Explicit Image Quality Detection Rules for Functional Safety in Computer Vision

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Abstract: Computer vision has applications in a wide range of areas from surveillance to safety-critical control of autonomous robots. Despite the potentially critical nature of the applications and a continuous progress, the focus on safety in relation to compliance with standards has been limited. As an example, field robots are typically dependent on a reliable perception system to sense and react to a highly dynamic environment. The perception system thus introduces significant complexity into the safety-critical path of the robotic system. This complexity is often argued to increase safety by improving performance; however, the safety claims are not supported by compliance with any standards. In this paper, we present rules that enable low-level detection of quality problems in images and demonstrate their applicability on an agricultural image database. We hypothesise that low-level and primitive image analysis driven by explicit rules facilitates complying with safety standards, which improves the real-world applicability of existing proposed solutions. The rules are simple independent image analysis operations focused on determining the quality and usability of an image.

1 INTRODUCTION

Safety certification of a robotic system concerns reliability towards errors identified in a manual safety analysis. The computer vision domain however often neglects this issue because requirements often are stated in terms of the performance of specific functions, as stated by Yang et al. "*one [issue] is to identify an obstacle surrounding the robot and the other is to determine the location of the obstacle*" (Yang and Noguchi, 2012). This limited view could be the result of the domain's focus on developing and improving solutions (Ingibergsson et al., 2015). There is a focus on probabilistic measures for failure detection based on analysis of distributions and using learning methods (Blas and Blanke, 2011; Wang and Bhanu, 2005; Zhang et al., 2014). The issue with these methods is that it is difficult to prove that the distributions cover the entire normal behaviour, as illustrated by the spurious behaviour learning methods can exhibit where images are indistinguishable for humans, but the neural network makes wrong classifications (Nguyen et al., 2015; Szegedy et al., 2013). A key problem is that classifiers and learning are complex tasks that are hard to prove reliable for humans, in particular through code reviews, which is an often-used procedure during safety certification.

Safety certification is a method for achieving industry-required levels of reliability and dependability, while addressing liability (for liability see (Santosuosso et al., 2012)). Compliance with safety standards is considered key to ensuring reliability by achieving an appropriate level of functional safety (TC 23, 2015). Critically, complying with safety standards is not about the systems nominal performance, functional safety should rather be viewed as guaranteed reliability towards specific errors with regards to the entire system (hardware components, hardware design and software) or as guaranteed reaction, e.g. reaching a safe state. Functional safety is a matter of firstly conducting a Hazard and Risk Analysis (HRA), where hazards are errors or failures of functions that the system relies upon called safety-related functions. A safety-related function could be detecting humans, where a hazard is that the image is overexposed, resulting in missed detections. The risk analysis of the hazards imposes requirements on the entire development process, through the formulation of safety goals. A safety goal would be to ensure that the image exposure is usable for the algorithms. Each

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safety goal will result in the development of safety function(s), that ensure or monitor that the safety goal will not be violated (Zenke et al., 2016). The safety functions need to be human-understandable to reflect the connection between the safety goals and the hazards, as to enable the certification authorities to certify the system based on code review. A safety function could, therefore, be to evaluate the fill level of bins in a histogram. We observe that safety certification is especially important for vision pipelines used for the autonomous operation of robots and vehicles operating in dynamic environments since the vision pipeline introduces an increased risk of failures in critical parts of the robots' functionality. Indeed, outdoor mobile robots fail up to ten times more often than other types of robots (Bansal et al., 2014; Carlson et al., 2004). This paper uses field robots operating on an agricultural field as sample domain.

We hypothesise that the use of explicitly written easily understandable computer vision rules supports certification authorities in reviews, and thereby provides an increased understanding of the system safety functions and functionality. The safety-critical functions are limited to simple tests on the images to verify the quality and functionality of the camera system. We hypothesise that these functions can ensure that the data stream is of high quality and that the images are reliable, thus verifying that a higher-level vision algorithm is given the pre-required quality to perform optimally, making the system as a whole more reliable. In this paper, we test different rules to ascertain the usability and applicability of a proposed set of simple rules, and we have conducted experiments that demonstrate the viability of the proposed rules.

The paper is structured as follows. In Section 2 we describe standards applicable for certification of vision systems and relevant sub-domains such as learning and hazards analysis. Section 3 introduces our proposed method of using simple explicit written imaging rules, along with methods, new concepts and dataset used in this paper. Section 4 is the initial verification of the rules tested using the area under the precision recall curves. Section 5 introduces an augmentation to the rules called soft-boundaries, were we experiment with multi-classifications to improve applicability for safety certification. In Section 6 we randomly split the dataset to verify the results and that the dataset is sufficient for preliminary conclusions. In Section 7 we have an overall discussion of the results and the validity of the study, ending with Section 8 with an overall conclusion for the work.

2 BACKGROUND AND RELATED WORK

This section first discusses functional safety in the context of computer vision, then gives an overview of current research in computer vision relevant to functional safety, and last reviews learning methods in the context of functional safety.

2.1 Safety Certifying Vision Systems

Functional safety standards only address human dangers, e.g., within agriculture ISO 25119 (TC 23, 2010). This leaves the designer and developer to categorise issues related to harming the robot, e.g. hitting non-human obstacles. This means that safety should be addressed for the entire operation of the robot, emphasising the need for compliance and certification.

No specific standards however cover the domain of robotic vision systems or outdoor robotics. Mikta et al. (Mitka et al., 2012) introduced an initial idea using national standards. Some of these concepts have been introduced in newer standards for robots, such as ISO 13482 (TC 184, 2014).Functional safety standards such as ISO 25119 for agriculture (TC 23, 2010), and ISO 13482, for personal care robots (TC 184, 2014), are important for the overall functional safety of the robot, and also for the subsystems. Specific for vision systems a standard exist for vision in industrial setting, IEC 61496 (TC 44, 2012) which could be usable, as would upcoming standards for performance of vision systems (TC 23, 2014; TC 127, 2015). These standards cover the design of hardware as well as software, which makes it cumbersome to get complex systems and algorithms certified.

The functional safety standards introduce the concept of safe states which are important during faults or malfunctions. Sensors, in general, have a risk of failing, where common sensor faults are sensor bias, locked in place and loss of calibration (Daigle et al., 2007). These failures are malfunctions which require that the sensors are robust, without robustness the robot may "hallucinate" and respond inappropriately (Murphy and Hershberger, 1999). It is therefore important for functional safety to look at software safety verification of the input image, and thereby to give assurance about the hardware and verifying inputs and outputs.

The importance of computer vision being compliant and certified is due to its use in connection with real-time control of autonomous systems, such as vehicles (Cheng, 2011) and robots (De Cabrol et al., 2008). For this reason, verifiability of controllers is important (Bensalem et al., 2010). Barry et al. propose a safety-verified obstacle avoidance algorithm (Barry et al., 2012) to enable Unmanned Aerial Vehicles (UAVs) to sense and avoid obstacles. However, the underlying data the system receives is not evaluated, and therefore implicitly requires trustworthy data and images. Despite the missing standards there have been steps towards verifying computer vision test data (Zendel et al., 2015; Torralba and Efros, 2011). Zendel et al. investigate test data using Hazard and Operability Analysis (HAZOP). which is a systematic examination of a process (e.g. computer vision) used to identify problems that represent a risk to personnel or equipment. As a complementary effort, we aim to identify safety functions that can be used to ensure that the system is able to detect failures and return to a safe state.

We hypothesise that the use of explicitly written computer vision rules supports certification authorities in reviews, providing an increased understanding of the systems safety functions and the functionality; similar approaches with simple rules to facilitate certification exists for other domains (Adam et al., 2016).

2.2 Learning Methods

Safety certification of neural networks (Kurd and Kelly, 2003) remains an open issue. Specifically, Kurd et al. refer to Artificial Neural Networks (ANN) that are understandable and readable by humans, and also allows for individual meaningful rules (Kurd and Kelly, 2003). Many industries have looked into the use of ANN (Schumann et al., 2010). Specifically, industries not related to agriculture, like aerospace and military. These industries have been investigating the use of ANN since the 1980s (Schumann et al., 2010). A particular interesting approach is from Gupta et al. looking into verification and validation of adaptive ANN (Gupta et al., 2004), although Gupta et al. focus on control systems. These ideas are mainely aimed at ensuring that the ANN will not react uncontrollably based on bad images, and that outputs can be controlled. However, there does not exist a standard to comply with for ANN systems, specifically the absence of analytical certification methods restricts ANN to advisory roles in safety-related systems (Kurd et al., 2003). We hypothesise the use of low-level safety as a means to be compliant with standards and thereby enable the use of high-level more complex vision systems for performance. Moreover, we note that deep neural networks and similar recently popular methods share the same issue of being hard to assess.

Zhang et al. describe the before mentioned systems as BaseSys (Zhang et al., 2014). They argue that introducing an evaluation would enable the BaseSys to have a measure of whether or not attributes are reliable for later detection schemes. A method proposed by Bansal et al. (Bansal et al., 2014) suggests to create a classifier that predetermines the "quality" of an image, but the authors argue that this boosts performance. Performance is a criterion that is highly sought for in the computer vision domain, e.g. for pedestrian detection (Dollár et al., 2010). However, functional safety does not deal with nominal performance of the system. Our approach would be to use low-level image analysis instead of high-level attributes as Zhang et al. do..We believe this facilitates compliance with safety standards, and generally improves the reliability of systems dependent on vision.

3 EXPLICIT IMAGE QUALITY DETECTION

We now introduce the concept of explicitly written computer vision rules, which is the basis of this paper. These rules will be initially analysed in Section 4. This analysis is based on Precision-Recall (PR) curves which are introduced after the rules. We want to enable certification and use of many sensors on a robotic system; we, therefore, introduce a concept called multiclass classification, as seen in other safety critical systems (Mekki-Mokhtar et al., 2012). In this preliminary study, we will focus on only three classes "bad", "warning" and "good". This will enable the decision system to decide the trustworthiness of different sensors, and thereby decide if the robot needs to stop or just slow down. Finally, because of the introduction of multiclass classification, we introduce a concept we call *soft boundaries* into our evaluation strategy, to ensure that small misclassifications are not penalised.

3.1 Rules

We choose explicit image quality detection rules that are computationally simple, and contribute to the test of our hypothesis, as follows;

1. **Filled Bins Ratio of a Histogram (FB):** The FB rule is based on histogram analysis. The analysis is the relation between the number of bins with pixels divided by the total number of bins. For a bin to be categorised as having pixels it has to have more than 100px to remove noise. Example hazard: Exposure.

$$FB = \frac{non\_empty\_bins}{total\_bins} = \frac{\sum_{i=1}^{number\_of(bin)} (\#bin_i > 100px)}{number\_of(bin)}$$

2. **Bin Distribution, Maximum vs. Minimum Bin (BN):** This rule finds the bin with most pixels and subtracts the pixel value with the pixel value of the bin with the lowest amount of pixels. The result is then divided by the total amount of pixels. Example hazard: Covered image.

$$BN = \frac{Max(\#bin_i) - Min(\#bin_j)}{total\_pixels} = \frac{Max(\#bin_i) - Min(\#bin_j)}{img\_width \cdot img\_height}, \#bin_{i,j} > 100$$

3. **Bin Fill Ratio in a Histogram Uniform (BF):** This rule is an extension to the BN rule, where this is the difference between the individual bins and the total amount of pixels. Example hazard: Exposure.

$$BF = \frac{Max(\#bin_i)}{total\_pixels} = \frac{Max(\#bin_i)}{img\_width \cdot img\_height}$$

4. **Energy Ratio Before and After High-pass Filtering (FR):** The image is filtered using a very aggressive high-pass filter (second order Butterworth filter applied in the frequency domain with a cutoff frequency of the full image). The rule then compares the energy of the image after filtering and before (representative of the relatively high-frequency energy content in the image). This gives a notion about the high-frequency content / sharpness of the image. Example hazard: Blurred image.

$$FR = \frac{energy\_after\_filter}{total\_energy} = \frac{BW\_filter(img)}{total\_energy(img)}$$

5. **Component Analysis (CA Top & Bottom):** Connected component analysis is used for finding over (e.g. sunshine) and under (e.g. covered image) exposed spots on the image. The rule works on binary images; therefore thresholding is used with thresholds of < 10 for the bottom, and > 245 for the top. After which, connected components is used, and the area of the biggest component is output. The rule is able to catch significant light and dark spots on the image. Example hazard: Overexposed image.

$$CA = \{max(area(component_i)) : component_i \in image\}$$

6. **Optical Flow (OF):** Optical flow using Lucas Kanade (Lucas et al., 1981) uncovers if an image is changing. This is done by evaluating how many areas of the image are moving above a certain threshold. Example hazard: Stuck image.

$$OF = \frac{\sum(movement(area_i) > 0.2)}{total\_areas} = \frac{\sum_{i=1}^{number\_of(area)} (movement(area_i) > 0.2)}{number\_of(area)}$$

All of the rules above use a threshold that defines if the image violates the rules. In this paper, we seek to define optimum thresholds for the individual rules. The rules were initially assessed individually to understand their applicability to distinguish "bad" from "good" images. This analysis is done in Section 4, where we have evaluated the individual rules on their own, by assessing their statistical attributes by looking at the Precision-Recall (PR) curves.

3.2 Precision-Recall

We used PR curves to identify the performance of the classifiers without having to choose a particular threshold. PR curves are chosen over Receiver Operating Characteristics (ROC), because we know that if a curve dominates in the PR-space, it will also dominate in the ROC space (Davis and Goadrich, 2006). Furthermore, ROC does not take the baseline into account, and since our categories are unbalanced, the PR-curves are a better statistical measure. Because we use PR for evaluation, we will use a trapezoidal approximation of the Area Under the Curve (AUC) to evaluate the resulting PR curves, to find an "optimum", this is because linear approximation is insufficient for PR (Davis and Goadrich, 2006). The use of AUC on PR instead of ROC is further supported by Saito et al. "The PRC [Precision-ReCall] plot is more informative than ROC, CROC [Concentrated ROC], and CC [Cost Curve] plots when evaluating binary classifiers on imbalanced datasets" (Saito and Rehmsmeier, 2015). With the hope of using these methods in connection with functional safety, a perfect score would be desirable, however not a plausible result to aim for. The results will, therefore, be used to decide upon which rules are feasible to test with the following multiclass classification and *soft boundaries* schemas.

3.3 Multiclass Classifications

In addition to the initial analysis of using PR, we want to extend the investigations, by not only assessing the image as "good" or "bad", as normally done when using PR. Instead, we want to introduce another region to improve the initial results. This we want to do by introducing a two-step classification and thereby an additional classification region, which is a system "warning". The concept of a warning region within safety systems for autonomous robots has also been introduced by Mekki-Mokhtar et al. (Mekki-Mokhtar et al., 2012). This would make the system able to categorise three regions "error", corresponding to "bad", "warning", and "good". The flow is illustrated in Fig-

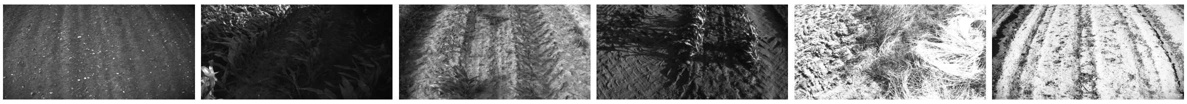


Figure 1: Exemplary images of field recordings done by a major agricultural company. The images are of crop structures and the ground, taken with a front facing camera placed on an agricultural machine.

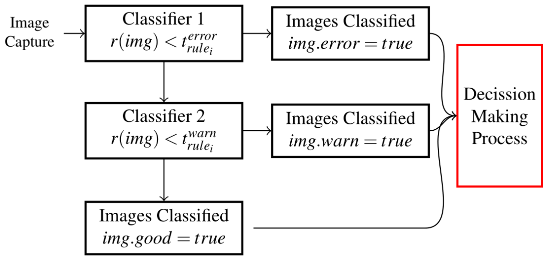


Figure 2: Concept of the extended classification approach, showing how the image propagates and how the system is told / made aware of the different steps. t is the threshold where $\forall t,i : t^{error}_{rule_i} \neq t^{warn}_{rule_i}$, and r is the rule, finally img stands for the current image.

Table 1: Example of the *soft boundary* region, enabling an overall system evaluation using PR curves.

Region Covered	*Good*	*Warning*	*Error*	*Zone*
1	FP	FP	TN	Error
2	FP	FP	TN	Region
3	FP	TP	TN	
4	FP	TP	TN	
5	FP	TP	FN	Warning
6	FP	TP	FN	Region
7	TP	TP	FN	
8	TP	TP	FN	
9	TP	FN	FN	Good
10	TP	FN	FN	Region

ure 2. Mokhtar et al. state that "*The set of warning states represents the safety margin between nominal safe states and catastrophic states, i.e. those corresponding to hazardous situations*" (Mekki-Mokhtar et al., 2012), inferring that more classes are possible to implement. The split into different regions would facilitate later combination of the rules, i.e. if a certain combination of rules produces warnings then the system could also interpret this as an error, we, however, leave this to future work.

3.4 Soft Boundaries

Soft boundary refers to the classification region for each of the rules. We want to make the transition smooth by allowing "small misclassifications". This is accomplished by moving the False Positive (FP) and False Negative (FN) that are calculated for the given PR curve, into the respective blocks True Positive (TP) or True Negative (TN), of course, this is only done within the *soft boundary* region. To exemplify both the *soft boundaries* and the "bad", "warning" and "good" regions, we choose the category *covered* and give the example in Table 1.

For this example the ground truth is specified such that all images below four (1-3) are "bad" and above 7 are good (8-10), then the warning region is in between (4-7). Where it normally is a strict line we propose a boundary region, example ± 1. When the analysis for the PR is made, the boundary region influences the FN and FP, in the following way:

- If an image hand labelled as 3 is categorised as "Warning", it is a FP. But because of our boundary region, this would not be an error; the data should, therefore, be interpreted as a TP.
- In the reverse example if an image hand labelled as 4 is categorised as "bad" corresponding to FN, it should be accepted and therefore be interpreted as a TN.

These two regions and the *soft boundary* concept is introduced as not to penalise the system for misclassifying some images as "warnings" or "errors". This should of course only be done in the *soft boundary* region, because classifying an image that is "good" or close to "good" as an error should still be an issue. This follows the idea from our hypothesis that our rules evaluate the images as shown in Figure 2. This enables the decision system to act based on the trustworthiness and functional safety of the system. Thereby making the system able to react by lowering speeds and/or relying more on other sensors to keep the system trustworthy.

3.5 Dataset

This paper focuses on images similar to those shown in Figure 1. The images come in pairs since they are recorded with a stereo camera. To enable the evaluation of the method 406 random images from the large database have been manually evaluated based on five criteria *exposure*, *movement*, *sharpness*, *covered* and *usable*. These are evaluated based on the different criteria listed in Table 2, resulting in the classification of 406 sample images shown in Table 3. The images have a resolution of 752x480 or 1280x1024.

Table 2: Overview of the classification criteria for the five image categories.

Category	Description
Exposure (1-3)	1: Under exposure. 2: Okay. 3: Over exposure.
Movement (1-2)	1: No. 2: Yes.
Sharpness (1-5)	1: No structure. 2: 25%. 3: 50%. 4: 75%. 5: Perfect.
Covered (1-10)	1: Everything. 2-9: Percentage increase. 10: Nothing.
Usable (1-5)	1: Not usable. 2: Bad. 3: Average. 4: Good. 5: Perfect.

Table 3: Overview of the ground truth data classification of the 406 sample images.

Exposure	1	2	3							
(count)	70	288	48							
Movement	1	2								
(count)	86	320								
Sharpness	1	2	3	4	5					
(count)	28	30	49	156	143					
Covered	1	2	3	4	5	6	7	8	9	10
(count)	1	1	6	7	16	38	30	33	35	239
Usability	1	2	3	4	5					
(count)	36	30	57	114	169					

4 SINGLE THRESHOLD PERFORMANCE EXPERIMENT

In this section, we describe our approach and results on using the rules presented in Section 3.1 individually, by assessing their statistical attributes by looking at the resulting PR curves. Instead of creating a learning scheme, we hypothesise that the creation of distinct rules will facilitate certification of CV systems. As an example for what we will analyse we choose the Fourier rule (FR). Using FR, we will try to detect *sharpness*, *covered* and *usable* for understanding what is possible to detect. The initial plots shown in Figure 3, are where only the lowest score one (for sharpness, covered and useable) is categorised as "bad", all others categories are "good" (please see Table 2 for classification criteria and scores).

To enable and simplify an analysis we use AUC. We are aware that the approximation can be incorrect as per Davis et al. (Davis and Goadrich, 2006). We are therefore manually inspecting the value during calculation to ensure that the trapezoidal approximation of the AUC is plausible. This analysis of the particular case shown in Figure 3 results in the AUC shown in Table 6, from the data we can conclude, per visual inspection on Figure 3 that the attribute *covered* is the best attribute to be found using FR. However, it should be noted that this is done using the classification that the lowest value, i.e. one, means "bad" image and the others are categorised as "good" values. Based on Tables 2 and 3 categorising only a score of one as "bad" might not be the most optimal. Additionally, it would be assumed that the correlation between the sharpness and frequency would be much stronger than shown in Table 6. For the analysis of all the rules, we change the classification border for the PR curves to find the optimal regions for distinguishing between "good" and "bad" images. The best region refers to finding the best classification of the ground truth. This analysis is based on the found AUC for PR curves and shown in Table 4. Comparing the results in Table 4 with the results in Table 3, it is evident that the first four categories for *Covered* are not that useful because they only amount to 15 images out of the 406 images.

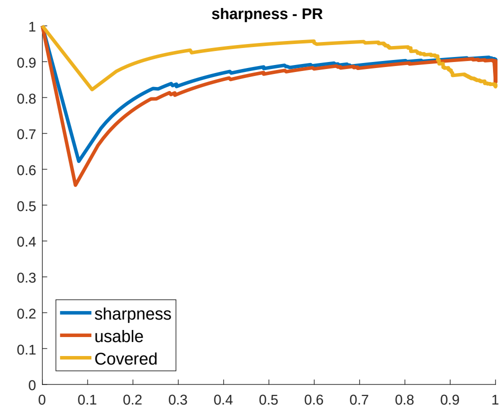


Figure 3: Initial PR curve of the ability to use rule FR for detecting "bad" images within the following categories: *Sharpness*, *covered* and *usable*.

From Table 4 it can be seen that certain rules can be used to detect certain attributes well. Because we are looking at this in connection with certification, we are interested in achieving as high PR scores as possible. In addition a classification of a "bad" image as "good" could have catastrophic consequences in our case. We have therefore tried to improve the results by introducing multiclass categorization.

5 SOFT-BOUNDARY REGION EXPERIMENT

In this section we describe our experiment of using a multiclass approach in connection with soft boundaries to assess images.

5.1 Experiment

Defining the scope of the boundary analysis is done based on the rules that are most promising within each attribute, this evaluation is done based on the results in Section 4:

Table 4: Evaluating PR curves using AUC on all categorisations through the entire range. The colour scheme emphasises the most relevant rules.

Sharpness	**FB**	**BU**	**BFU**	**FR**	**CA bot**	**CA top**	**OF**
1:bad | 2-5 good	0.9618	0.9509	0.8621	0.9986	0.9789	0.9603	0.9658
1-2:bad | 3-5 good	0.9125	0.8554	0.7381	0.9875	0.7922	0.7649	0.7623
1-3:bad | 4-5 good	0.8136	0.6941	0.6276	0.9066	0.7146	0.7041	0.7024
1-4:bad | 5 good	0.4988	0.3421	0.2869	0.5001	0.2110	0.1890	0.1761
Usable	**FB**	**BU**	**BFU**	**FR**	**CA bot**	**CA top**	**OF**
1:bad | 2-5 good	0.953	0.926	0.849	0.998	0.970	0.953	0.960
1-2:bad | 3-5 good	0.904	0.837	0.748	0.983	0.790	0.756	0.755
1-3:bad | 4-5 good	0.744	0.730	0.608	0.770	0.709	0.669	0.677
1-4:bad | 5 good	0.339	0.326	0.249	0.320	0.484	0.457	0.481
Covered	**FB**	**BU**	**BFU**	**FR**	**CA bot**	**CA top**	**OF**
1:bad | 2-10 good	1.000	1.000	0.994	1.000	1.000	0.999	0.999
1-2:bad | 3-10 good	0.998	0.993	0.994	1.000	0.998	0.997	0.998
1-3:bad | 4-10 good	0.990	0.985	0.979	0.994	0.996	0.989	0.990
1-4:bad | 5-10 good	0.976	0.958	0.963	0.992	0.989	0.979	0.982
1-5:bad | 6-10 good	0.936	0.938	0.927	0.946	0.834	0.804	0.795
1-6:bad | 7-10 good	0.804	0.919	0.844	0.768	0.800	0.751	0.749
1-7:bad | 8-10 rest good	0.677	0.882	0.792	0.670	0.769	0.710	0.712
1-8:bad | 9-10 rest good	0.582	0.848	0.734	0.565	0.725	0.666	0.672
1-9:bad | 10 rest good	0.473	0.796	0.691	0.481	0.674	0.625	0.629
Over exposure	**FB**	**BU**	**BFU**	**FR**	**CA bot**	**CA top**	**OF**
3:bad | 1-2 good	0.914	0.734	0.950	0.921	0.917	0.947	0.941
2-3:bad | 1 good	0.106	0.106	0.757	0.095	0.338	0.431	0.431
Under exposure	**FB**	**BU**	**BFU**	**FR**	**CA bot**	**CA top**	**OF**
1:bad | 2-3 good	0.945	0.952	0.670	0.981	0.635	0.596	0.581
1-2:bad | 3 good	0.100	0.811	0.104	0.088	0.059	0.063	0.059
Movement	**FB**	**BU**	**BFU**	**FR**	**CA bot**	**CA top**	**OF**
1-good | 2-bad	0.309	0.202	0.225	0.179	0.417	0.386	0.448
2-good | 1-bad	0.730	0.832	0.827	0.830	0.601	0.585	0.561

Table 5: Overview of the best F_1 scores and their accompanying precision-recall combinations, for the chosen rules.

Usable	precision	recall	F1-score
Rule FB	0.8374	1.0000	0.9115
Rule BN	0.8374	1.0000	0.9115
Rule BF	0.9828	1.0000	0.9913
Rule FR	0.8374	1.0000	0.9115
Rule CA bot	0.9052	0.9891	0.9453
Rule CA top	0.8370	0.9971	0.9101
Under exposure	precision	recall	F1-score
Rule FB	1.0000	1.0000	1.0000
Rule BN	1.0000	1.0000	1.0000
Rule BF	1.0000	1.0000	1.0000
Rule FR	1.0000	1.0000	1.0000
Rule CA bot	1.0000	1.0000	1.0000
Over exposure	precision	recall	F1-score
Rule FB	1.0000	1.0000	1.0000
Rule BF	1.0000	1.0000	1.0000
Rule FR	1.0000	1.0000	1.0000
Rule CA top	1.0000	1.0000	1.0000
Rule OF	1.0000	0.9951	0.9975

Sharpness	precision	recall	F1-score
Rule FB	0.8571	1.0000	0.9231
Rule BN	0.9021	0.9511	0.9259
Rule BF	0.9901	0.9925	0.9913
Rule FR	0.8571	1.0000	0.9231
Rule CA bot	0.9010	0.9945	0.9455
Rule CA top	0.8568	0.9971	0.9216
Rule OF	0.9398	0.9398	0.9398
Covered	precision	recall	F1-score
Rule FB	0.9236	1.0000	0.9603
Rule BN	0.9261	1.0000	0.9616
Rule BF	0.9282	1.0000	0.9628
Rule FR	0.9236	1.0000	0.9603
Rule CA bot	0.9378	0.9974	0.9667
Rule CA top	0.9233	0.9947	0.9576
Rule OF	0.9091	0.7979	0.8499

Table 6: The AUC value from the plot in Figure 3 approximated, analysed according to the three categories chosen, *Sharpness*, *covered* and *usable*.

	sharpness	*usable*	*covered*
PR AUC	0.8554	0.8368	0.9186

1. **Sharpness:** Rule FB, Rule BN, Rule BF, Rule CA (top and bottom) and Rule OF are the most promising.
2. **Usable:** Rule FB, Rule BN, Rule BF, Rule FR and Rule CA (top and bottom).

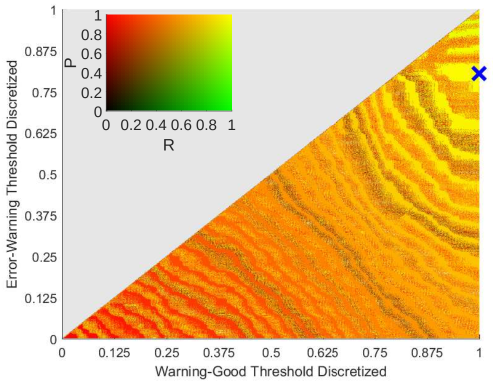


Figure 4: 2D plot of the precision-recall are made using BF (Rule 3) and the sharpness measure. In addition, the blue cross is the location of the highest *F1 score*. The colour map in the corner depicts the relation between precision and recall. The darkest yellow colour displays the highest sum of the precision-recall measures, and grey is no data.

3. **Covered:** Rule FB, Rule BN, Rule BF, Rule FR, Rule CA (top and bottom) and Rule OF.
4. **Over Exposure:** Rule FB, Rule BF, Rule FR, Rule CA (top) and Rule OF. The border is FB bad, BN warning and BF good.
5. **Under Exposure:** Rule FB, Rule BN, Rule BF, Rule FR and Rule CA (bottom).
6. **Movement:** Not applicable because it is only divided into two categories.

With the rules chosen for the investigation, the thresholds need to be found, by changing the threshold in steps between the minimum and maximum for the specific dataset, different PR values are found. However, since two thresholds are changed at the same time, it is no longer valid to use AUC as above. Instead, we use a colour map to show the individual PR calculations for the changes in thresholds, because we now have a precision and a recall value for each point in the plot. The definition for the colour map is:

$$RGB(Red, Green, Blue) = RGB(Precision, Recall, 0)$$

In addition, an optimum point is chosen based on the F_β *score*. The F_β *score* is a statistical measure that can be used to evaluate the classification performance. The β is a number reflecting a weight on either recall or precision. We have chosen 1 which results in the harmonic mean of precision and recall. The F_1 *score* is a weighted average where the best value is at 1 and the worst is 0.

An example plot for the analysis is shown in Figure 4. The chosen example is using the sharpness measure and BF (Rule 3), which is divided into five categories according to Table 2. The error→warning threshold on the categories is set so that 1-2 is categorised as "bad" and 3 is a "warning". The "warning→good" threshold is set at 4, meaning that images in category 5 are categorised as "good". The images that have been categorised as "bad" could be removed, but are not at this time.

Table 7: The result of combining the "error→warning" and "warning→good" threshold, including the soft boundaries, for Rule 4 "under exposure".

Collected	TP	FP	TN	FN
1	70	0	0	0
2	288	0	0	0
3	48	0	0	0

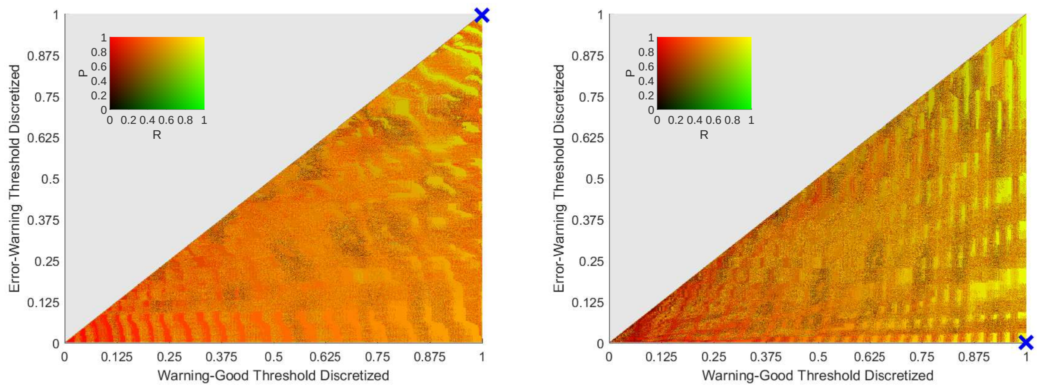
The results in Figure 4 are found by changing the two thresholds on the value of the outcome of the rule in use (here BF - Rule 3), one for "bad→warning" and one for "warning→good". The use of the soft boundary results in the precision-recall and the F1 score is depicted on the Figure 4 as the blue cross. Concretely, an F1-score of 0.9913 was found at the blue cross in Figure 4, this is found using the combination of precision 0.9901 and recall 0.9925. The specific values were found using the combination of thresholds $t_{bad \rightarrow warn} = 0.5106$ and $t_{warn \rightarrow good} = 0.1076$, meaning that if the most filled bin has more than half of all pixels in it, the outcome is "error" and if it has less than 10.76%, the outcome is "good".

These results indicate that it is possible to create simple rules relevant to this problem domain. The same procedure is applied to all the *relevant rules*, resulting in multiple F1 scores with their accompanying precision-recall combinations, shown in Table 5.

5.2 Discussion of Results

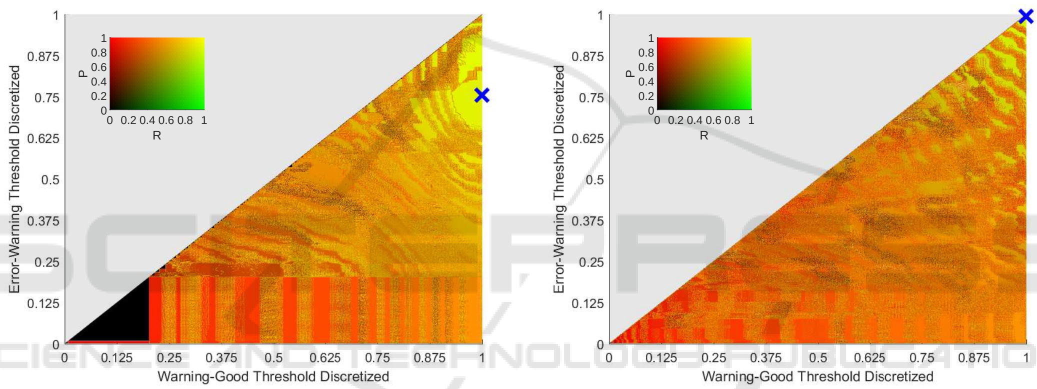
Some results in Table 5 stand out as being very poor or nearly too good to be true. As an example, "under exposure" (Rule FR), seems to overperform strongly compared to the initial results from Section 4 (see also Figure 5a), and "sharpness" (Rule FR) seems to underperform. The issue with "under exposure" is that the category is only divided up into three subcategories. This means that the soft boundary rule removes FP and FN completely, an example can be seen in Table 7, which imposes that ground truth categories should be divided into more than three categories.

This means that we can only assess the categories "usable", "sharpness" and "covered". Looking to the other example chosen using "sharpness" on Figure 5b, it shows that the optimal point is in the top right corner, suggesting that the manually labelled categories are not precise enough or that the filter used is too strong because this measure should be a strong indication of *sharpness*. Looking at the area where the



(a) The result of using Rule FR as a means to determine "under exposure".
(b) The result of using Rule FR as a means to determine "sharpness".

Figure 5: Rule FR has been chosen, and two exemplary categories for under and over performance respectively. The blue cross specifies the Highest F1 score.



(a) The result of using CA bot to determine "usability".
(b) The result of using FR to determine "usability".

Figure 6: "usability" is estimated to be the best-performing categorisation, plots illustrate the performance of example rules.

F1 score is the highest it is when "error→warning" is close to maximum and "warning→good" is at maximum, resulting in an F1 score of 0.9231. Seeing that the precision value is not that high, it might be possible to amend with a better filter. The results show promise but emphasise the need for a bigger dataset.

The results in Table 5 indicate that further work is interesting, especially when looking at the "usable" category. Nearly all of the rules perform adequately, despite some of them being at the extreme ends of the plots (right edge), see Figure 6. On Figure 6a it can be seen that the yellow region is a large area towards the top (the blue cross could be multiple places, with only small deterioration in F1-score), inferring that this is a measure for detecting "usability". Nevertheless, more data is needed to determine the effectiveness of the rule. For Figure 6b, the F1 score is also at its maximum one, see Table 5. Nevertheless, since the optimal point is in the top right corner, it indicates that the dataset is skewed, a larger dataset is therefore needed to test the chosen threshold.

6 RANDOMISED VERIFICATION TEST

As a preliminary verification of the found F1 scores and their thresholds, we test our apporach by randomly choosing half the labelled image dataset for testing, corresponding to 203 images. The selected images are used to find the optimal F1 score and extract the "error→warning" threshold and the "warning→good" threshold, as was done in Section 5. The determined thresholds are then used on the remaining 203 images not used for defining the thresholds. This is done to verify the detection capabilities and the performance of the specific thresholds.

The test has been conducted for 200 runs, resulting in the mean and standard deviation shown in Table 8. The Table is split into two tables, left side representing the results from the rule FR and the right is the rule CA bot. Both rules have been run for 200 times for the three categories "sharpness", "usability" and "covered", for each of the categories the mean and standard deviation is found for precision, recall and the F1-score. The values found are for the training and test datasets found through the random splits described above.

6.1 Discussion of Results

From Table 8 it is evident that the mean (μ) for the training set and the test set are very similar. This is a sign that we are not overfittng the model to the data with 203 training images and thereby that that the results in Table 5 with 406 training images are not suffering from this problem either. In addition the standard deviations are very low, implying that the change in the found P, R and F1-values are converging. This means that the 200 runs defined above are enough for the test-trial split.

Comparing the results with Table 5 where the 406 images were used to find the P, R and F1-values, where it can be seen that most of the values are comparable. Nevertheless, rule CA bot has a small deviation for P results for the category "covered". This could be because a larger dataset is harder to fit.

7 DISCUSSION

Based on our experiments, we observe that using the combination of multiclass data and *soft boundaries*, the "covered" category can be detected and distinguished rather well. While "sharpness and "usability" are performing adequately for an initial run. This observation supports our hypothesis of using simple rules. An added bonus of having simple and explicit rules is that it enables the system designer to obtain a higher diagnostics coverage, which is significant for safety certification (diagnostic coverage is used to describe the reassurance that the safety function is working or that a dangerous error is detected). We however leave this aspect to future work as it is tightly coupled with an HRA. We believe that the results presented in this paper could be improved by combining the different rules, thereby improving the overall image categorisation. The "sharpness" category shows strong performance using rule BF. Nevertheless, the other rules are not performing as well, especially rule FR which was initially assumed to be a strong detection measure. However, we believe that the result could be improved by optimising the filter. The "covered" category seems to be performing quite well for the different rules. We believe the combination of the different rules would give higher precision and recall values. The combination could be done using learning methods which are intuitively understandable, e.g. decision trees or structural analysis. The use of intuitively understandable learning methods could improve the choice of combination of rules, nevertheless to facilitate certification this learning should ideally not be done "online". We have refrained from discussing the categories, "over exposure", "under exposure" and "movement", because they are not applicable with our current multiclass categorization. An amendment to increase the subcategories of each categorization to at least four would be needed.

A threat to the validity of the study is that the categorisations are skewed, that "bad" and "good" images are not evenly distributed, which means that the thresholds could have overfitted the data.

Furthermore, the current dataset is too small to make any definitive conclusions and needs to be extended not only for the investigation of the PR and F1 scores but also for the test dataset to verify the found values. From the preliminary investigation we created an overview of the simple rules that could be used as safety functions. These functions need to be mapped to hazards using safety goals, for complying with functional safety, through the use of an HRA. We emphasise that functional safety is critical for industrial systems and that more and more standards are entering the area of autonomous systems (TC 127, 2015; TC 23, 2014). However for the current results to be applicable for safety certification it needs to be done in the context of an HRA. We would therefore need to create an HRA according to ISO 25119. A helpful overview of hazards can be found publicly (Zendel et al., 2015). Therefore this paper should be viewed as an initial investigation into plausible safety functions, to enable safety-certification of a larger set of autonomous robotic systems.

8 CONCLUSION AND FUTURE WORK

The simple and explicit rules show an indication of being able to detect external (e.g. exposure) and internal (e.g. focus) failures of a camera system. This is a first step to understand what is needed and possible to be done in connection with certifying perception systems. This initial step was done to uncover and test

Table 8: The standard deviation (σ) and mean (μ) value of Precision (P), Recall (R), and F1-score for the FR rule used on "sharpness", "usability", and "covered". This is done for the training and test dataset.

FR	Training dataset results			Test dataset results			**CA bot**	Training dataset results			Test dataset results		
σ	P	R	F1	P	R	F1	σ	P	R	F1	P	R	F1
Sharpness	**0.0175**	**0.0018**	**0.0101**	**0.0175**	**0.0089**	**0.0105**	Sharpness	**0.0141**	**0.0039**	**0.0079**	**0.0150**	**0.0080**	**0.0089**
Usability	**0.0180**	**0.0025**	**0.0109**	**0.0182**	**0.0109**	**0.0111**	Usability	**0.0145**	**0.0063**	**0.0078**	**0.0166**	**0.0080**	**0.0086**
Covered	**0.0131**	**0.0015**	**0.0071**	**0.0132**	**0.0085**	**0.0082**	Covered	**0.0146**	**0.0132**	**0.0060**	**0.0193**	**0.0190**	**0.0066**
μ							μ						
Sharpness	**0.8580**	**0.9993**	**0.9232**	**0.8552**	**0.9919**	**0.9184**	Sharpness	**0.9000**	**0.9946**	**0.9449**	**0.8977**	**0.9918**	**0.9423**
Usability	**0.8389**	**0.9988**	**0.9118**	**0.8358**	**0.9905**	**0.9065**	Usability	**0.9059**	**0.9911**	**0.9468**	**0.8980**	**0.9872**	**0.9404**
Covered	**0.9238**	**0.9995**	**0.9602**	**0.9229**	**0.9926**	**0.9564**	Covered	**0.9540**	**0.9843**	**0.9694**	**0.9430**	**0.9769**	**0.9593**

specific, easy to understand rules that would allow a monitoring unit to verify the data stream from a camera. We introduced *soft boundaries* and two thresholds to reflect real-world needs during certification to better distinguish "bad" from "good" images. Nevertheless, more work is needed with a larger dataset. We believe this approach will contribute to certifying perception system allowing them to be used in more and more autonomous applications.

The use of simple and explicit rules is intended to facilitate communication with the safety expert but has the added benefit of eventually enabling further use of formal methods, such as automatic code generation of the safety system based on a formal specification of the rules for a given system.

In terms of future work, we want to extend the labelled dataset (Ground Truth) not only size wise but also by verifying the categorisations, thus improving our test and training dataset and ultimately the found thresholds. Additionally extending the dataset to address more scenarios in the agricultural domain is also interesting, to see if the thresholds can be utilised over many areas. This will help us understand the applicability of the detections on real-world scenarios. A comprehensive hazard and risk analysis are needed to understand if all camera errors can be detected by the computationally simple rules. This should be matched with defined hazards as is done in the HAZOP by Zendel et al. (Zendel et al., 2015), facilitating an investigation into diagnostic coverage.

The database used in this paper is recorded using stereo cameras, and 3D points can, therefore, be produced. 3D points would allow the introduction of a new rule. For example, introducing a real-world marker will let us know how many points should be found in that area of the image, thereby verifying the 3D point cloud. Another rule could be to compare the two images from the stereo camera to ensure that errors such as different exposures or partially covered lenses would be caught.

We believe that this paper is an important first step to introduce and facilitate safety certification of perception systems.

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