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Application of Machine Learning and Vision for real-time condition monitoring and acceleration of product development cycles

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Abstract

Development work within an experimental environment, in which certain properties are investigated and optimized, requires many test runs and is therefore often associated with long execution times, costs and risks. This can affect product, material and technology development in industry and research. New digital driver technologies offer the possibility to automate complex manual work steps in a cost-effective way, to increase the relevance of the results and to accelerate the processes many times over. In this context, this article presents a low-cost, modular and open-source machine vision system for test execution and evaluates it on the basis of a real industrial application. For this purpose a methodology for the automated execution of the load intervals, the process documentation and for the evaluation of the generated data by means of machine learning to classify wear levels. The software and the mechanical structure are designed to be adaptable to different conditions, components and for a variety of tasks in industry and research. The mechanical structure is required for tracking the test object and represents a motion platform with independent positioning by machine vision operators or machine learning. An evaluation of the state of the test object is performed by the transfer learning after the initial documentation run. The manual procedure for classifying the visually recorded data on the state of the test object is described for the training material. This leads to an increased resource efficiency on the material as well as on the personnel side since on the one hand the significance of the tests performed is increased by the continuous documentation and on the other hand the responsible experts can be assigned time efficiently. The presence and know-how of the experts are therefore only required for defined and decisive events during the execution of the experiments. Furthermore, the generated data are suitable for later use as an additional source of data for predictive maintenance of the developed object.

Keywords: Machine vision; Machine learning; Industrial application

1. Introduction

In industrial manufacturing, machine vision technology is used for a wide range of activities and offers innovative solutions for industrial automation [3]. Its application is mainly directed towards quality inspection and assurance and ranges from the production of electronic components[12, 1] to various material examinations[13]. The warranty of quality represents a competitive advantage and is one of the essential corporate objectives of manufacturing companies. Inspection can be sensory, visual or by means of both, whereby visual quality inspection is often performed by human experts[8]. However, visual human inspection is usually time-consuming and can be very difficult or even dangerous depending on the given environment. In these special cases, digital image processing is a suitable replacement and supplement for human inspection. For the image acquisition of the object to be examined, one or more cameras are installed in the environment with appropriate lighting. The image processing analysis and classification of these cameras are carried out by one of the task-specific software. As a rule, the processing software systems are set up in such a way that only known objects can be examined [7]. In the case of time-consuming or computationally intensive image processing, special hardware for faster processing can be used for this purpose. The acquired and evaluated images can be sent via the network to information systems for further processing or to other processing systems.

For the conception of an image processing system, according to Malamas et al. evaluation, the parameters and requirements should be the:

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- Fields and domain of application,
- Environment,
- Processing speed and
- analyses to be carried out

be considered. In accordance with these requirements, the design and development of the automated image processing system require an understanding of the type of information and features that should be extracted from the images. By using machine learning, the scope of use of machine vision systems can be extended for new industrial application fields.

2. Related work

Golnabi and Asadpour describes the main task of the image processing system as converting optical images into numerical data by means of the image sensors so that these can be processed, segmented and the features extracted by computers [3]. For automated visual inspection, the image processing operations binary, grayscale, color and area image analysis can be used [15]. The appropriate analyses shall be selected on the basis of the application and environmental characteristics. From the specified requirements, the image processing system is developed with the selection of suitable software and hardware. First of all, it must be determined how adaptable the system should be to changed conditions deviating from the requirements. In addition to adaptability, usability, in the form of interaction options that are specified for the user, as well as the number and types of interfaces for connection to other systems. These parameters to be considered can be implemented by large modularity of the system.

2.1. Machine learning in image processing

Basically, the machine learning (ML) approach uses multilayered artificial neural networks (NN) implemented in a computer to learn the representation and abstraction of digital data, making the performance of machine learning comparable to human experts [6]. In industrial image processing, NN is mostly used for classification, such as surface recognition [11]. NN are neurons arranged in layers that interact with each other in a network by means of connections, where the neurons of the first layer represent the data input and the last layer of the output. NN with several layers between the input and output layer are called deep neural networks (DNN) [2]. During data input, all layers from the input to the output layer are passed through. The strength of the connections between the neurons are called weight and are adjusted by training. If the result is known during training, it is called supervised training. NN is particularly suitable for complex data that cannot be considered directly by mathematical calculations. This also applies to direct image processing for the recognition of surfaces where the damage is visible but can only be filtered by image processing operations in a very complex way. For the use of NN in image processing, each pixel of the image represents an input neuron, so the images must always have the same resolution. This allows different image classification and pattern recognition applications for the states to be performed on the basis of the images and used for training. Machine Learning provides a classification for a variety of pattern recognition applications, but the performance of these applications depends heavily on the training material of the classifiers. Polikar et al. describes a major problem in the practical application of machine learning that the training material is expensive and time-consuming to obtain and therefore often only small amounts of data are available for training over a certain period of time[10]. For this purpose, transfer learning offers the execution of training and testing on different domains, tasks and distributions, whereby the learned material can be used for new domains with a smaller number of training data sets[9].

2.2. Adaptability and expandability of an image processing system

The image processing system consisting of hardware and software should have a modular structure to ensure long functionality and safe maintainability of the system in case of changes in use or requirements. This also makes sense from the point of view of the interchangeability of the algorithms used or machine-trained models. With the new data and images, which increase with time of use, more suitable algorithms can be selected or models trained with this new data set can be exchanged and used. Due to the complexity requirements for the information to be evaluated from the images, the hardware required for this should always be taken into account. While the hardware equipment may be sufficient at the beginning of the use of the image processing system with the specified requirements, the hardware equipment can quickly become a bottleneck for the usability of the image processing system as the amount of data and information to be extracted increases. Depending on the requirements for speed, data security and infrastructure, the image analysis can also be transferred to outsourced computer systems connected via the network. For this reason, the exchange and expandability of hardware, including specialized hardware for image processing, and connection via a network component should be considered as one point in the software architecture.

3. Design of an image processing system for product and technology development

The architecture proposed in this paper examines the surfaces of the test objects after a load interval. In contrast to binary, grayscale, color and area image analysis, this approach classifies the states of the test object using a machine-trained model. For this purpose, the model is trained for classification using the images initially recorded and divided into wear groups. To do this, the images from the initial test procedure are manually classified by the respective area expert into the degree of wear and then used for training. In this context, a novel system for test execution by means of image processing with condition monitoring of test cycles is explained and a methodology

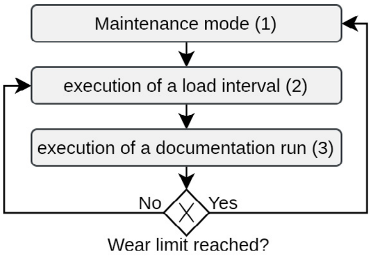

Fig. 1: Simplified process flow Display of a test object from the beginning to the wear limit

with three phases is proposed, with the aim of performing automated test cycles, documenting the process and independently evaluating the generated data. An overview of the process sequence of the test objects from the beginning to the wear limit and the inspection parameters to be exchanged is divided into 3 areas and can be seen in figure 1.

The maintenance mode allows the exchange of the test object as well as the parameters to be tested or optimized on the test system. After the maintenance mode, the test object is started with the execution of a load interval. During the loading interval, a multiple or a single number of maximum loads is applied over the entire test path of the object. After completion of a loading interval, the documentation run takes place. During the documentation run, the test object travels at a slow, steady and smooth speed from the beginning to the end of the test object. During this process, images of the test object are taken continuously, always starting and ending at the same position, so that a comparison of the individual sections of the test object over the entire wear development is possible. When the end of the test object is reached, the documentation run is completed and either the run of the load-interval begins again or the termination of the test is started when the wear limit of the test object is reached. In case of termination, the next test object with modified test parameters must be set up in maintenance mode, which starts a new process cycle.

3.1. Detailed process flow of the test runs

The process flow starts with the need for a product or technology investigation and ends with the completion of the investigations, as shown in figure 2. For this purpose, the test object with the test parameters must be prepared on the test facility in the already described section Maintanance Mode (1). Before first use, an initialisation of the image processing setup and system must be performed. During this process, the image processing operators are defined manually so that only the test object is tracked by the camera. Once the image processing operators have been determined, the camera checks the image over the entire positioning path with the focus on the test object. Thereby, the process path is traced by the camera over the entire positioning range of the module, whereby the test object should be located in the middle of the camera if possible. If a too large deviation from the center of the camera is detected, the interval

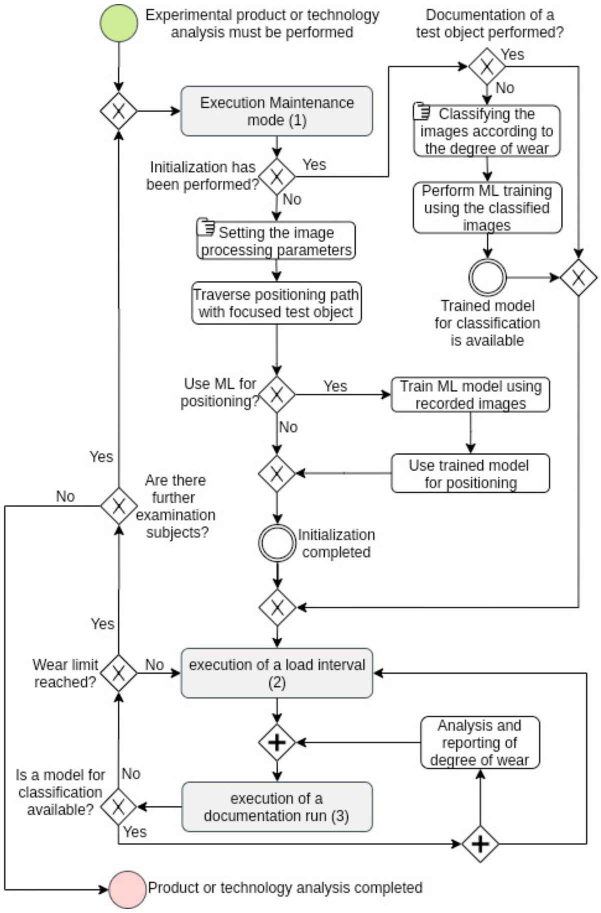

Fig. 2: Detailed process flow of the image processing system

between the images to be examined must be reduced for positioning or the image processing operators must be readjusted. If the test object should be tracked using ML, the already taken images of the entire positioning path with an additional marking of the test object can be used for training. The tracking of the test object by means of ML is an optional step, as it should usually be sufficient to perform the tracking by means of the image processing operators. However, the use of an ML model can be more reliable when environmental parameters such as lighting or modifications to the test equipment are changed. Switching to the use of an ML model for tracking can also be done later by a repeated initialization, where additional images from the documentation runs performed can be used for training.

After initialization, the first load-interval (2) is carried out and then the documentation run (3). If this is the very first test object as documented in the described methodology, there is no model for the classification of the images on the degrees of wear, therefore, the execution of a loading interval (2) and then the documentation run (3) is repeated until the complete wear of the test object is reached. Afterward, manual classification of the images is performed based on the degree of wear. The exact

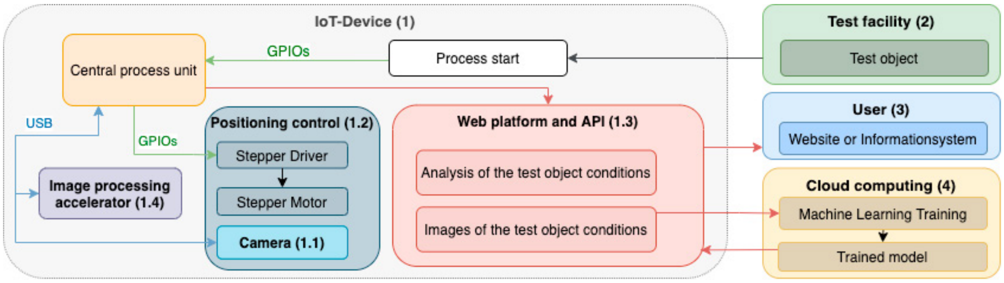

Fig. 3: Architecture of the IoT device with hardware and software components and interactions to other systems

procedure for classifying the images into wear groups is explained in section 3.3. The ML training is then carried out with these classified images. The trained model is then available and can be used on the hardware of the image processing system for all subsequent test objects. The analysis of the degree of wear by the model is performed each time after the document run (3). The results of the analysis can then be processed by further information systems, for example, to notify the responsible employee when a certain degree of wear is reached in order to prepare the materials for the next inspection run.

3.2. Hardware architecture and software interaction of the IoT device

The architecture of the Internet of Things (IoT) device consists of the one hand of the hardware used and on the other hand of the individual software modules for processing the data and interacting with other systems, as shown in figure 3. At the IoT device (1), the camera (1.1) is first connected via USB and is moved along the test object on the process path via the mechanical structure of the positioning control. The positioning control (1.2) is driven by a stepper motor that is connected to a stepper motor driver that is communicated and parameterized with the IoT-Device via the GPIOs. The documentation run is started by triggering from the test facility (2) so that a procedure for documentation of the test object is carried out.

A web server runs on the IoT device which provides a web interface and API for the users (3) to ensure fast commissioning and flexible use. The web interface can be used to parameterize the image processing operations and the positioning control, such as the acceleration values or the counter of the images up to the analysis, on the one hand, and provides access to the historical and real-time documentation data on the other hand. Via the API this data can also be used directly in information systems. Furthermore, the web interface can also be used to download and manage the collected images of runs. These image sets can then be used for ML training of a model for classification on a device with the appropriate hardware equipment, such as using cloud computing (4), where the final trained model is then transferred back to the IoT device via the web platform.

The trained model is then used on the image processing accelerator (1.4). The main task of the image processing accelerator is to evaluate the images for positioning during the documentation run. Due to the time required for the analysis of the degree of wear of all images taken during a documentation run, the images are only evaluated during the load-interval. In this way, the resources of the image processing accelerator are only used when available.

3.3. Procedure for the manual classification of signs of wear

The manual classification of the images used to create the training material is only carried out after all document runs from commissioning to complete wear of the test object has been recorded. The classification is done from the last document runs, i.e. from the images where the complete wear is visible. Thus the visible damage can be clearly identified and in chronological order, the development can be sorted into the individual wear degree classes at the same place as the test object, as shown in figure 4.

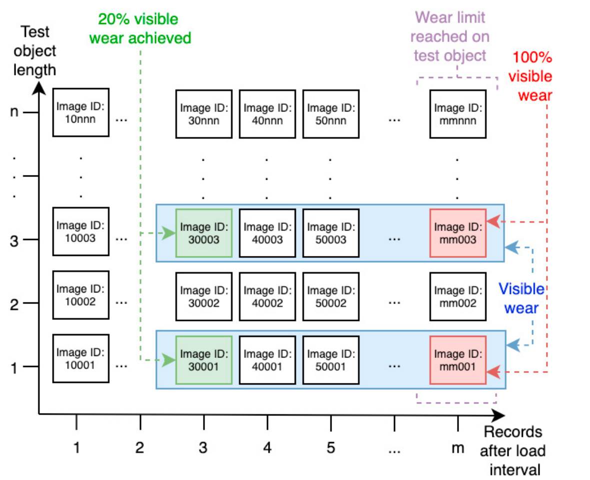

Fig. 4: Schematic representation of the process of classifying the images into wear levels

4. Implementation

The feasibility and effectiveness of the proposed system for product development are demonstrated by means of a process-accompanying architecture with image processing and integrated into the product development cycle. The developed system uses a commercially available low-cost camera with adjustable lens and additional light source in order to allow a cost-effective setup and to minimize errors during image acquisition.

A wire rope for elevator cabins was used as test object. Due to the complex stress conditions, the wear of the wire rope varies depending on the application, so that a purely theoretical calculation of the service life is not possible and only experimental investigations can provide a service life forecast with high reliability [14].

For tracking the test object a developed two-dimensional motion platform with independent positioning based on image processing is presented. The camera lens is always carried along with the test object, as shown in figure 5. For positioning, certain image features are extracted for pattern recognition. Pattern recognition of the test object is performed by the image processing operations of the color filter with thresholds in the HSV (hue, saturation, value) color space, blur, contrast adjustment and closed areas within the color threshold range in order not to analyze areas with stray light.

For the transformation of the motion data from the camera lens, the deviation from the center of the test object to the absolute center in the x-axis is used to calculate the instructions for the positioning steps of the platform. The positioning steps of the platform to be moved are implemented by controlling the stepper motor. The check, from when a movement of the camera lens is necessary, is carried out by specifying after how many images an analysis for positioning should be carried out. As described in section 3, an ML-trained model can optionally be used for positioning. In the course of the tests, using the ML-trained model proved to be more reliable when environmental parameters changed, such as lighting or changes to the test facility.

To evaluate the condition of the test object, a classification was trained from the image data set of the first fully documented test run. For this purpose, the images were used where the test object showed exactly visible damage, where a statement about the degree of wear or damage could be made purely from the visual observation of the images. To find the images with signs of wear, as described in section 3.3, all images of the last recordings where the test object was completely worn out were looked at first and then the same places in retrospect were observed, so that a backward development of the identified damage places could be seen. Based on these development images of the damage points, the expert responsible for the test setup sorted them into different wear groups. figure 6 shows an example of the development of wear.

The training of the classification was carried out using these image data sets divided into wear groups through transfer learning. The advantage of using transfer learning is that a model trained with a large number of generic images is used, in which only the last layers are trained for a new task. Thus, transfer learning does not require large image data sets and allows faster training with lower-performance hardware. Nevertheless it should be mentioned that there is a high risk of overfitting if the image data set is too small. For the classification of the degrees of wear we used the images with a resolution of 224x224 pixel with the ResNet. Keras offers a variety of models to be used for this purpose in the Applications area [5], which can be selected according to the respective task. The trained model was used for the analysis of the states of the test object on the Coral[4] as an external image processing accelerator on the IoT Device, so that an evaluation can be done directly on site and only the data on the states have to be transferred. The mechanical construction is done with 3d printed parts and with self-developed printed circuit board (PCB) for the control of the stepper motor driver.

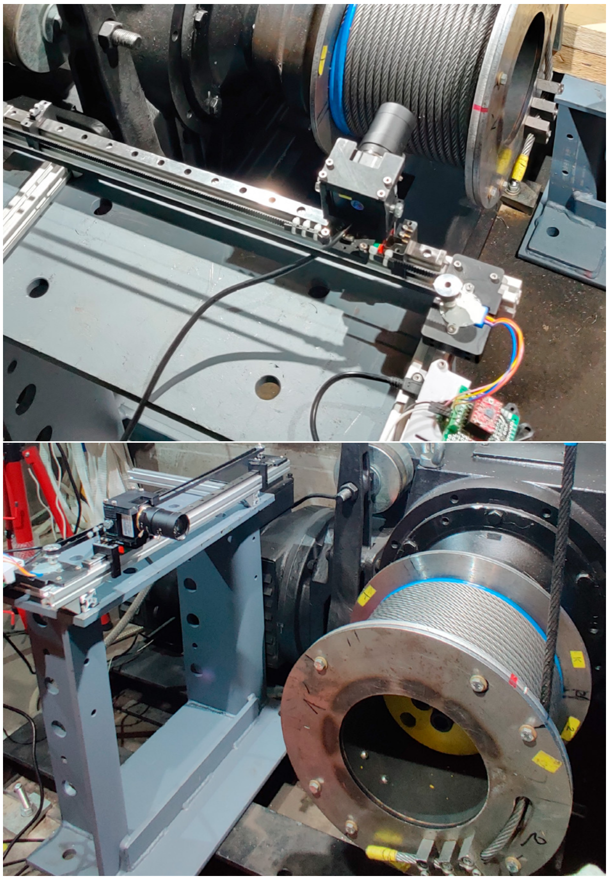

Fig. 5: Developed image processing system with self positioning mounted on the experimental setup

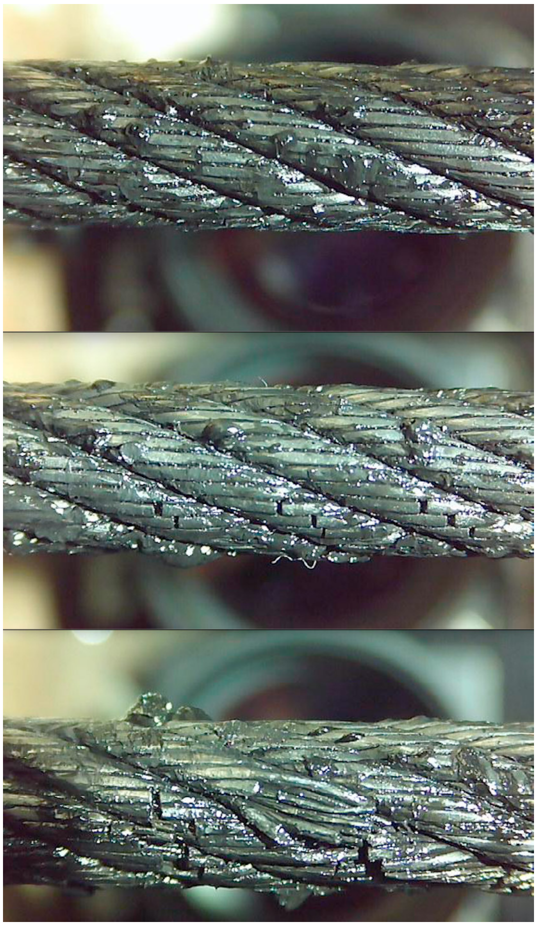

Fig. 6: Test object the wire rope with classified wear development due to the load intervals (above slight wear, middle 60% wear and below wear limit reached)

5. Conclusion

The presented image processing system and methodology enable a location-independent real-time monitoring and analysis during experimental investigations. Experimental investigations are necessary for complex stress conditions, where a purely theoretical calculation of the lifetime of the test objects is not possible.

In this article a methodology was presented which allows a cost-effective automated execution of continuous load intervals for testing optimization parameters with image processing and machine learning for product and technology development. This leads to an increased resource efficiency on the material as well as on the personnel side, as on the one hand the meaningfulness and traceability of the performed experiments can be increased and on the other hand experts responsible for the execution of the experiments can be employed in a time-efficient way, if defined and meaningful events have actually occurred.

Due to the modular design and the adaptability of the hardware and software, the presented setup can be used for a variety of applications in research and industry. It could be shown which direct added value the application of ML offers for product and technology development outside the usual industrial areas, such as quality assurance. Furthermore, the generated data are suitable for reuse for predicting the lifetime of the measured objects in the finished products or technologies, which offers a direct added value especially for safety-critical components.

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