed to detect virtual persons with higher than 50% probability, regardless angle and distance to the object. In addition, YOLO algorithm with Mobilenet1.0 CNN was capable to detect virtual persons with moderate probability (approximately 50%) but was subjected to significant false positives. In general, it is possible to notice that preliminary suitability could be evaluated based on size of the networks, where bigger means more precise. Considering this, only SSD-Resnet50-VOC, YOLO-Darknet53-VOC and YOLO-Darknet53-COCO solutions were subjected to further experimentation.

For testing purposes, a virtual autonomous system is configured to follow a path, while 3 virtual operators stay in its proximity; during most of the movement all persons are visible to the camera, while during the final turn those are only partially visible. In this setup, the chosen algorithms performed as following.

Table 2. Results.

Algorithm	Detection duration, relative	Success Rate, %
SSD-Resnet50-VOC	46	67
YOLO-Darknet53-VOC	85	67
YOLO-Darknet53-COCO	100	70

It is possible to notice, that SSD algorithm performed much faster, employing approximately half of time used by the YOLO algorithm. At the same time, success rate in correct detection of persons was almost the same; during some parts of the path not all persons were visible, so the 100% success rate would be impossible to achieve by analyzing video from the forward-looking camera only. However, during the tests SSD algorithm demonstrated low-frequency presence of false positive identifications of other objects, probably caused by quality of textures of the synthetic environment.

It is important to note, that various versions of same algorithms could perform with significantly different efficiency and the speed and success rate could be significantly different. Another factor of uncertainty is related to the fact of utilization of a virtual environment for video, as the training datasets, e.g. VOC and COCO contain images of real-life persons and assets. Considering this, it is evident that in different case studies the results could differ significantly, from these ones.

While the system is capable to correctly identify virtual human operators in range of several meters, which is sufficient for the target system, it had several limitations. In particular, the pre-trained network demonstrated insufficient performance on mid-range development computer, as it was capable to analyze up to 4 frames per second; considering that the autonomous vehicle is equipped with 4 cameras, the overall performance of the pre-trained network is insufficient. While for the purposes of this study the speed and accuracy were sufficient, additional work is required in order to boost the overall performance.

7. Conclusions

Increasing use of autonomous systems in industry leads to situations when human operators should work in their proximity, which poses safety risks. One of possible solutions to this problem is the equipping of autonomous vehicles with various sensors and their combinations, capable to recognize human operators and other obstacles as well as to identify best course of actions.

Simulation emerges as a very important tool for creation of new generation of autonomous systems to operate in industrial plants, allowing testing and optimization of the control system before real-world deployment. It allows to assess performance in different boundary conditions, boost sensor fusion, detect anomalies and handle edge cases.

By carefully addressing safety concerns and using best practices, the combined work of autonomous systems and human personnel in industrial plants could unlock new possibilities for productivity and efficiency. Indeed, the right balance between automation and human supervision could lead to scenarios where autonomous vehicles and human operators collaborate, improving industries while ensuring a safer and more productive working environment.

References

Braglia, M., Frosolini, M., Gabbrielli, R., & Marrazzini, L. (2019). Process Engineering and Optimization. Operations, Logistics and Supply Chain Management, 399-415.

Bruzzone A.G., Sinelshchikov K., Giovannetti A. & Pernas J. (2022a). Digital twins for developing innovative industrial autonomous system. In proceedings of the 21st International Conference on Modelling and Applied Simulation (MAS 2022).

Bruzzone, A. G., Vairo, T., Cepolina, E. M., Massei, M., De Paoli, A., Ferrari, R., Giovannetti, A. & Pedemonte, M. (2022b). Cooperative Use of Autonomous Systems to Monitor Toxic Industrial Materials and Face Accidents & Contamination Crises. In International Conference on Modelling and Simulation for Autonomous Systems (pp. 231-242). Cham: Springer International Publishing.

Bruzzone A., Sinelshikov K., Massei M., Giovannetti A., Tarone F., Longo F., Fancello G., Giliberti C., Mariconte R., Diano M., Gotelli M. & Fabbrini G. (2021a). Reducing Dangers within Industrial Plants by Extended Reality. In proceedings of the 33rd European Modeling & Simulation Symposium (EMSS 2021), pp. 413-417.

Bruzzone A., Sinelshchikov K., Cepolina E.M., Giovannetti A. & Pernas J. (2021b). Autonomous Systems for Industrial Plants and Iron & Steel Facilities. In proceedings of the 33rd European Modeling & Simulation Symposium (EMSS 2021).

Bruzzone, A. G., Massei, M. & Di Matteo, R. (2018). Modeling, interoperable Simulation and Serious Games (MS2G) for healthcare and first responders in disasters within industrial plants. In Proceedings of the 50th Computer Simulation Conference (pp. 1-11).

Cepolina E., Venkata A.M. & Zoppi M. (2022).The use of autonomous coupling capable trailer to reduce the cost per delivery and increase profit for logistic companies: a simulative analysis. In proceedings of the 24th International Conference on Harbor, Maritime and Multimodal Logistic Modeling & Simulation (HMS 2022).

Cepolina, E. M., Cepolina, F. & Ferla, G. (2021). On line shopping and logistics: a fast dynamic vehicle routing algorithm for dealing with information evolution. In Proceedings of the International Conference on Harbor, Maritime and Multimodal Logistic Modeling & Simulation (HMS 2021) (pp. 27-36).

Derrouz, H., Cabri, A., Ait Abdelali, H., Oulad Haj Thami, R., Bourzeix, F., Rovetta, S. & Masulli, F. (2022). End-to-end quantum-inspired method for vehicle classification based on video stream. Neural Computing and Applications, 34(7), 5561-5576.

Diwan, T., Anirudh, G. & Tembhurne, J. V. (2023). Object detection using YOLO: Challenges, architectural successors, datasets and applications. multimedia Tools and Applications, 82(6), 9243-9275.

Elbasheer, M., Longo, F., Mirabelli, G., Nicoletti, L., Padovano, A. & Solina, V. (2023). Shaping the role of the digital twins for human robot dyad: Connotations, scenarios, and future perspectives. IET Collaborative Intelligent Manufacturing, 5(1), e12066.

Giovannetti A., Mashayekhizadeh M., Cefaliello D., Shamlu F. & Taib H. (2022). UGV Digital Twin for garbage detection through AI. In proceedings of the 10th International Workshop on Simulation for Energy, Sustainable Development & Environment (SESDE 2022).

Longo, F., Padovano, A., De Felice, F., Petrillo, A. & Elbasheer, M. (2023). From “prepare for the unknown” to “train for what's coming”: A digital twin-driven and cognitive training approach for the workforce of the future in smart factories. Journal of Industrial Information Integration, 32, 100437.

Mazal, J., Bruzzone, A., Turi, M., Biagini, M., Corona, F. & Jones, J. (2019). NATO use of modelling and simulation to evolve autonomous systems. Complexity Challenges in Cyber Physical Systems: Using Modeling and Simulation (M&S) to Support Intelligence, Adaptation and Autonomy, 353.

Phadtare, M., Choudhari, V., Pedram, R. & Vartak, S. (2021). Comparison between YOLO and SSD mobile net for object detection in a surveillance drone. Int. J. Sci. Res. Eng. Man, 5, 1-5.

Stodola, P., Mazal, J. & Podhorec, M. (2014). Improving the Ant Colony Optimization Algorithm for the Multi-Depot Vehicle Routing Problem and Its Application. In Modelling and Simulation for Autonomous Systems: First International Workshop, MESAS 2014, Rome, Italy, May 5-6, 2014, Revised Selected Papers 1 (pp. 376-385). Springer International Publishing