

Evaluation of Vision Systems for Outdoor Protection of Humans and Domestic Animals

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According to the new Machinery Regulation (EU) 2023/1230, autonomous mobile machinery and related products must comply with specific safety requirements designed to prevent collisions or other risks due to their movement (travelling) or hazardous moving parts. In detail: “*it shall move and operate in an enclosed zone fitted with a peripheral protection system comprising guards or protective devices and/or (depending on the risk assessment) it shall be equipped with devices intended to detect any human, domestic animal or any other obstacle in its vicinity.*”

A promising approach to meet this requirement involves integrating advanced sensing technologies, such as vision systems, capable of detecting objects and living beings within the machine’s trajectory during autonomous motion. Camera-based systems, already widely used in indoor applications such as Automated Guided Vehicles (AGVs) in warehouses, are potential candidates for outdoor autonomous operations as well.

This paper explores the useful state of the art for the investigation of the performance of cameras, evaluating their usability, reliability and effectiveness in external working environments. Indeed, outdoor conditions introduce significant challenges, including varying weather, light exposure, and surface soiling, that can degrade the functionality and accuracy of these sensing devices. This study synthesizes key requirements from diverse standards regarding AI, industrial trucks, autonomous and road vehicles to establish a framework for the definition of a vision system evaluation methodology.

The overarching goal is to support the design of safer autonomous systems for working environments by exploring robust perception solutions suitable for real construction sites.

Keywords: Machinery Regulation, Safety of machinery, Vision systems, Autonomous motion, Artificial intelligence.

1. Introduction

The rapid expansion of autonomous and semi-autonomous mobile machinery in industrial and construction environments has led to the introduction of new regulatory concepts explicitly addressing increasing levels of autonomy. The EU Machinery Regulation 2023/1230 defines an

autonomous mobile machine as a “mobile machinery which has an autonomous mode, in which all the essential safety functions of the mobile machinery are ensured in its travel and working operations area without permanent interaction of an operator”. The Regulation significantly extends the traditional framework

for machinery safety in order to address the risks introduced by variable levels of autonomy, learning capabilities, and self-evolving behaviors. With specific reference to the travelling function, Annex III, clause 3.3.3 establishes that autonomous mobile machines “*shall comply with one or both where necessary according to the risk assessment, of the following conditions:*

- (i) *it shall move and operate in an enclosed zone fitted with a peripheral protection system comprising guards or protective devices;*
- (ii) *it shall be equipped with devices intended to detect any human, domestic animal or any other obstacle in its vicinity, where those obstacles could give rise to a risk to the health and safety of persons or domestic animals or to the safe operation of the machinery or related product.”*

The use of perception and detection sensors therefore emerges as a fundamental integration or alternative (depending on the risk assessment) to physical segregation. However, the Machinery Regulation only addresses this possibility as an Essential Health and Safety Requirement (EHSR): to allow for technological innovation, it remains technology-neutral and does not prescribe how detection systems should be designed, implemented, or validated. As a consequence, manufacturers and conformity assessment bodies may rely on harmonized standards (where available) or find support in other technical standards or state-of-the-art technical references to assess whether such systems can be used as safety components.

The main technical references for safety-related sensors (SRS) and safety-related sensors systems (SRSS) intended for the protection of persons are provided by the ISO/IEC 62998 series, which covers a wide range of sensing technologies, including lidar, radar, cameras, and ultrasonic sensors. In current industrial practice, detection-based protective functions are predominantly applied in indoor environments, where boundary conditions are controlled and well defined. Extending their use to outdoor, non-segregated environments significantly increases the complexity of the perception task, due to the presence of humans, animals, variable layouts, and strongly changing environmental conditions. This paper focuses on the use of computer vision (CV) systems, already widely adopted in

industrial trucks in indoor applications, as sensing devices for implementing safety functions in autonomous mobile machines operating outdoors. Since modern vision systems increasingly rely on AI-based perception algorithms, the problem cannot be addressed without also considering standards and methodologies related to artificial intelligence and learning-based systems.

The use of CV for a safety function raises a fundamental question: how can its performance, robustness, and suitability be assessed in a manner consistent with the new regulatory framework and with the state of the art in functional safety?

This work addresses the problem from a methodological and normative perspective. The main objective is to perform an overview and a structured analysis of the relevant standards and technical specifications in the fields of machinery automation, autonomous systems, and AI-based perception, in order to determine the key parameter and criteria for evaluate a system equipped with perception-based safety functions. Based on these requirements, the paper proposes the development and definition of a test methodology for camera-based detection systems specifically intended for autonomous mobile machines operating in construction environments. The approach is being developed within the MACHINE5.0 research project funded by INAIL, with the long-term objective of supporting the design and assessment of safe autonomous machinery that will be presented in chapter 3.

2. Normative and standardization framework

2.1 Contributions from Agricultural Machinery Domain

EN ISO 17757 (2019), which addresses autonomous and semi-autonomous earth-moving and mining machinery, explicitly identifies the perception system as a safety-related subsystem responsible for detecting, localizing, and classifying obstacles to provide the information required for safe machine control without operator intervention. The standard links a significant portion of operational risks to collision events and explicitly associates these hazards with perception failures, including incorrect estimation of the machine pose and misclassification of obstacles. Examples of misclassification causes explicitly mentioned include obscurants such as dust or rain blurring

object contours and inadequate training or validation of the classifier. While ISO 17757 does not define a structured test protocol for perception systems, Annex G requires documented validation activities and test results (e.g. pass, fail, defects, issues) without specifying a clear methodology.

A concrete and operational testing methodology is instead provided by ISO 18497-4 (2024) for agricultural autonomous machines and tractors, which directly address obstacle protective systems and perception-based safety functions. In particular, Annex C defines a standardized reference for the test object with prescribed geometry and surface characteristics, while Annex D specifies a reproducible dynamic test procedure. The machine is commanded to follow a predefined or previously learned straight trajectory at steady maximum speed toward the test object and shall stop before any contact occurs. For each case, shown in Fig. 1, the test shall be repeated at least seven times in order to quantify the dispersion of the stopping position with respect to the theoretical trajectory.

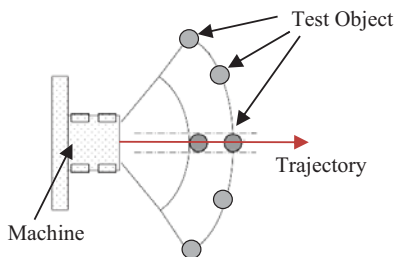


Fig. 1. Test obstacle positions near boundary in accordance with ISO 18497-4.

The stopping position is measured only after the machine has come to a complete standstill. Acceptance criteria are explicitly defined: the machine shall never contact the test obstacle for all the positions analyzed; also the machine should stop and reconfigure itself in safe state. For test object positions that are close to the machine trajectory but do not lead to a collision, even if the machine passes the object without stopping, the test outcome is considered acceptable. Furthermore, among the recommended verification methods, simulation and virtual testing under defined environmental and operational stresses are clearly included. Physical testing should also be executed in accordance

with environmental conditions, specified by ISO 15003 (2019) complemented by simulation, fault injection, and analytical methods such as FMEA and FTA.

2.2 Contributions from Road Vehicle and ADS Domain

The road-vehicle standards ISO 34502 (2022) and PD ISO/PAS 8800 (2024) provide a wide methodological framework for the application of camera-based perception systems, in light of the similar operating environments and associated risks and hazards. ISO 34502 formalizes the logic chain, perception–judgment–control, and introduces the concept of perception-related critical scenarios, i.e. situations in which the Automated Driving System (ADS) may fail to correctly perceive the environment due to intrinsic factors (e.g. sensor mounting tolerances, vehicle inclination, shielding or misalignment) or extrinsic factors (e.g. dirt, cloudiness, lighting, weather, or occlusions by surrounding objects). Moreover, Annex C structures these scenarios based on physical causes and sensor limitations and requires that tests combine multiple causal factors (e.g. snow, glare, and low contrast) in order to cover realistic worst-case conditions. The standard explicitly addresses blind-spot scenarios arising from road geometry and environmental occlusions, as illustrated in Fig. 2.

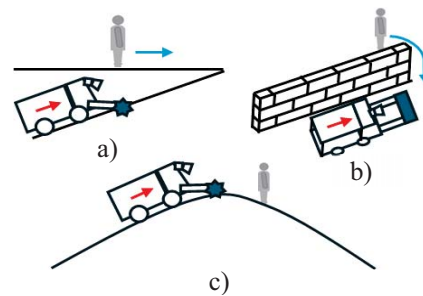


Fig. 2. Blind-spot examples in accordance with ISO 34502, Fig. C.25: a) parallel slope; b) vehicle behind a structure; c) vertical curve.

Such blind spots may be generated by vertical road profiles or height discontinuities along the same roadway, as well as by external obstacles such as walls or other infrastructural elements that partially or completely obstruct the sensor field of view. PD ISO/PAS 8800 further translates these

principles into a concrete verification strategy for AI-based perception systems, stating that verification shall rely on a combination of real testing, simulations, and statistical evaluation. The standard requires the explicit definition of the input space of the perception system (including distance, target speed, illumination, weather, and perturbations such as noise, blur, vibration, smear, blooming, and darkening) and the derivation of test scenarios that include both nominal and failure-prone conditions leading to false positives, false negatives, or unacceptable estimation errors. Verification and validation are discussed in clause 12.5. This is performed using defined test cases with ground truth, associated pass/fail criteria (test oracles), and quantitative performance targets, including coverage metrics and error-rate thresholds evaluated with statistical confidence. The standard explicitly mentions statistical testing, scenario replay, random and perturbation-based testing, metamorphic testing, and large-scale virtual testing as possible methods to achieve sufficient breadth and depth of coverage.

2.3 Contributions from Industrial Trucks

BS EN ISO 3691-4 (2023), which specifies safety requirements and verification methods for driverless industrial trucks and autonomous mobile robots, provides a fully operational reference framework for the validation of person-detection functions based on cameras or other Electro-Sensitive Protective Equipment (ESPE). The standard requires vehicles in automatic mode to be equipped with personnel detection systems covering the full vehicle and load width in the direction of travel and capable of stopping the machine before any contact with a stationary person occurs. The performance of the detection system is verified through standardized dynamic tests defined in Clause 5.2. Two reference test pieces are prescribed: a horizontal cylinder of 200 mm diameter and 600 mm length (Test A), and a vertical cylinder of 70 mm diameter and 400 mm length (Test B), both with controlled surface reflectance (2 % to 6 %) and optical density. The truck shall approach the test object at maximum speed and at least 110 % of the rated load, under worst-case conditions (e.g. slope, turning, forward and backward motion), and shall stop before contact. Test A shall be performed with the obstacle positioned left, center, and right in the

detection zone, while Test B shall be repeated three times at the center and at both edges of the detection field.

3. Case study: Construction Machine

The reference machine considered in this work is a compact tracked carrier originally designed for agricultural purposes but modified to perform operations in construction environments.

The machine is normally teleoperated via remote control, but during specific working phases it is intended to operate in autonomous mode by following a predefined path and task. In such state, the vision system shall be able to monitor the area ahead of the tool, as shown in Fig. 3, stopping the machine operations whenever a target enters the perimeter of the hazard zone along the machine path.

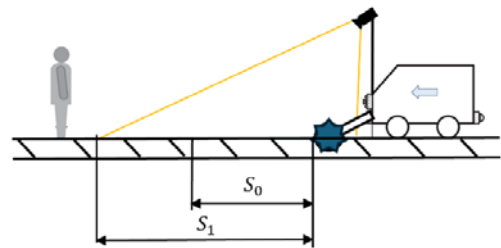


Fig. 3. Mounting position and sensing zone in accordance with IEC 62998-2:2020.

A pair of characteristic distances S_0 and S_1 or equivalent distances, defined by IEC 62998-2 (4.2.6 and 5.2.6) and illustrated in Fig. 3, can be used for hazard zone definition. S_0 represents the minimum stopping distance and S_1 the minimum distance required to allow the maximum machine speed. Given a maximum speed of 10 m/min, the case study does not require the monitoring of space S_1 operating with a speed reduction; alternatively, this space may be implemented only as a warning zone. The risks posed by a subject intentionally approaching the equipment laterally from outside the machine trajectory are not covered by this sensor. Furthermore, this paper only considers the risks associated with the travelling of the mobile machine and does not consider the risks associated with the moving parts of the machine involved in the process.

The intended application domain is the construction site, which represents a highly unstructured and dynamic outdoor environment.

Typical characteristics of this environment include:

- irregular terrain and varying ground conditions;
- presence of different construction companies, interference between work processes, presence of materials and temporary structures;
- strong variability of environmental conditions such as lighting, weather, dust and dirt;
- direct sunlight, shadows and high contrast scenes.

These conditions are representative of realistic outdoor scenarios, as also derived from earth-moving machinery (ISO 17757) and road vehicle (ISO 34502) and are known to be critical for camera-based perception systems.

4. Testing Methodology

This section provides an overview of camera-based vision systems and describes the proposed methodology for analysing their performance and robustness for perception-based safety functions in outdoor industrial applications.

4.1 Categories of Camera-Based Vision Systems

First, it is necessary to distinguish between two main categories of computer vision (CV) safety sensors applicable to machinery. The first category includes non-AI vision-based sensing systems, which rely on deterministic image processing and three-dimensional geometric reconstruction techniques, such as stereo vision, structured light, or time-of-flight (ToF) cameras. These systems, based on approaches including threshold segmentation, blob detection, edge extraction, or 3D geometry analysis, represent a promising solution for outdoor safety monitoring applications. In these systems, a safety-related monitoring zone can be configured through the sensor setup, and intrusion into this zone is detected. The critical performance parameters of such safety-related sensors are therefore the minimum detectable object size, the spatial resolution, the field of view, and the reliability of detection under varying environmental conditions.

The second category consists of AI-based vision systems, which use one or more cameras as primary sensors to acquire information inside the field of view and subsequently apply machine learning algorithms to perform object detection

and classification. In this case, the safety function does not rely solely on the revelation of an intrusion into the hazard zone, but also on the correct semantic interpretation of the scene, introducing additional failure modes related to misclassification.

4.2 Testing Concept

The testing method consists of two distinct phases applied to both types of CV sensors and explained in the following paragraphs. The common first step is the precise definition of the operational context and safety requirements to be addressed. This includes the identification of the protected zones, detection areas, blind spots and safety-critical targets but also the nominal camera latency declared by the producer.

In the second stage, tests are executed while outdoor environmental conditions are applied to the system in order to assess the degradation of detection performance in terms of increased response time, reduced detection range, or partial loss of coverage. Information on operating environmental conditions is provided in various standards, including EN 60654-1, ISO 15003 and the EN 60721 series, which provides a general and systematic classification framework that includes the ranges and severity levels defined in the above standards and is therefore adopted as the main reference. The guidelines and test procedures for verifying environmental conditions are defined in the IEC 60068 series and in the ISO 15003 standard. Table 1 provides a summary of the representative weather and environmental conditions that can affect sensor performance, highlighting the operational limits expected during real-world use. By progressively stressing the system under these conditions, the evaluation captures both the robustness and the reliability of the sensor in scenarios reflecting foreseeable environmental variations. Finally, according to PD ISO/IEC TR 5469 (2024), IEC TS 62998-1 and related documents, virtual testing represents a fundamental complement to real-world testing and is strongly recommended. Its primary role is to enable a level of scenario coverage that would be impractical to achieve through physical tests alone, by allowing the systematic exploration of a large number of operating conditions and corner cases. In addition, scenarios that would be dangerous, difficult, or prohibitively expensive to reproduce

in real-world conditions can be safely and efficiently evaluated through virtual test campaigns.

Table 1. Environmental influence according to EN 60721-3-5.

Condition	Range indoor	Range outdoor
Temperature	5/40 °C	-40°C/40°C
Temperature variation	Stationary	5 °C/min
Relative humidity	75%	95%
Rainfall	Absent	6 mm/min
Snow/Fog/Icing	Absent	Presence
Solar radiation	Absent	1120 W/m ²
Vibration and Shock	See Table 6 Class 5M1	See Table 6 Class 5M2
Sand	Absent	0,1 g/m ³ of air
Dust	1,0 mg/(m ² h)	3,0 mg/(m ² h)

In this context, simulation environments are fully controlled and allow the systematic recording and analysis of all metadata associated with each test case. Among the virtual test approaches of particular relevance are model-in-the-loop (MIL), software-in-the-loop (SIL), and hardware-in-the-loop (HIL) simulations.

Moreover, simulated trials make it possible to generate a sufficiently large and diverse set of test cases to systematically identify failure modes such as false positives, false negatives, and misclassifications, and to build reproducible datasets that enable statistically meaningful performance and confidence analyses. Fig. 4 illustrates the principle of the virtual testing approach. In a simulated environment, representative situations are defined and used to build a baseline set of scenarios, which can then be varied systematically to create a broad range of test conditions.

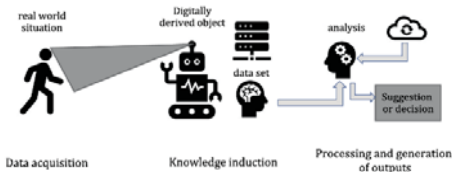


Fig. 4. Three-stage principle of functional safety for AI systems in accordance with ISO TR 5469.

These scenarios are finally executed within the simulation platform, allowing the camera's

detection performance and safety behavior to be assessed under controlled, repeatable conditions.

4.3 Non-AI-based Cameras

Physical tests are performed by driving the machine along predefined paths with the hazardous end-effector installed, using standardized test objects representing safety-related targets. These test objects typically consist of black cylinders whose geometry and surface reflectivity are selected according to the type of target under evaluation. The physical properties of these objects are derived from both IEC TS 62998-2 and ISO 18497-4 including dimensions, reflectivity, velocity, and acceleration. Specific human information can be found inside ISO 7250-1 (2017). For adult persons, walking speeds up to 1,600 mm/s and accelerations up to 2,000 mm/s² are considered, together with appropriate models for smaller targets (e.g. animals).

The test procedure defined in ISO 18497-4 does not explicitly prescribe a target velocity. Since the worst-case scenario involves the relative motion of both the machine and the target, a more conservative and representative approach is to adopt the procedure suggested by IEC 62998-2. In this case, a linear positioning system is used to move the test object toward the safety-related zone from controlled directions and at defined relative speeds, as shown in Fig. 5.

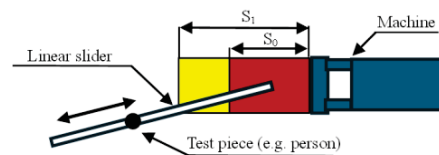


Fig. 5. Physical test procedure in accordance with IEC 62998-2:2020.

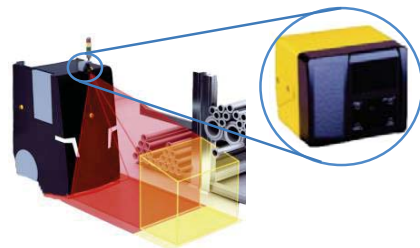


Fig. 6. Example of TOF camera built for safety purposes.

The tests are repeated by varying the relative position and direction of approach of the test object, including at least frontal and lateral approaches, in order to cover the full field of view of the sensing system and to verify the consistency and reliability of the detection function. An example of a safety camera setup is shown in Fig. 6.

4.4 AI-based Cameras

Since AI-based cameras rely on object classification (see Fig. 7), both real and virtual tests cannot be conducted in the same manner as described in paragraph 4.3. The tests shall be performed using representative real targets, such as adults and different species of animals. However, since exhaustive testing of every possible subject category is not feasible, the use of virtual testing becomes increasingly necessary and justified to ensure coverage of diverse scenarios.

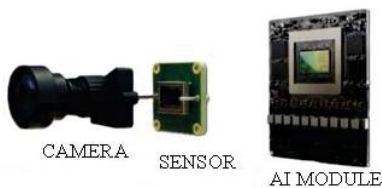


Fig. 7. Example of AI-based camera.

4.5 Handling of Preliminary Results

Data obtained from experimental tests shall be systematically analyzed to assess the applicability of SRS to the machine within the defined case-specific scenario. It is worth noting that the proposed testing methodology is also suitable for the comprehensive experimental characterization of the sensor's performance in a broader context. At present, however, there are no explicitly defined or standardized conditions, thresholds, or criteria that formally establish the applicability of such sensors to a given machine. The only specific quantitative criterion currently provided to machine manufacturers for specific outdoor environmental conditions is given in Table 4 of IEC TS 62998-1, where sensor degradation is evaluated.

Standards specify to execute real-world tests to experimentally characterize the system's behavior under representative operating and environmental conditions. ISO 18497-4 suggests a minimum of seven repetitions for each test,

nevertheless, no statistical interpretation of the results is suggested. The outcome of real-world testing is, for the moment, the systematic documentation of failures and performance degradations. Although no specific acceptance criteria are motioned, the absence of dangerous failure of the SRS can be assumed as the valuable first step for the applicability.

When large-scale virtual testing is performed in addition to real-world testing, a large and diverse set of scenarios are generated, enabling the construction of a confusion matrix (an example is shown in Fig. 8).

		Predicted Value	
		Detection	Non-Detection
Real Value	Target Presence	True Positive	False Negative
	Target Absence	False Positive	True Negative

Fig. 8. Generic confusion matrix concept.

The huge number and variety of test cases provide a statistically meaningful sample, allowing a quantitative assessment of the system performance and supporting the evaluation of its robustness across a wide range of operating conditions. In this context, false positives primarily affect the usability of the perception system, as they can lead to unnecessary stops that may disrupt machine operations. False negatives, on the other hand, directly reduce the effectiveness of the safety function, as they correspond to missed detections of real hazardous situations. A possible acceptance criterion may be established by introducing a threshold on the false negative rate, thereby quantifying the residual level of risk deemed tolerable.

More generally, the outcomes can be leveraged to identify specific scenarios or environmental conditions that critically degrade the performance of the camera system. These results can help the designer to take into account mitigation measures like solar shield for preventing the direct sun exposition of cameras or damping system to reduce vibrations. As an ultimate resource, it is possible to restrict the operating condition of the

system when an acceptable rate of detection failure is observed.

5. Conclusion and future work

Machinery Regulation explicitly acknowledges the use of AI-based modules for safety-related applications, including vision-based systems. However, there is currently no well-defined and widely accepted procedure for the systematic evaluation of these devices in outdoor applications, for both AI-based and non-AI-based sensors. In response, this study proposes a structured analysis of currently applicable standards for the assessment of safety functions based on computer vision (CV) systems, with a specific focus on construction sites and outdoor environments.

The research highlights the critical role of comprehensive risk assessment, including the definition of operational and environmental domains, as well as the identification of hazards under both intended use and reasonably foreseeable misuse scenarios, prior to test execution. Two standard-based methods are introduced to evaluate the performance of vision systems. The combined use of physical and virtual testing is recommended to enable the generation of a wide range of scenarios, including those that are hazardous or impractical to reproduce experimentally. This integrated approach supports statistically meaningful performance evaluations, including confusion matrices and system response times, thus providing a robust basis for safety-oriented assessment and potential future certification activities.

It is therefore recommended that future research and standardization efforts focus on the definition of structured experimental campaigns, applying the proposed methodology to different camera technologies and safety functions. The current verification phase remains only coarsely addressed in emerging standards, partly due to the novelty of the technologies under investigation. In this context, further work should support the development of validation procedures and contribute to the definition of acceptance criteria and thresholds by standardization bodies, enabling a clear and consistent assessment of the applicability of camera-based systems based on both experimental and virtual testing outcomes.

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