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ADVANCES IN ACTIVE NEAR-INFRARED SENSOR SYSTEMS FOR MATERIAL CLASSIFICATION AND SKIN DETECTION FOR SAFETY APPLICATIONS

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ABSTRACT

This paper presents recent research on an active multispectral scanning sensor capable of classifying an object's surface material in order to distinguish between different kinds of materials and human skin. The sensor itself has already been presented in previous work and can be used in conjunction with safeguarding equipment at manually-fed machines or robot workplaces, for example. This work shows how an extended sensor system with advanced material classifiers can be used to provide additional value by distinguishing different materials of work pieces in order to suggest different tools or parameters for the machine (e.g. the use of a different saw blade or rotation speed at table saws). Additionally, a first implementation and evaluation of an active multispectral camera system addressing new safety applications is described. Both approaches intend to increase the productivity and the user's acceptance of the sensor technology.

Keywords: safeguarding equipment, optical sensors, multispectral sensors, near-infrared imaging, machine learning

1. INTRODUCTION

Contactless detection of human limbs at manually-fed machines or robot workplaces is a desirable feature for safety applications. Both manually-fed machines and robots are often equipped with potentially dangerous moving parts that are difficult to shield off from the reach of the user. Therefore, robot workplaces are often caged in completely and the robot is stopped while there are people within the cage, making it impossible for humans to work together "hand in hand" with the robot in a so-called joint-action scenario. On manually-fed machines such as bench saws or presses, this is no feasible solution as well, as productive working requires the user to be near the machine at all time, rendering these machines very prone to accidents (see Reinert et al. 2009).

State of the art safeguarding equipment, such as safety light curtains, uses a technique known as muting to allow workpieces or moving parts of machines and robots to enter dangerous areas while all other objects (e.g., human limbs) will cause an emergency stop of the machine. The main problem of this technique is that it requires detailed model knowledge about the application, including exact parameters about timing, position, orientation, shape and size of the workpieces. Therefore, muting is not easily applicable to manually-fed machines and restricts joint-action scenarios for humans and robots.

This paper addresses this problem and presents recent research on an active multispectral scanning sensor capable of classifying an object's surface material in order to distinguish between different kinds of materials and human skin. The concept of a fast and reliable LED-based scanning sensor using several LEDs of distinct wavebands within the near-infrared (NIR) spectrum has already been introduced in our previous work (see Schwaneberg et al. 2011, 2012) and will be summarized shortly in section 2.

In section 3, new research on an extended sensor system with additional wavebands in the ultraviolet and visible spectrum using advanced material classifiers based on machine learning algorithms is presented. This advanced sensor system can be used to provide additional value to the users of manually-fed machines by distinguishing different materials of workpieces in order to suggest different tools or parameters for the machine (e.g. the use of a different saw blade or rotation speed at table saws). Possible applications are described and an (exemplary) safety assessment is discussed.

Additionally, section 4 describes and evaluates a first implementation of an active high resolution NIR-camera system based on the same sensor principle. This skin-detecting camera system extends the applicability of the sensor technology and addresses new safety applications.

2. BACKGROUND AND PRIOR WORK

The characteristic remission properties of human skin in the NIR spectrum below 2000nm have already been described in a number of publications. One of the first studies on this topic was published in 1955 by Jacquez et al., who compared very different skin tones in the NIR spectrum and found that "...the reflectance of human skin above 1.2µm is primarily the reflectance of a scattering component mixed with water." This makes the NIR spectrum very interesting for human skin detection, as it is widely independent of skin type and other individual factors such as gender and age.

Figure 1 presents remission spectra of six skin samples, ordered from very light (1) to very dark (6) skin tone according to the categories proposed by Fitzpatrick (see Fitzpatrick 1988), compared to different materials. While there are great differences in the remission intensities of the different skin samples within the visual spectrum, the differences within the near-infrared spectrum are rather small, as all remission spectra of the skin samples form a common pattern in the wavelength range above approximately 900nm. Other materials, however, can be easily distinguished from skin.

By using spectroscopy in the NIR spectrum, these characteristic features can be easily detected. However, spectroscopy is not well suited for the use in safeguarding equipment on machines, as the measurement procedure is too slow and susceptible to interfering light. To overcome these problems, the Institute for Occupational Safety and Health of the German Social Accident Insurance (IFA) and the Bonn-Rhine-Sieg University of Applied Sciences (BRS-U) ran several research projects on the problem of human limb detection for safeguarding equipment. The researchers proposed the use of the so-called spectral signatures, which allow the development of contactless, inexpensive, fast and robust sensor systems for safety applications. Patents for the respective sensor technology in conjunction with safety and security applications have been issued (Jung et al. 2006, Schwaneberg et al. 2008). A spectral signature consists of a small number of remission intensities at different narrow wavebands, which represent the most important features to distinguish the given materials. Only three well-chosen wavebands are sufficient to reliably distinguish skin from wood, for example.

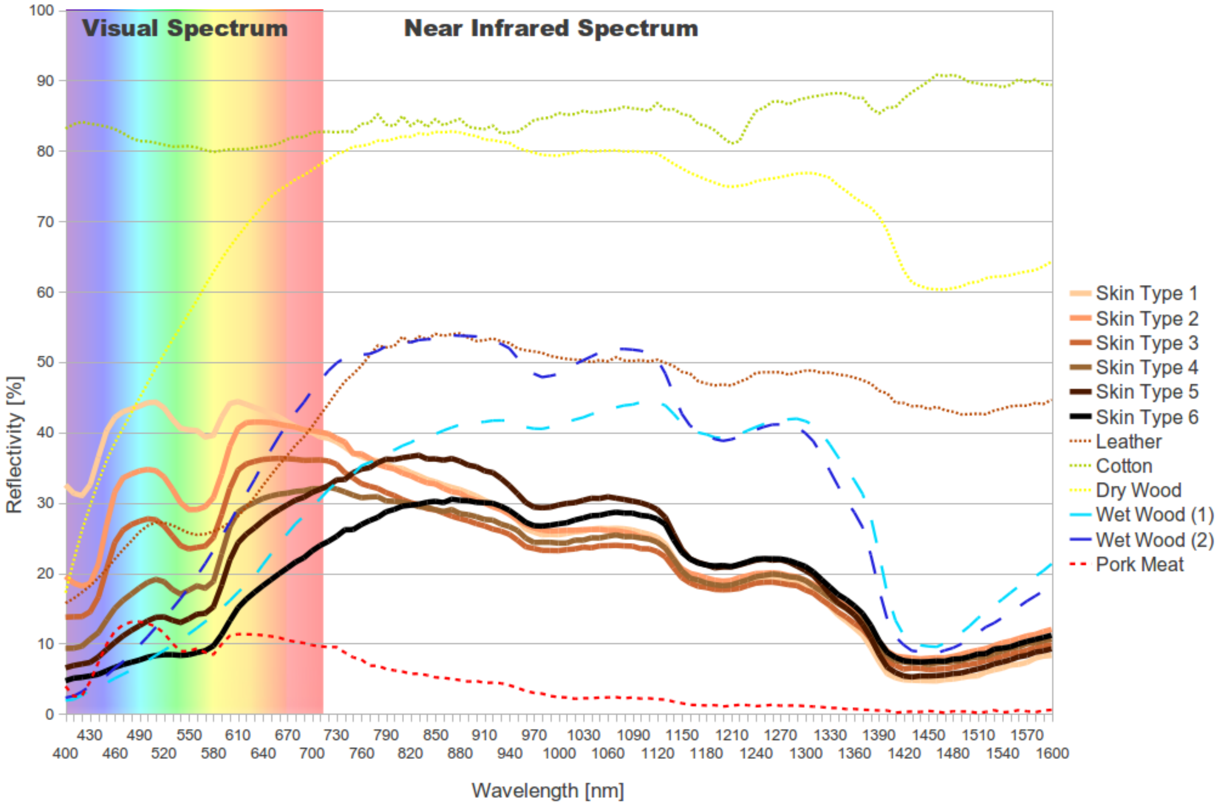

Figure 1: Remission spectra of different materials compared to human skin.

A simple and comparably cheap microcontroller-based sensor system with pulsed narrow-band illumination and a receiver (e.g. different LEDs and a photodiode) can perform such a measurement and classification in less than one millisecond and trigger an emergency stop of a connected machine. A respective sensor and control system which can be used as safeguarding equipment on a bench saw, for example, can easily be designed and build according to applicable safety standards (i.e. DIN-EN-ISO 13849-1). On the basis of hardware and software structure, the extent of fault detection mechanisms, the reliability of the used components, the probability of common cause failures, and other influences such as environmental conditions, a performance level can be calculated, which denotes the ability of the safety-related parts of a control system to perform the intended safety function. According to a preliminary safety assessment performed using the SISTEMA software tool provided by the IFA (see Huelke et al. 2008), the system could achieve a performance level of “c” to “d” (if build up with one channel and an additional test channel with a high diagnostic coverage) or even “e” (if build up as a two channel system). The safety assessment of a basic version of the proposed sensor system has been published and presented on the 9th International Symposium of the TÜV Rheinland Group (see Steiner et al. 2010). A certification as additional safeguarding equipment, which would not replace passive safeguarding equipment such as a guard or protective housing, should be easily possible, according to the IFA. However, if the sensor system was meant to replace such passive safeguarding equipment, an intensive study proving the underlying principles would be necessary for the certification.

In the following sections, two new research and development projects which are based on this previous work are described and preliminary results are presented.

3. ADVANCED CLASSIFICATION METHODS

Recent research at the BRS-U investigates the use of ultraviolet and visible wavebands as an addition to the near-infrared wavebands within the spectral signature with the goal to enhance the classification performance of different materials. The basic idea is to expand the functionality of the safety sensor in order to provide additional value for the users of manually-fed machines. If the sensor system is able to distinguish different materials of workpieces from each other, it can be programmed to automatically change the machines parameters for the handling of the respective material or suggest the use of different tools to the user, for example the use of a different saw blade or rotation speed at multi-functional table saws or a warning to a carpenter if the wood he is working on is too wet. Such features add a practical value to the safety function and help to increase the productivity of the machine, thus making the sensor system economically more attractive.

A series of measurements with ultraviolet, visible and NIR range spectrometers was conducted in order to analyze a variety of typical materials used on bench and band saws. A special measurement setup was build that allows to perform spectroscopic measurements of a material's surface from viewing angles between 0° and 90° in small increments automatically. First results of this measurements show that the ultraviolet waveband below 280nm can provide important information to distinguish otherwise generally "bright" and shiny surfaces such as polished metal, while some visible wavebands such as those found in RGB-systems greatly enhance the ability to distinguish wood, leather and textiles.

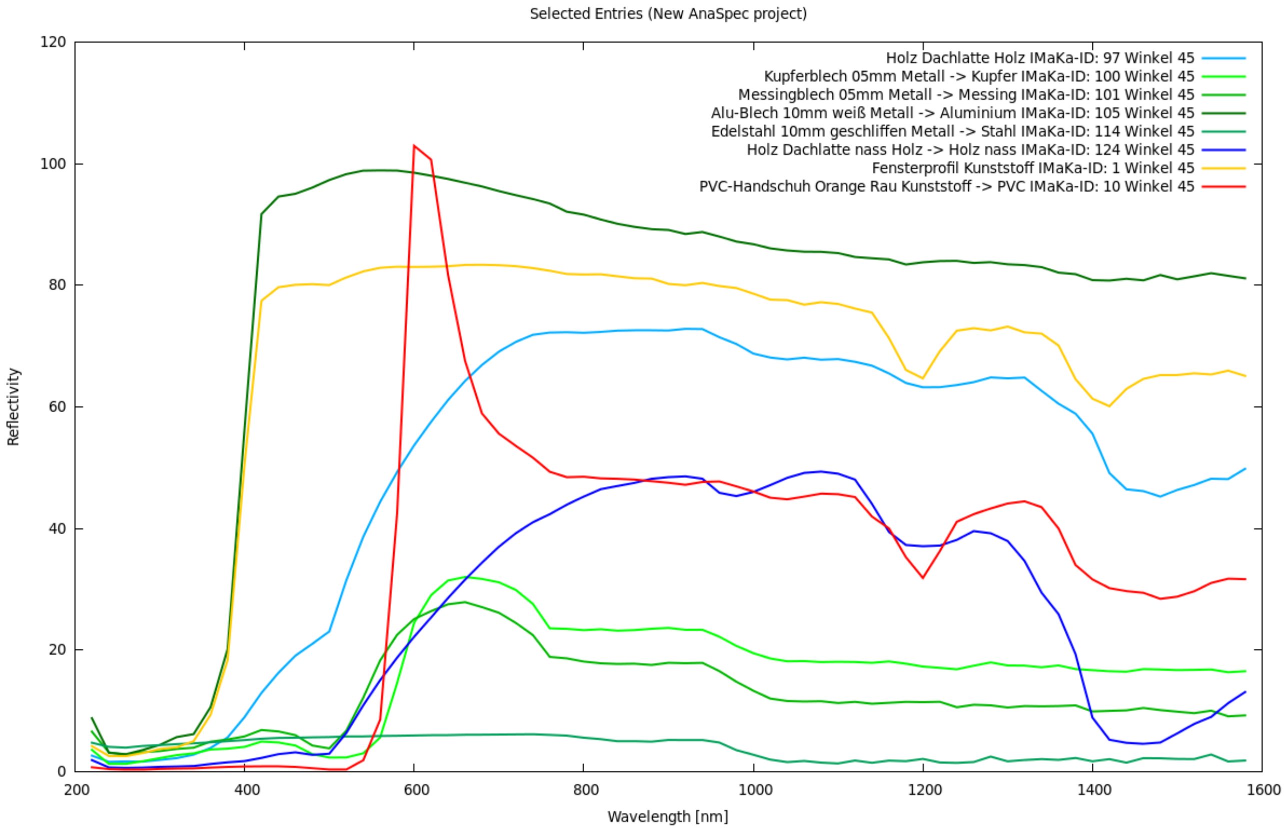

Figure 2: Remission intensities of different materials from UV to NIR.

Figure 2 shows the spectral remission intensities of a selection of relevant materials from the deep ultraviolet to the near-infrared wavelength range (200nm to 1700nm). It can be seen that the different metal samples (plotted in green), for example, cannot be distinguished from each other or some other materials such as leather (plotted in red) in the near-infrared wavebands alone, as the absolute intensities cannot easily be used for the classification due to unknown viewing angles and possible highlights. Some material samples, on the other hand, rely strongly on these wavebands: wet wood (plotted in dark blue), for example, is almost completely dark in the ultraviolet and visible range, but shows a characteristic pattern in the near-infrared range, which can be distinguished from the pattern found for dry wood (plotted in light blue). A combination of four near-infrared wavebands (830nm, 1060nm, 1300nm and 1550nm, as proposed in previous work, see Schwaneberg et al. 2011), one additional waveband in the ultraviolet range (280nm) and three additional wavebands in the visible range (425nm, 530nm, 625nm) was found to be a good solution. This combination takes into account availability, price and lifetime of the respective components, as these are important factors in order to find a feasible solution for the given application.

The resulting extended spectral signatures were extracted from the spectrometric measurements with a self-made software tool called AnaSpec, which is able to simulate the remission spectra of real LEDs and to calculate the expected remission intensities at the selected wavebands. The spectral signatures have been analyzed in great detail by using both the previously used quotient-based bounding box filter approach as well as advanced classification and machine learning algorithms.

The bounding box filter simply defines lower and upper thresholds for all 28 possible quotients (between two waveband values in each case), thus forming a multi-dimensional bounding box which encloses all samples of the target class. Quotients are favored over absolute intensity values as they are more independent from varying measurement distances or angles. For each material, one set of filter rules was trained on the task of deciding whether or not a material sample belongs to this material class. As shown on the left side of table 1, this simple approach is already able to classify and discriminate all skin samples against all other material samples without errors on an NIR-only sensor system. The given parameters are the correct classification rate (CCR), which denotes the relative amount of correctly classified samples in total, the true positive rate (TPR), which denotes the relative amount of positively classified samples that are in fact positive, the false positive rate (FPR), which denotes the relative amount of positively classified samples that are actually negative, as well as the precision (PREC), which is the most interesting parameter as it denotes the probability that a positive classification result is correct. It can be seen that distinguishing other material samples from each other shows a very weak performance. However, as shown on the right side of table 1, the use of the additional UV and VIS wavebands strongly increases the classification accuracy of the bounding box filters compared to the NIR wavebands alone, just as it was expected.

		NIR only with Quotient-Filter				UV-VIS-NIR with Quotient-Filter			
Target Material	**Samples**	**CCR**	**TPR**	**FPR**	**PREC**	**CCR**	**TPR**	**FPR**	**PREC**
Skin	20	100%	100%	0%	**100%**	100%	100%	0%	**100%**
Wood	41	75%	100%	34%	**51%**	98%	100%	3%	**93%**
Wood (dry)	17	76%	100%	27%	**30%**	98%	100%	2%	**85%**
Wood (moist)	8	68%	100%	34%	**13%**	92%	89%	8%	**40%**
Wood (wet)	17	69%	100%	34%	**26%**	89%	100%	12%	**48%**
Metal	29	50%	100%	61%	**27%**	74%	100%	32%	**41%**
Copper	3	64%	100%	37%	**5%**	100%	100%	0%	**100%**
Aluminum	9	89%	100%	12%	**33%**	99%	100%	1%	**90%**
Brass	4	100%	100%	0%	**100%**	100%	100%	0%	**100%**
Steel	11	74%	100%	28%	**21%**	94%	100%	6%	**55%**
Leather	6	66%	100%	38%	**23%**	99%	83%	0%	**100%**
Cloth	10	77%	100%	25%	**21%**	97%	100%	3%	**67%**
Acrylglas	6	88%	100%	12%	**24%**	99%	100%	1%	**75%**
Plastics	46	54%	100%	65%	**38%**	60%	100%	56%	**42%**
Kevlar	2	96%	100%	4%	**22%**	100%	100%	0%	**100%**
Polyurethan	4	88%	100%	12%	**17%**	99%	100%	1%	**67%**
PVC	16	59%	100%	45%	**20%**	65%	100%	39%	**22%**
Nylon	5	91%	100%	10%	**25%**	99%	100%	1%	**83%**
Nitril	4	80%	100%	21%	**11%**	100%	100%	0%	**100%**
Latex	4	94%	100%	6%	**31%**	99%	100%	1%	**80%**

Table 1: Classification results using the quotient filter approach of the old NIR-only sensor compared to the new UV-VIS-NIR sensor. Correct classification rate (CCR), true positive rate (TPR), false positive rate (FPR) and precision (PREC) are shown.

Several machine learning algorithms were trained on the same data using the Weka software tool (see Hall, 2009). As machine learning algorithms tend to “overfit” the classification algorithms to a small data set, the available material samples have been multiplied and treated with uniformly distributed noise of 5% to simulate measurement noise of an actual sensor system. This way, 100 samples for each material (sub-) class were available for learning. As before, the 28 quotients were used as input data instead of the 8 absolute intensity values. The results of the different algorithms were compared using a ten-fold cross-validation, which (in turns) uses 90% of the data for testing and 10% for evaluation. Support Vector Machines (SVMs) showed the best classification results on the data. With this technique, even minor differences in the signatures can be used to differentiate the materials. Similar to the bounding box filter approach, one SVM was trained for each material class. As the output of each SVM is the probability that a given sample belongs to the respective class, the individual SVMs can easily be combined into a multiclass SVM that classifies a sample as the material class with the highest probability. Table 2 shows the correct classification rate, precision, true positive rate and the predicted relative absolute error, which is a measure for the (un-) certainty of the result, for different material classes.

		UV-VIS-NIR with C-SVM			
Target Material	**Samples**	**CCR**	**TPR**	**Rel. Abs. Error**	**PREC**
Skin	100	100,0%	100,0%	2,4%	100,0%
Wood	220	98,8%	91,0%	10,2%	100,0%
Wood (dry)	100	98,2%	83,0%	29,0%	86,5%
Wood (moist)	20	99,4%	57,1%	56,8%	92,3%
Wood (wet)	100	99,6%	94,0%	9,9%	100,0%
Metal	400	100,0%	100,0%	1,1%	100,0%
Copper	100	100,0%	100,0%	3,2%	100,0%
Aluminum	100	100,0%	100,0%	2,8%	100,0%
Brass	100	100,0%	100,0%	1,2%	100,0%
Steel	100	100,0%	100,0%	2,5%	100,0%
Leather	100	99,9%	100,0%	2,4%	99,0%
Cloth	100	100,0%	100,0%	2,3%	100,0%
Acrylglas	100	99,4%	98,0%	10,3%	92,5%
Plastic	617	99,4%	98,4%	3,5%	100,0%
Kevlar	20	100,0%	100,0%	8,0%	100,0%
Polyurethan	100	100,0%	100,0%	1,6%	100,0%
PVC	100	98,8%	80,0%	19,3%	100,0%
Nylon	100	100,0%	100,0%	1,1%	100,0%
Nitril	100	100,0%	100,0%	1,1%	100,0%

Table 2: Classification results using a C-SVM with 10-fold cross validation on synthetically supplemented data. Correct classification rate (CCR), true positive rate (TPR), the (predicted) relative absolute error and the precision (PREC) are shown.

It is easy to see that the SVMs produce much better results than the bounding box approach. Most material classes can be distinguished almost perfectly from each other. However, as the analyzed data was produced by spectrometric measurements under laboratory conditions, the data recorded in practice by an actual sensor system might be very different. The performance of SVMs on this more practical data has to be evaluated again after the ongoing development of a new sensor system is finished.

4. IMAGING SYSTEM

Further current research investigates the use of an imaging sensor instead of single point sensors in order to widen the applicability of the sensor system. A camera-based system allows to monitor large areas of interest and to gain much more detailed spatiotemporal information about the scenery.

To demonstrate the feasibility of this research approach, a prototype of an active high resolution NIR camera system based on the same sensor principle has been developed. It uses a digital NIR camera with an InGaAs CMOS sensor sensitive to radiation between 900nm and 1700nm in conjunction with a custom-made ring flash consisting of 84 LEDs in three different wavebands within this wavelength range. The LEDs are arranged in a mixed pattern in order to achieve a uniform illumination. For each waveband the ring flash emits a total optical output power of approximately 160mW. A microcontroller is used to synchronize each flash with the camera by a signal line connected to the camera's external trigger port. A specifically developed software running on a PC can configure the flash light (e.g. by setting frequency and pulse width) and control it's operation, while it is able to receive images from the camera via a different interface simultaneously. The system setup is shown in figure 3.

A respective software tool with a simple graphical user interface to display images and control the operation has been developed. A screenshot of the output of the software is presented in figure 4. It shows the images taken with the camera system before and after the image processing and classification algorithm. The top left image was taken without illumination, while the top middle, lower left and lower middle images were taken with illumination in one waveband each. The dark image is already subtracted from each of these images to make sure that only the active illumination emitted by the LEDs of the respective waveband has an influence on them. The lower right image shows a false color composition of the three images taken with illumination and subtracted dark image. The lower waveband was mapped to the red, the middle waveband to the green and the upper waveband to the blue color channel. Finally, the upper right image shows the result of a simple skin classification.

Due to the chosen mapping of wavebands to colors in the false color image, skin appears to have a reddish color close to reality, while textiles and hair, for example, are completely white. The actual and individual skin tone of people in the field of view of the camera, however, does not at all have any effect on the resulting images, just as it was expected. In the skin classification image, a very simple algorithm was used to remove all regions of the false color image in which the quotients of the wavebands are below or above a certain threshold marking the expected boundaries for skin.

Figure 3: Setup of the camera system with attached ring flash.

Figure 4: Screenshot showing the resulting and generated images.

5. CONCLUSION AND FUTURE WORK

The research on the use of extended spectral signatures and advanced classification algorithms showed that the ability of the sensor system to distinguish between different materials can be greatly improved. To prove these research findings in practice, a new prototype with eight instead of four wavebands (one in the ultraviolet, three in the visual and four in the near-infrared wavelength range) is currently in development and will be evaluated in both laboratory and field tests.

The first results of the active camera system show that the approach of using a camera as an imaging sensor with the proposed sensor principle is feasible and very promising. Together with the ring flash, the working range of the camera system was up to 5 meters indoors. As bright daylight has a high proportion of NIR radiation, the camera sensor might get easily saturated if the system is used outdoors and in bright sunlight. If this happens, the sensitivity has to be reduced, leading to a reduced working range. However, detailed investigations of the possibility of an outdoor use have not been performed yet.

In future work on the camera system, the skin classification algorithms will be enhanced and suited machine learning algorithms will be applied. For this purpose, the results achieved with the single point sensors and the new findings with the advanced classification methods will be used as a basis. With reliable and sensitive classification algorithms, more complex safety applications, for example the safeguarding of a robot workplace by monitoring the complete area around the robot with a camera system above it, can be addressed. However, it is currently not possible to perform a preliminary safety assessment for a such system, as an achievable safety integrity or performance level strongly depends on the reliability of the camera itself, which has (in this case) not been rated in terms of safety. Commercially available safety products such as the SafetyEye from Pilz GmbH, which is also camera based, show that achieving a performance level of D is possible even for systems with such high complexity.

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