Towards Declarative Safety Rules for Perception Specification Architectures

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Abstract—Agriculture has a high number of fatalities compared to other blue collar fields, additionally population decreasing in rural areas is resulting in decreased work force. These issues have resulted in increased focus on improving efficiency of and introducing autonomy in agriculture. Field robots are an increasingly promising branch of robotics targeted at full automation in agriculture. The safety aspect however is rarely addressed in connection with safety standards, which limits the real-world applicability. In this paper we present an analysis of a vision pipeline in connection with functional-safety standards, in order to propose solutions for how to ascertain that the system operates as required. Based on the analysis we demonstrate a simple mechanism for verifying that a vision pipeline is functioning correctly, thus improving the safety in the overall system.

I. INTRODUCTION

Agriculture is an overexposed field in relation to injuries and fatalities, both in the EU [1] and USA [2]. This implies that even in developed countries there is a significant problem with safety. In addition to the safety issues, rural areas in developing countries are losing inhabitants to the cities, which decreases the labour forces and puts extra emphasis on improving efficiency. This has given birth to the idea of replacing human labour for field work. To this end outdoor mobile robots are a solution. A subclass of mobile robots is given by field robots, and refers to machinery applied for outdoor tasks, e.g., in construction, forestry and agriculture [3], [4]. Undertaking the job of creating field robots is however a large task, in part due to the many domains that overlap within robotics, e.g., mechanical and software. Additionally the dynamical environment in which a field robot operates introduces additional strain on the robots, and as result outdoor mobile robots fail up to 10 times more often than other types of robots [5]. The issue with field robots being more prone to failure has resulted in research within software quality for robotics [6]. The same issue is present in more mature domains, such as the avionics and automotive domains, which adopted Model-Driven Engineering (MDE; [7]). This adoption has led to utilizing of MDE in robotics to improve development time and reliability, examples are SmartSoft [8] and for computer vision Robot Perception Specification Language (RPSL; [9]). These MDE approaches are however not developed with a functional safety focus and are therefore missing some important aspects to make the robots trustworthy in relation to certification, and thereby improving the safety in the agricultural industry. For robots the vision domain is critical, this is also the case for many other applications ranging from monitoring operation on airfields [10] to real-time controlling of autonomous systems, such as vehicles [11] and robotics [12]. Robotics is highly dependent on computer vision to understand and react to the environment. This dependability imposes high constrains on the reliability of the software and the vision pipeline. For computer vision systems the issues are pointed out by Yang et al. “one is to identify an obstacle surrounding the robot and the other it to determine the location of the obstacle” [13]. For field robots to assist in field work, the robots have to be safety certified so as to minimise the liability (liability is addressed in [14]) of the producers. Our goal is to investigate if it is possible to extend an MDE approach such as RPSL to incorporate safety aspects. Concretely we propose ideas of how to achieve sufficient safety levels for the vision system in a field robot, and report on preliminary experiments demonstrating the viability of the proposed methods.

II. BACKGROUND AND RELATED WORK

Functional safety standards only address human dangers, e.g., ISO 26262 [15] and ISO 25119 [16]. This leaves the designer and developer to categorise issues related to harming the robot, e.g., untraversable ground and non-human obstacles. Hedenberg et al. [17] use EN 1525 (driver-less trucks [18]), and argue that the focus on humans is sound based on Asimov’s “A robot may not injure a human-being or, through inaction, allow a human-being to come to harm”. This law is however much broader than the standards, because a person can be hurt by colliding with an object that indirectly harms people, or figuratively if material damages resulting from a crash are high. The same issue exists in European law: Loss can be both economic and non-economic; it includes loss of income or profit, burdens incurred and a reduction in the value of property; and also physical pain and suffering and impairment of the quality of life [14]. Overall this means that safety should be addressed for the entire operation of the robot.

Standards such as ISO 25119 for agriculture [16], and ISO 13482, for mobile robots [19], are important for the overall functional safety of the system. Additionally IEC 61496 is important for the specific sensors [20] and lastly ISO/DIS 18497 is an upcoming performance standard within agriculture to quantify detection performances [21]. There are many requirements to a computer vision system: it has to be able to observe a large area; it must be fast, reliable and robust; and it is constrained to function with low computing resources because it normally has to run on embedded hardware, and might furthermore have lower priority than control and must not jam [12]. Standards within software for field robots are used to a very limited extent and not existing within computer vision [4]. This lack of standard is a paradox since autonomous mobile robots rely on robust sensing to react, without robustness the robot may...
“hallucinate” and respond inappropriately [22]. This issue puts constraints not only on the software but also on the hardware. As an example a RAW image has different degrees of being “RAW” [23]. This difference in RAW can be seen in different A/D converters, gains, and hardware image optimizations. Because of this wide range input changes in hardware can be problematic, it is therefore important for functional safety to look at software safety verifications of the pipeline, and to give assurance about the hardware and thereby verifying inputs and outputs.

MDE in robotics is an area that receives significant attention, such as research within control [24], vision [9] and general robot model-driven development [8], [25]. All the before-mentioned MDE methods describe safety issues, however these issues are not addressed according to any standards. Instead focus has been on quality, as with Reichardt et. al who as an example deter from using code generation to improve transparency [6]. Nevertheless we see code generation as an improvement to reliability and the possibility of lowering the demands for achieving certification, as is done by Bensalem et. al. [26]. Bensalem et. al. guarantee safety using code generation, it is however not done according to any standard. There exists several attempts to extend well-known MDE environments such as RoboML and SysML to incorporate Failure Tree Analysis (FTA) and safety analysis according to IEC 61508 [27].

### III. Problem Definition

#### A. Safety Requirements

To achieve any safety level a hazard analysis needs to be created, often called a preliminary hazard analysis (PHA). At the stage of creating a PHA the system configurations is unknown, during the development the PHA becomes a hazard and risk analysis (HRA), when the hazards are evaluated according to the standards functional safety index, e.g., Agricultural Performance Level (AgPL) or System Integrity Level (SIL). Then, depending on the standard, either an iteration over the risk assessment is done when the system has been redesigned, or the assessment becomes the basis of the system design and puts constraints on the system, e.g., redundancy as a hardware requirement.

Based on the introduction of field robots in an agricultural setting, we propose to evaluate field robots within ISO 25119, for agriculture and forestry [16]. For the evaluation of hazards we refer to ISO 13482, which is for personal robots, but also covers “multiple passengers” or “non-standing passengers” or “outdoor” or “uneven surfaces” or “not slow” or “not lightweight” or “autonomous” (ISO 13482, Sect. 6.1.2.3, Person Carrier Robots, Type 3.2), which covers field robots. Annex A in ISO 13482 [19] gives an overview of hazards to be evaluated. We refer to the broader system functionality from ISO 13482 specifically for type 3.2 field robot, Table I.

Note that if the field care robot is inherently unstable, PL e is required. Moreover, the control system shall achieve PL e, but this might not be achievable for sensing mechanisms. In this case, the risks caused by systematic failure of sensors shall be reduced as low as reasonably practicable. When assessing functional safety, then the entire path for the function needs to be the same level, e.g., sensor input to control output. This means that the vision system, based on Table I would reach an e-level. This has implications both on hardware redundancy and software development practices; we assume that the hardware system can be acquired.

We hypothesize that since the requirements are on functional safety and not on performance, then the algorithms are not directly implicated by the safety level. Moreover, if the detection algorithms perform as proposed in ISO 18497, and are developed according to Misra [28] software development practices, then it would be acceptable. The functional safety requirements would therefore be addressed by developing a system that can test and verify the functionality of the functions, and thereby ensure that the algorithms and sensor are functioning. This interpretation is also in line with the standard IEC 61496, inferred from the descriptions of the different types of Electro-Sensitive Protective Equipment (EPSE). The EPSE types addresses monitoring of the system working condition, and ability to perform, e.g. response time. Another point is based on the Note for Table I considering the sensors, it might be not achievable to get all parts of the sensor certified, in this case the highest level should be achieved. The essence of our interpretation of implementing functional safety is that one must ensure that all the preconditions for an action hold before that action can be safely and correctly executed, similar to the notion put forth by Rahimi et. al. [29].

We draw the following aspects on EPSE from IEC 61496: Detection Zone, Detection capability, adjustment (failure to danger not possible). These points needs to be addressed in order to ascertain the functionality of the sensor. Specifically for software it is stated that it should be developed in accordance with IEC 61508-3 or ISO 13849. IEC 61508 covers all machines, however forestry and agricultural machinery has ISO 25119 which is a type C standard, i.e., shall be used within the covered machinery types. Therefore software for our system should be developed according to ISO 25119, supporting our prior commitment to this standard.

### IV. Proposal and Experiments

#### A. Proposal

Based on the discussed safety and the scenario overview, we propose a systematic MDE-based approach to introducing safety in a vision pipeline. As an example, we use a simple vision pipeline that generates a 3D point cloud from two RAW images. The pipeline uses a debayer filter

| Safety functions of robots | Type 3.2 |
|---------------------------|----------|
| Emergency Stop            | d        |
| Protective Stop           | e        |
| Limits to workspace       | e        |
| safety-related speed control | e    |
| safety-related force control | N/A  |
| Hazardous collision avoidance | e    |
| Stability Control (incl. overload protection) | d    |

TABLE I: Performance levels for field robot.
to convert the RAW images into grayscale images, they are then rectified and undistorted using camera calibration information, to enable the creation of disparity maps. Finally, the disparity maps are converted to a 3D point cloud. The pipeline is described as a UML model using metamodels from RPSL [9], the model is shown in Fig. 1. We would in this pipeline hypothesize that it is possible to achieve a higher safety level by using an extended version of RPSL that has the ability to annotate the model with safety and validity requirements. These annotations would be used to generate code that continuously checks the integrity and correctness of the vision pipeline. A camera is a sensor influenced by many factors, lenses, processors and software, so the safety functions should therefore not only address software errors but also both mechanical and hardware errors.

Concretely, we propose two simple methods of improving knowledge about faulty cases and verifying the functionality of the system, by introducing declarative rules that specify the behavior of the pipeline according to: histograms of grayscale images and known landmark recognition. The rules should be introduced in a simple way by using a domain-specific language (DSL). A DSL would give flexibility to the user, meanwhile using code generation it would provide high reliability in the safety functions. The two methods introduced above would contribute to knowledge about the working condition of the software pipeline and the verification of the input and the working condition of the camera.

The histogram analysis could give a description of how much of the intensity spectrum is used and how large a spread exists between the different intensity values. This information would supply basic information about the sensor’s working condition and if the lens is covered (in that case most pixels would have a very low intensity). The proposed rule DSL could express the histogram concepts as follows:

\[
\begin{align*}
h &= \text{Bayer2Mono\_Left}\%.\text{output}\%.\text{histogram}; \\
\text{length}(\text{nonempty}(h.bins))/\text{length}(h.bins) &> 0.1; \\
\text{max}(h) - \text{min}(h) &> 1000\text{p}; \\
\end{align*}
\]

The rule extracts a greyscale histogram of the specific cameras image, i.e. Camera\_Left (more precisely the bayer filtering result based on an image from Camera\_Left). The found histogram consists of bins representing the number of pixels for each tonal value. The division gives the ratio of bins with at least one pixel. The rule imposes that 10 percent of the bins should be filled to make the image trustworthy. This rule could also be used directly on the RAW image from “Camera\_Left” filtering in Fig. 1. This would allow to separate the verification process between camera problems and processing errors. Since the RAW image approach would require a more complicated technical description we stayed with the grayscale case here since we believe that this gives the reader a better understanding.

The second idea is to introduce a known landmark in a defined area of the real world that the camera observes. This known landmark would then result in some 3D points in a defined area. If the points are not found in that region, then there is an error in the vision pipeline, and the results from the system cannot be trusted. Again the proposed rule DSL could introduce this check by the following rules:

\[
\text{length}(\text{PointCloud\_3D}\%.\text{output}.\text{inArea}(\text{Camera\_Left\_Landmark})) > 900;
\]

The rule uses the resulting point cloud of the vision pipeline, Figure 1. The rule uses the output and extracts the points from a specific area, in this case Camera\_Left\_Landmark. The rule then specifies that at least 901 3D points should be found in this area. Since it is known that the landmark should exist in the specified area the rule would verify the functionality of the functions and focus of the lens.

### B. Experimental Setup and Results

Our experimental setup consists of a camera with CAN and USB interface. The camera is a CLAAS Cam Pilot stereo camera [30]. The interface to the camera uses CLAAS hardware to convert USB signal to messages for controlling the camera. The raw pictures are extracted using the USB interface to the camera and enables easy analysis on a PC.

The above rules were implemented by hand in the vision pipeline (Fig. 1). The simple function of analysing histograms of the raw pictures has made it possible to ascertain that the input falls within expected ranges. Which made it possible to catch cases such as (a) and (b) shown on Figure 2. As an example, the software is able to prompt an error message, and will not let the system continue with the analysis of the images. This error prompt could be used in field robots in the decision module to stop the robot from moving, and signalling an operator to come and solve the issue. The landmark that was introduced was a white square in field robots in the decision module to stop the robot from moving, and signalling an operator to come and solve the issue. The landmark that was introduced was a white square in the lower part of the field of view of the camera. This enabled a test of the entire software pipeline, by evaluating the output of the 3D point cloud to have a result in the expected area. If the landmark is not detected the system will give an error of the lens and software pipeline, giving a higher reliability. This was quite robust, nevertheless it was possible to create scenarios where the results were trusted wrongly, as with the case for the
pictures (c) and (d) on Figure 2. In this case neither of the rules caught the fault. We however believe that extending the histogram to look at distributions may have a change of catching issues of partially covered lenses. The results verify that the functionality of the camera can be improved with simple rules. However extensions to the rules are needed, such as the proposal for looking at distributions of exposures, perhaps extended to the entire colour range.

V. CONCLUSION

This paper has introduced concepts and ideas of how to improve safety in relation to standards. The idea was based on the notion of splitting the performance and functionality requirements of the system and thereby minimizing certification requirements of a sensor system. Our implementation and tests gives an indication that our approach to annotate safety requirements in a vision pipeline leads to improved safety. In terms of future work, this is a first step toward introducing safety certification within vision systems for field robots. To further investigate the concept and validity of the approach, we are currently discussing it with certification authorities to understand the extent of the safety needed.

Our safety concept could be extended by introducing an “imaginary cage”. The idea is to make the system trustworthy enough that the cameras could make a perimeter around the robot, which for example could be calculated on the basis of the approach suggested by Täubig et. al. [31].

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