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AI-supported surface topography characterization of cylinder liners in large ICEs

Digitalizatiion, Connectivity, Artificial Intelligence & Cyber Security

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ABSTRACT

Digitalization provides multifaceted opportunities to enhance internal combustion engine (ICE) technology, thereby addressing global challenges such as climate change, environmental pollution, and conservation of resources. In particular, methods from the field of artificial intelligence and its subfield machine learning have become increasingly powerful in recent years. This study focuses on facilitating a condition monitoring approach for the running surface of cylinder liners in large ICEs, which provides an opportunity to avoid out-of-spec function, unforeseen downtime, and premature component replacement. This approach requires quantitative condition detection of the running surface topography. However, accurate in-situ surface topography measurements are currently not possible. The current reference method requires disassembly and cutting of the liner before the surface topography can be measured with a sophisticated confocal microscope. Correspondingly, component reuse and further condition assessments at later stages become impossible. This paper presents an approach that overcomes this issue: the combination of surface images obtained with a simple optical device and deep learning. To develop the deep learning model, a database consisting of approximately 100 liners from INNIO Type 6 gas engines with varying histories was created from scratch. First, the liners were cut and high-resolution depth maps of relevant surface areas were measured following the reference method. Second, comparatively low-resolution RGB reflection images of the same areas were taken with a simple handheld microscope. By employing convolutional neural networks and adversarial learning techniques, the reference equivalent can be predicted from simple device images. This enables the reliable prediction of the surface topography and yields derived information with sufficient accuracy for detection of liner running surface condition. It is expected that the training database must be expanded to further enhance prediction accuracy. Since sourcing, cutting, and measuring of suitable cylinder liners requires considerable effort, a concept that generates a generic database for model training is presented. Geometries similar to those of a liner honing structure are created in a sandbox and measured with a stereo vision camera that provides both depth and reflection images. This permits easy and quick generation of a large amount of data. These images can be utilized to train deep learning methods similar to those employed for the liner images. Current research focuses on evaluating whether real liner depth images can be accurately predicted with a model trained with generic data. Field application of the investigated approaches is thought to be possible and has the potential to enable condition-based and predictive maintenance approaches.

1 INTRODUCTION

Large engines are well established energy converters in applications such as power generation and transportation on land and at sea [1–3]. Digitalization provides multifaceted opportunities to enhance internal combustion engine (ICE) technology, thereby addressing global challenges such as climate change, environmental pollution, and conservation of resources [4].

Condition monitoring (CM) and related condition-based maintenance (CBM) and control approaches for ICEs are key tools to increase engine durability and to conserve resources by exploiting more of the useful lifetime of engines and their components while avoiding critical operating conditions due to wear and failure [4]. In the recent past, the extensive instrumentation of ICEs and their subsystems as well as the availability of advanced and powerful machine learning (ML) data analytics methods have resulted in a variety of CM, CBM, and control concepts for entire engines [5–7] as well as for individual components such as sliding bearings [8–10], flexible couplings [11, 12], torsional vibration dampers [11, 13], fuel injectors [14–16], and cylinder liners [17–20]. Such concepts are particularly relevant for large ICEs since the effort taken for CM is comparatively small in relation to the overall engine investment at stake. In addition, the trend is for the spatial restrictions for instrumentation to decrease as engine size increases.

1.1 The condition monitoring process

Condition monitoring (CM), the process of which is illustrated in Figure 1, is defined as “activity, performed either manually or automatically, intended to measure at predetermined intervals the characteristics and parameters of the physical actual state of an item” [21]. According to Weck [22] and based on similar summaries in [4, 9], CM can be divided into the following subtasks:

1. **Condition detection**: One or more informative parameters reflecting the current condition of the machinery are acquired.
2. **Condition comparison**: The actual condition is compared with a reference condition of the same parameter, thereby generating “symptoms” as input to the diagnosis task.
3. **Diagnosis**: The results of the condition comparison are evaluated and the type and location of failure are determined.

The diagnosis results determine which of several subsequent activities is triggered:

- **Wear/damage compensation**: Impaired machine performance caused by wear or other forms of damage may be fully or at least partly compensated for by control systems which ensure minimal performance losses for as long as possible [22].
- **Preventive maintenance**: Early failure indicators may also be used for preventive maintenance, which is defined as “maintenance carried out intended to assess or to mitigate degradation and reduce the probability of failure of an item” [21]. In Figure 1, the preventive maintenance is additionally classified as **condition-based** since it includes “assessment of physical conditions, analysis and the possible ensuing maintenance actions” [21]. If a forecast of significant parameters of the degradation of the item is involved, CBM can be subcategorized as “predictive” [21].
- **Corrective maintenance** is “carried out after fault recognition and intended to restore an item into a state in which it can perform a required function” [21].

As outlined in detail in [4], the potential of ML approaches may be exploited in various ways within the three subtasks of CM and the additional activities following the diagnosis. The present study focuses on the condition detection subtask. The challenge is that the informative parameter (or more generally the relevant information) for condition detection cannot be directly measured by a related sensor. Thus, a virtual sensor concept is employed in which a different type of information is measured and used as an input to a data-driven model that predicts the actual information needed for condition detection. The data-driven approach is required because a physical model would be either too complex or not accurate enough.

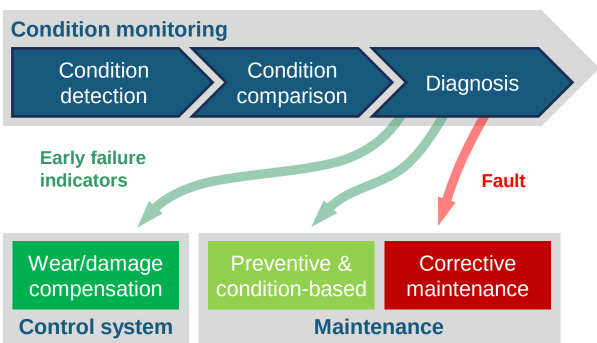

Figure 1: Condition monitoring process and subsequent activities based on Weck [22].

1.2 Cylinder liner condition detection

The specific technical problem dealt with in this study is the condition detection of the inner surface of cylinder liners, which acts as a running and sealing surface for pistons and piston rings and is thus critical to failure-free operation of the engine [23]. The tribological interaction in the piston-piston ring-cylinder system is determined by surface characteristics and the surface topography in particular [23].

One well-established process that achieves a defined and appropriate surface topography is the plateau honing process. On the one hand, it creates a fine plateau structure to minimize friction. On the other hand, comparatively deep grooves with a defined pattern ensure optimal oil retention [23]. Figure 2a) presents an example section of a surface topography from a plateau honing process. Such a surface structure can be characterized by a material ratio curve (MRC, also known as Abbott-Firestone curve, cf. Figure 2b), which represents the height of a relative share of the surface which is exceeded by it [24–26]. To describe the essential topography of a surface in compressed form, texture parameters according to EN ISO 25178-2 can be derived from the material curve [27]. They include the core height (Sk), the reduced peak and valley heights (Spk and Svk), the material ratios of the peaks and valleys (SMr1 and SMr2), the peak material volume (Vmp), and the valley void volume (Vvv). During engine operation, the liner is subject to continuous wear because of the relative movements and related metal-to-metal contacts in the piston-piston ring-cylinder system. In turn, this leads to deterioration of the liner running surface (i.e., an unfavorable change in surface topography), which impairs hydrodynamic lubrication and increases friction and thus the risk of damage to the engine [24].

Condition detection of cylinder liners is particularly challenging because the running surface is not accessible during engine operation. Indirect methods such as vibration measurement or lubricating oil analysis permit continuous monitoring [28]. In particular with the latter, however, quantitative and position-related wear determination is not possible. In contrast, position-related wear assessment of the inner surface of the liner based on subjective visual inspection with the naked eye is feasible during engine standstill, but precise quantification is not possible. Given the fine surface structure, this can only be achieved in a process involving high-performance microscopic surface topography (i.e., depth) measurements which require the liner to be disassembled, cut into segments, and then examined in a laboratory, cf. Figure 3a). Due to the necessary destruction of the cylinder liner, further use and repeated measurement of wear is impossible.

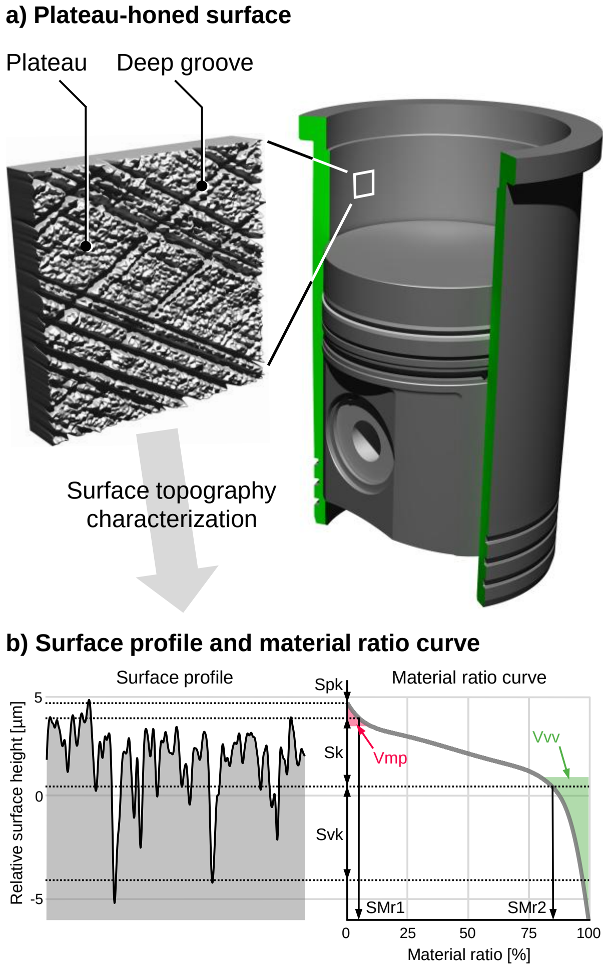

Figure 2: Cylinder liner plateau honed running surface and corresponding topography characterization by the material ratio curve.

The objective of the present study is to investigate if this issue can be overcome by a simplified process (cf. Figure 3b) in which ordinary color (RGB) surface images are obtained with a comparatively small and simple optical device that fits into the cylinder bore (e.g., mobile phone camera or small handheld microscope) and then used to acquire reliable, quantitative surface depth information with the help of computer vision methods, cf. Section 2. In turn, this could facilitate an overall CM approach for the running surface of cylinder liners in large ICEs, which provides a valuable opportunity to avoid out-of-spec function, unforeseen downtime, and premature component replacement.

While the main goal described above (including related subtopics) has already been pursued in previous studies [17–20], this paper also presents a novel approach to extending the training database for the computer vision methods to include generic data. This has the potential to significantly reduce the overall effort require to generate a sufficiently large training database.

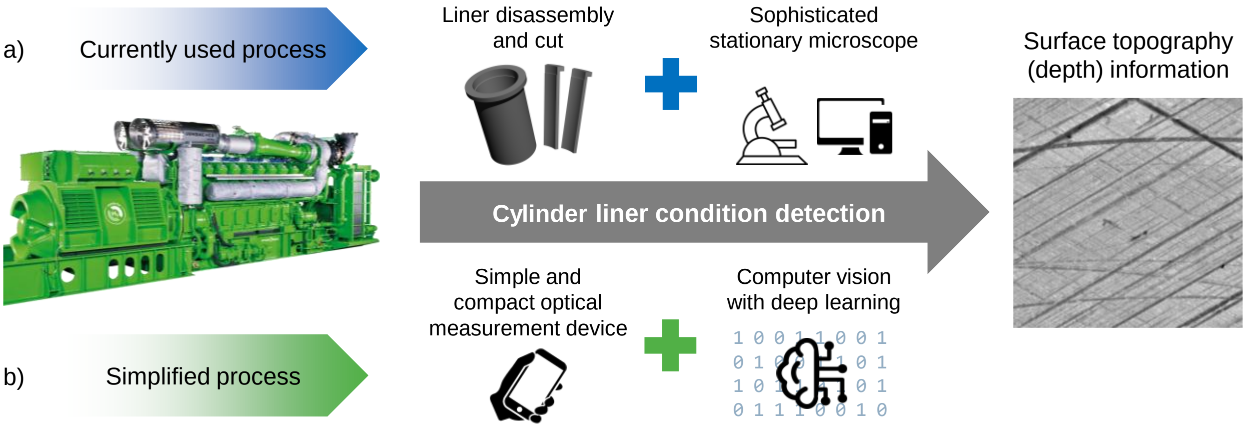

Figure 3: Comparison of currently used and simplified cylinder liner condition detection processes.

2 GENERAL METHODOLOGY

[4] describes how the usage of ML data analytics methods for enhancing large engine technology is commonly based on specific technical objectives in combination with the hypothesis that the correlations inherent in an associated database will allow these objectives to be achieved with ML approaches. Such hypotheses are often generated by experts who have significant domain knowledge in the field of large ICEs. To determine whether a hypothesis can be confirmed, the data-driven methodology illustrated in Figure 4 is applied by the Large Engines Competence Center (LEC). Indicated by the three arrows, it covers the entire spectrum from data generation to knowledge discovery and knowledge application.

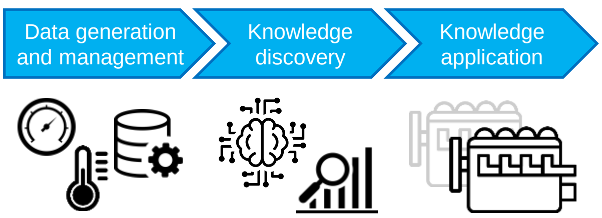

Figure 4: The data-driven methodology applied by LEC [4].

Data generation and management, the first stage, deals with methods that generate, acquire, transmit, and store data, yielding a database that provides a solid foundation for further tasks as described below. The selection of suitable measurement parameters and the employment of advanced sensor and data acquisition systems play key roles. Design of experiments (DoE) is a valuable tool for efficiently generating databases suitable for employment in a data-driven context.

In the ***knowledge discovery*** stage, the overall objective is to obtain new insights, expressed as the discovery and the modeling of still unknown or unconfirmed correlations. In addition, there is the potential to obtain a significant gain in domain knowledge by considering the entire spectrum of different ML and statistical methods [4]: From explorative correlation analyses to easily interpretable statistical regression models, to classical ML methods such as clustering algorithms or support vector machines, to highly sophisticated neural networks for deep learning, a problem-related trade-off between the required complexity, interpretability, and performance is achieved. This ensures that models are both accurate and as easily understandable as possible. The obtaining of new insights through the utilization of optical data in particular falls into the domain of computer vision, an interdisciplinary research field that studies how machines process and interpret image data. Today a vast number of implemented solutions are based on artificial intelligence or ML methods. They have achieved outstanding results in various applications, especially with deep learning—a subfield of ML that is essentially based on deep neural networks.

In the last stage of the data-driven methodology, ***knowledge application*** is achieved either by integrating technology in an application (e.g., virtual sensor in a CM/CBM framework, as outlined in Section 1) or by taking the knowledge gain as an incentive for further research and development work.

In the present study, the main hypothesis is that a correlation exists between the information contained in an ordinary RGB image of a liner running surface and the corresponding surface topography, i.e., the related surface depth information. The data-driven methodology is applied to evaluate whether this hypothesis can be confirmed and if the correlation (given its existence) is significant enough to be employed in the pursued condition detection application.

One of the main challenges emerges right away in the data generation and management stage. The first and obvious approach (Figure 5a) was to source, cut, and measure real cylinder liners. A corresponding image database was created relying on both sophisticated reference and simple hand-held microscope measurements to obtain depth and RGB image information, respectively, at the same cylinder liner running surface locations. However, the database in its current state is comparatively small for computer vision purposes (2,850 image pairs from approximately 100 cylinder liners) and its generation involved considerable effort, which will make it difficult to significantly expand the database in the future. Yet expansion of the database could be the key to enhancing the accuracy of related data-driven models generated during the knowledge discovery stage that predict surface depth information from RGB images.

a) Real liner approach

Real liner image database obtained with sophisticated reference and simple hand-held microscopes

Advantages/disadvantages

- + Real cylinder liner problem data
- − Large database creation effort
- − Comparatively small database created

b) Generic approach

Generic image database obtained with sandbox and 2-in-1 monocular/stereo vision camera

Advantages/disadvantages

- − Data similar to real problem but not the same
- + Low database creation effort
- + Comparatively large database created

Figure 5: Real liner vs. generic approach for image database generation.

As a result, a second, generic approach to database generation (Figure 5b) was followed. In this approach, a “sandbox” was used to replicate groove and plateau structures as they are found on the running surface of real liners. These structures were then measured with a 2-in-1 monocular/stereo vision camera able to obtain depth as well as RGB data of the same structure. Overall, the process of structure generation and related measurement is simple and fast, allowing efficient generation of a large database. 5,000 image pairs have been created, but the potential exists to significantly extend the database with comparatively little effort (a few weeks compared to several months or even years with the real liner approach). Yet despite its similarity, the image data obtained does not include real liner structures. It must be explored whether and to what extent it is possible to use models trained on the generic database in a real liner data environment (or how these models could be transferred to the real liner environment).

Following the framework of the presented data-driven methodology, sections 3 and 4 outline in detail the real liner and the generic data generation pathways as well as the related modeling tasks in the knowledge discovery stage, evaluating their potential for application.

3 REAL LINER DATABASE GENERATION AND MODELING

To directly evaluate the potential of simple optical devices and deep learning as an alternative to the current destructive reference method, the same in-cylinder surface areas were measured following both approaches. The previously cut liners were also measured using the simple alternative approach. To ensure the comparability of the measured surface sections, specially tailored mechanical equipment was employed for supporting data acquisition at the exact same measurement locations with both approaches, cf. Figure 6.

Figure 6: Cylinder liner segment support device for sophisticated stationary reference microscope measurements (left) and liner segment holder for simple handheld microscope measurements (right).

Two segments were cut out of each liner being measured: one containing the area near top dead center (TDC) parallel to the piston pin axis (where the highest surface wear is expected) and one containing the area near bottom dead center (BDC) perpendicular to the piston pin axis (where no surface wear is expected since the piston does not come into contact with the running surface there). Surface wear at the area near top dead center can be evaluated by comparing its surface topography with that of the reference area near bottom dead center. To enhance the probability of observing variations in surface topography changes, liners with varying operating hours were considered, ranging from 2,550 h to 30,000 h. More than 100 liners from

Type 6 gas engines manufactured by INNIO Jenbacher GmbH & Co. OG were obtained and measured using both approaches, thereby providing a comprehensive representation of the spectrum of surface topographies associated with different stages of cylinder liner wear.

In each measurement area, up to 15 distinct measurement positions representing non-overlapping sections were optically measured with both the high accuracy stationary reference device [29] and the handheld microscope [30]. While the confocal microscope is capable of acquiring both depth images and RGB reflection images of the same surface section, the handheld device is limited to capturing RGB images of a larger surface section. To compensate for the differing image sections, resolutions, and minor tolerances of the measurement equipment (relevant for the handheld measurements in particular), a postprocessing step was carried out in which the images from both approaches were registered algorithmically (i.e., pixel-wise alignment using a mutual information criterion). Figure 7 illustrates this data generation process for the real liner approach. Throughout the creation of the database over the course of a multi-year research project, the process underwent continuous enhancement and slight adaptations.

For example, explorative data analysis and initial results showed that there was only a small gain in information from very high-resolution depth images compared to those with slightly lower resolution (4407 × 4395 pixels vs. 1104 × 1101 pixels). Therefore, the resolution of the depth images from the reference method was reduced in order to minimize measurement effort and increase storage efficiency. In addition, the exposure settings for the RGB images obtained with the handheld microscope were gradually optimized. A total of 2,850 image pairs were obtained with the final setting (which also includes remeasurement of previously measured liners). They represent the final basis for all data-driven modeling approaches. While prior results may have been derived from older database versions, the validity of the conclusions remains unaffected.

The stated problem of replacing the demanding surface evaluation process with the reference method by using simpler optical methods was handled primarily by means of deep learning. Within the field of deep learning, there are a variety of approaches that differ significantly in their architecture and their manner of tackling a problem. All levels of surface information (i.e., depth/RGB image, MRC, or surface texture parameters) could serve as targets for deep learning approaches.

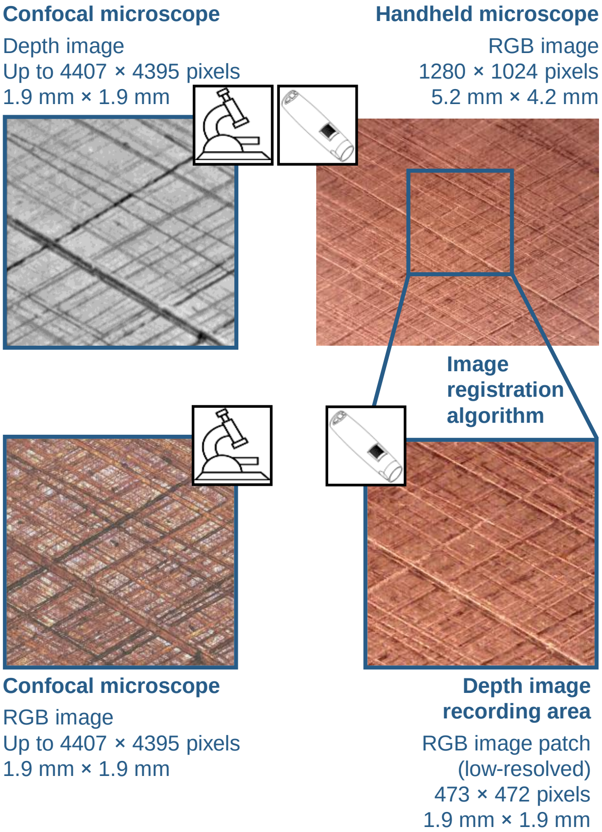

Figure 7: Comparison of data generation with reference device (depth and RGB image) and handheld microscope (RGB image only).

There are two main types of machine learning: Supervised learning relies on known target data and unsupervised learning does not rely on this type of information [31]. With a generative adversarial framework [32], there is also the additional option of learning the generation of a target and critiquing whether it is realistic. To process image inputs such as the surface RGBs, a convolutional neural network (CNN) is commonly used, which extracts the relevant information from the image based on the inherent grid structure of the pixels. For CNNs as well, a wide variety of network architectures exist depending on the specific purpose, e.g., the so-called U-Net for image segmentation. Generative adversarial networks (GANs) are a widely used and effective method for image-to-image translation.

Given all these options, several modeling approaches have been investigated. Table 1 summarizes some of the studies already conducted. All basically demonstrate that the approach that simplifies the condition detection of cylinder liners is technically feasible.

Table 1: Summary of the most significant implemented approaches and studies

Study	Input(s) & Target(s)[1]	Approach
[17]	RGB_HR → Depth Depth → RGB_HR	RGB to depth reconstruction (and vice versa) using supervised CNN (U-Net) with physics-based reconstruction term
[18]	RGB_LR → Depth	GAN (U-Net generative function, DCGAN adversarial function) with uncertainty-aware loss
[19]	RGB_LR → MRC	Two-stage MRC prediction via explicit surface texture parameter prediction (both CNN-based, supervised)
[20]	RGB_LR ⇌ Depth	Cycle-consistent GAN for RGB to depth translation and vice versa with perceptual reconstruction loss

[1]“RGB_HR” and “RGB_LR” refer to the high- and low-resolved RGB images, respectively, “Depth” to the depth images, and MRC to the material ratio curves derived from the depth images.

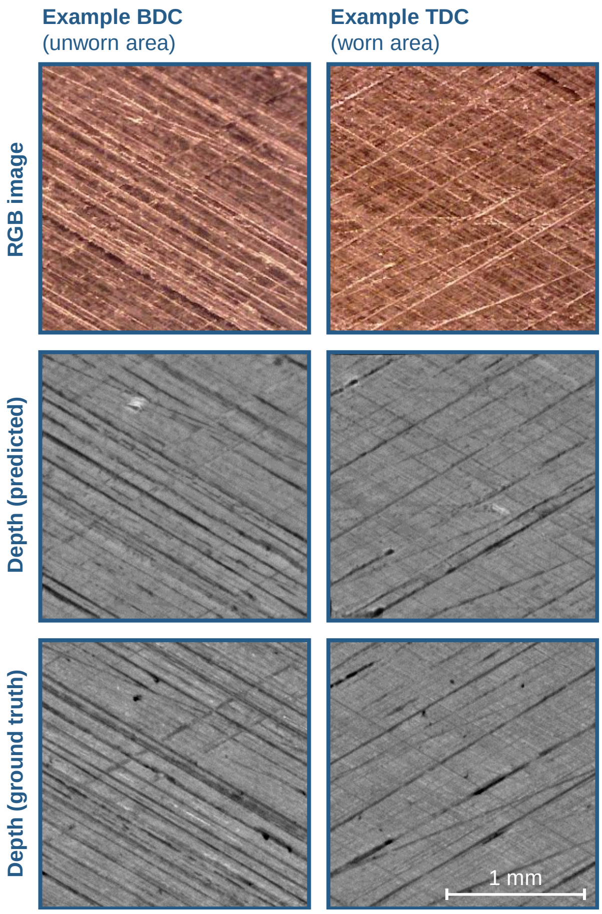

Figure 8: RGB input image, predicted depth image and measured depth image at two example positions on the cylinder liner running surface.

Considering that the depth bandwidth of the liner surface is about 10 µm, fairly accurate results have been achieved: a mean absolute error of 0.465 µm for the depth image and 0.102 µm for the MRC prediction, both evaluated on unseen data not used during training [4]. Figure 8 illustrates example results from BDC and TDC positions of the cylinder liner running surface (unworn/worn areas) in which the depth images have been predicted from low-resolved RGB images. The measured depth images serve as a ground truth reference for comparison. In addition to depth image prediction, an uncertainty quantification approach elaborated in [18] allows detection of quality deficiencies in the input images, thereby strengthening the reliability of the results.

Although the potential of simple optical devices and deep learning for cylinder liner surface assessment has been extensively studied and the feasibility of this approach has been successfully demonstrated, data generation to further develop the approach remains challenging. For deep learning (and ML in general), however, the opportunity exists to use different but similar data to train and improve the models. In addition to the real liner approach, a related generic database generation and modeling approach was therefore developed as outlined in section 2; it is further elaborated in Section 4.

4 GENERIC DATABASE GENERATION AND MODELING

Two criteria must be met to generate a comprehensive generic database of RGB and depth images similar to real liner optical data in a convenient, fast and generally efficient manner: On the one hand, the approach must be able to swiftly and flexibly generate artificial groove and plateau structures (mimicking the liner running surface) by hand. On the other hand, these structures must be created at a larger spatial scale than that of real liners so that standard stereo vision depth cameras may be used. The ENGinnSAND database was created to meet both of these criteria. It is available publicly and free of charge on the internet at https://lec.at/go/ENGinnSAND.

The key idea behind ENGinnSAND is to generate groove and plateau surface structures with easily shapeable sand—as in a Japanese dry garden. Figure 9 shows the specially tailored experimental setup that includes a sandbox, illumination devices, and a stereo vision camera. With internal dimensions of approximately 70 × 42 cm, the sandbox is easily handled by human operators and the generated surface topographies can be accurately measured with standard stereo vision cameras. The present study employed an Intel RealSense D415 camera [33] capable of recording both depth and RGB images of the same scene. Two separate light sources allow the evaluation of different types of illumination. In ENGinnSAND, groove and plateau structures in the sand were shaped manually by a human operator with several specific V-shaped tools. Other tools may be used to create more structures and shapes. In addition to the variety of shape options, the type and size of the sand may be varied. In this way, the generic approach is applicable not only to liner surfaces, but also to a wide range of different yet similar depth surface prediction problems.

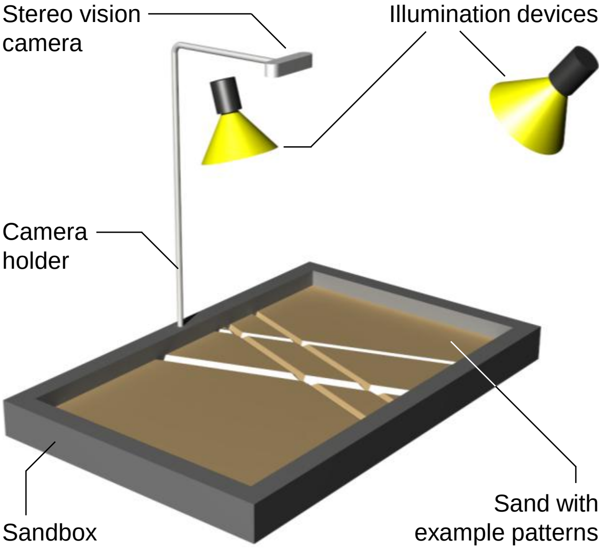

Figure 9: Experimental "sandbox" setup used to generate a generic image database with groove and plateau structures.

The final ENGinSAND database consists of a total of 5,000 recorded scene pairs of RGB images and corresponding depth images (distances of 480 mm to 530 mm measured, resolution of 720 × 1280 pixels for both image types, cf. selected square image sections in Figure 10). Similar to the real liner approach, this data can be used for modeling with computer vision methods. For example, [34] studies a so-called hybrid Radon transform network for depth image prediction, where usage of both image and Radon space (i.e., transformation via the Radon transform function) has been demonstrated to be beneficial compared to separate CNNs (U-Net). Figure 11 shows example results for three selected groove and plateau structures in which the depth images have been predicted from low-resolved RGB images. The measured depth images serve as a ground truth for comparison.

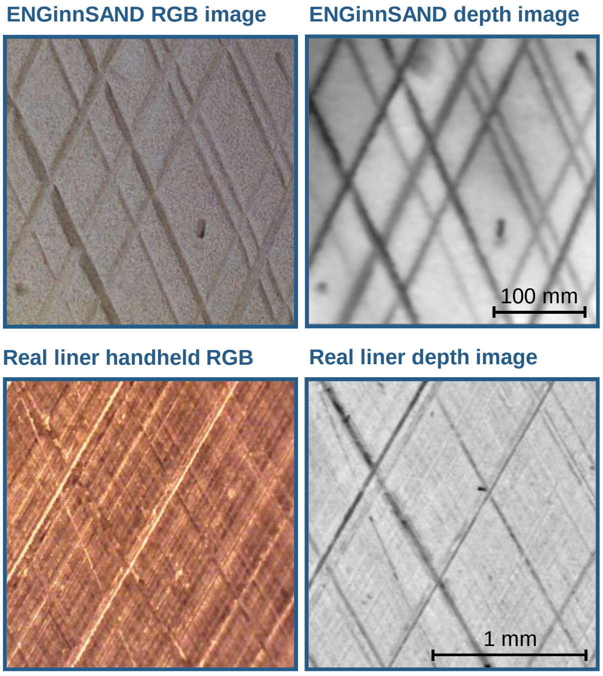

Figure 10: Comparison of ENGinnSAND RGB and depth image sections and real liner approach image sections of handheld RGB and reference depth image.

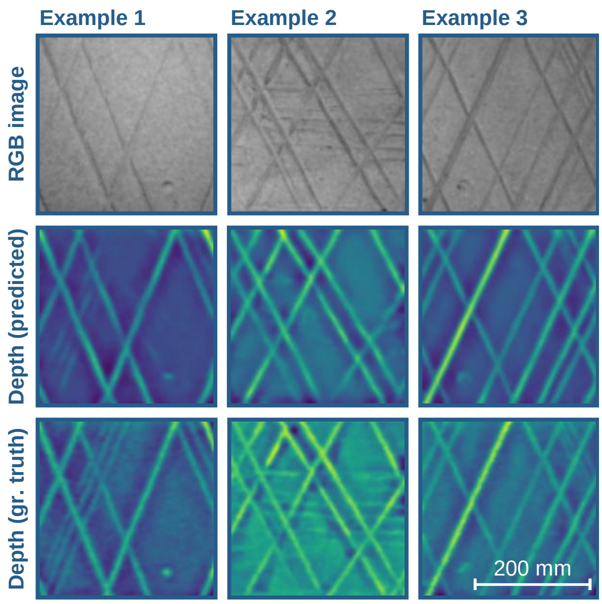

Figure 11: RGB input image, predicted depth image and measured depth image for three example groove and plateau structures.

For the depth ranges modeled in the sand, which have a bandwidth of approximately 25 mm, again fairly accurate results have been achieved with unseen validation data [34]: a root mean squared error of 0.79 mm for the depth image prediction and mean absolute error of 0.25 mm for the MRC prediction. These errors have the same order of magnitude as the errors of the real liner approach (0.465 µm and 0.102 µm, respectively, at 10 µm depth range, cf. Section 3). Thus, the results obtained motivate using the surrogate surface images of the ENGinnSAND dataset to train and correlate the real linear RGB reflection and depth images.

Current research focuses on using the data-driven model from the generic approach to predict real liner depth images (i.e., using real liner RGB surface images as model input), which poses some additional challenges. While the different target depth ranges can be easily aligned via linear rescaling (normalization), a preprocessing step to align the input images with the color or grayscale histograms is essential to producing valuable model output. Yet given the optical comparison in Figure 10, the comparable magnitude to the results obtained, and the capabilities of ML-based computer vision approaches in general, a considerable information gain is expected from the generic approach with regard to previously developed or even entirely new deep learning approaches. Once the real liner and generic pathways are merged, relatively little effort would be needed to extend the generic database, permitting an investigation of the potential to further increase prediction accuracy.

5 FIELD APPLICATION POTENTIAL

Promising results have been achieved with the real liner approach for simplified surface structure characterization. With the generic approach, there is great potential to further enhance prediction accuracy due to the comparatively low effort required for training database extension. However, several additional technical challenges need to be addressed before the measurement procedure for real cylinder liners can be advanced towards a low-cost image acquisition device for use on production engines in the field.

Particularly challenging for on-site application are the cleaning of the liner surface (i.e., the removal of oil deposits), the establishment of defined exposure conditions, and the fixing of the position of the optical device with respect to the investigated surface area. During the investigations performed so far under laboratory conditions these challenges have not been of major concern. Although a detailed discussion of technical solutions to address these issues is beyond the scope of this study, they are considered to be technically feasible.

While the handheld microscope used in this study fits into the bore of the INNIO Jenbacher Type 6 engine (bore diameter 190 mm), the cylinder head still needs to be removed to investigate an area of interest in the combustion chamber. Optical data obtained from the fully assembled engine, e.g., with an endoscope through a bore in the cylinder head, would require less effort for engine disassembly but likely pose additional challenges such as lower achievable RGB image quality and thus lower quality of surface topography characterization. In addition, the previously mentioned challenges of surface cleaning, exposure definition, and measurement position fixation would be made more difficult, if not impossible, to overcome.

The primary benefit of implementing the real liner approach lies in its scalability, a feature that is particularly advantageous for entire engine fleet applications. While there are microscopic solutions for highly sophisticated surface measurement—at least for automotive applications—that could potentially be utilized on-site, these methods are often accompanied by substantial costs for the required measurement devices, akin to the microscope employed in the reference method (e.g., factor 20–100 compared to the handheld microscope employed for the real liner approach). Thus, such devices are unlikely to be employed extensively in large numbers in the field.

A well-established, fleet-wide, low-cost solution for quantitative cylinder liner wear assessment can facilitate a distinct shift from predetermined maintenance (combined, to some extent, with qualitative CBM) to a proper quantitative CBM approach, thereby lowering the risk of unnecessary, costly premature component replacement based on maximum operating hours (while the cylinder liner might not have reached its end of service life) as well as false positive qualitative wear detections by service technicians. In addition, comprehensive field application of a quantitative cylinder liner wear evaluation process can generate the knowledge needed to understand liner running surface wear formation and evolution in detail and to model these processes, e.g., as a function of key engine operating parameters. Such models could subsequently be employed in predictive maintenance approaches, potentially reducing costs further by exploiting the majority of the useful life of the liner and scheduling maintenance based on the actual need. Note that the full potential of predictive maintenance is only likely to be developed if the engine (with all its relevant components) is considered as a whole.

6 SUMMARY AND OUTLOOK

This study has focused on evaluating the potential of a simple surface topography characterization method based on computer vision for quantitative cylinder liner running surface wear assessment. The investigations involving the presented data-driven methodology indicate that predicting the surface topography (or derived information) from RGB surface images using data-driven models is technically feasible with an accuracy sufficient for liner running surface condition detection. Two approaches for database generation have been followed:

- A real liner approach, in which a real liner image database is obtained with sophisticated reference and simple handheld microscopes capable of recording depth and RGB images, respectively. This approach has the advantage that it collects real problem data but requires considerable effort for database generation and thus has restrictions in the amount of data available for model training.

- A generic approach, in which a generic image database is obtained with a sandbox and a stereo vision camera capable of recording both depth and RGB images. This approach requires relatively little effort for database generation so that a comparatively large image database could be generated. On the downside, the images appear similar to the real problem but are not identical.

Both databases served to train data-driven models, relying on deep learning approaches from computer vision. It was found that the errors for depth image and MRC prediction have the same order of magnitude. Current research focuses on using the data-driven model from the generic approach to predict real liner depth images (i.e., using real liner RGB surface images as model input). While this poses additional challenges due to the differences in image color/greyscale histograms, a considerable information gain from the generic approach and thus an increase in prediction accuracy are expected with previously developed or even entirely new deep learning approaches.

Field application of the investigated approach to quantitative cylinder liner wear assessment is considered technically feasible but requires the overcoming of specific challenges beyond the scope of this study such as cylinder liner cleanliness as well as defined exposure conditions and positioning of the optical device in relation to the investigated surface area. A well-established, fleet-wide, low-cost solution for quantitative cylinder liner wear assessment can facilitate a quantitative CBM approach, thereby lowering the risk of unnecessary and costly premature component replacement. In addition, data from the field can serve to generate the knowledge needed to further understand liner wear formation and evolution in detail and to model these processes, e.g., as a function of key engine operating parameters. Such models could subsequently be employed in predictive maintenance approaches, potentially reducing costs and engine downtime.

7 DEFINITIONS, ACRONYMS, ABBREVIATIONS

BDC: Bottom dead center
CBM: Condition-based maintenance
CM: Condition monitoring
CNN: Convolutional neural network
DoE: Design of experiments
GAN: Generative adversarial network
ICE: Internal combustion engine
LEC: Large Engines Competence Center
ML: Machine learning
MRC: Material ratio curve
Sk: Surface core height
SMr1: Surface peak material ratio
SMr2: Surface valley material ratio
Spk: Surface reduced peak height
Svk: Surface reduced valley height
TDC: Top dead center
Vmp: Peak material volume
Vvv: Valley void volume

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