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Troubleshooting: a dynamic solution for achieving reliable fault detection by combining augmented reality and machine learning

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Abstract

Today's perplexing maintenance operations and rapid technology development require an understanding of the complex working environment and processing of dynamic and real-time information. However, the environment complexity and an exponential increase in data volume create new challenges and demands and hence make troubleshooting extremely difficult. To overcome the previously mentioned issues and provide the operator real-time access to fast-flowing information, we propose a hybrid solution made of augmented reality further combined with machine learning software. In particular, we present a dynamic reference map of all the required modules and relations that connect machine learning with augmented reality on an example of adaptive fault detection. The proposed dynamic reference map is applied to a pilot case study for immediate validation. To highlight the effectiveness of the proposed solution, the more challenging task of measuring the impact of combining augmented reality with machine learning for fault analysis on maintenance decisions is addressed.

Keywords: Troubleshooting; augmented reality; artificial intelligence; knowledge-based system; maintenance;

1. Introduction

The increasing requirement of reliable, available, maintainable, and safe systems makes traditional maintenance strategies less effective and obsolete [1]. Due to the complexity of the systems and thus the maintenance procedures, in-depth knowledge is needed to detect and resolve failures. However, often the operator does not have this knowledge, and as a result, requires more support for troubleshooting.

Traditionally, the fault diagnosis is based on manual inspection of the machine's health state [2]. However, some maintenance tasks are relying on many dependencies and relations with other assets and systems, and are therefore too complex to be understood by the operator. In modern industrial applications are therefore automatic fault diagnosis methods required, able to recognize the health state of a machine and identify the causes of this state. Such an approach would enable the operator to diagnose failing components in an early stage and hence would make the production flow more effective and efficient.

The ongoing digital transformation of industrial environments and practices in the light of Industry 4.0 is a perfect scene for future automation. In this aspect, the open-ended development of augmented reality (AR) can help in addressing increasing complexities in machinery, and provide remote maintenance, whereas artificial intelligence (AI) and cloud/edge computing can help in the analysis of the collected extensive data sets to automatically diagnose the machine state, perform quality inspections and effectively predict the failure of the machine in advance. The use of the combination of AR and AI hence can further reduce maintenance costs and unexpected downtime [3].

In the context of Industry 4.0, both AR and AI have evolved independently, and are only recently studied in combination [4]. However, most of the existing research in this direction is limited to tasks such as detecting, localizing, and identifying objects by AI approaches in an AR environment [4]. To extend these research fields, AI can potentially be used as a tool in the AR software environment [4].

The literature includes applications of anomaly and structural damage detection for prognostic health monitoring [1]. However, the application of integrating AI with (AR) wearable computing technologies for predictive analytics should be explored further [1]. AI and AR are both individually likely to help advance troubleshooting complex failures and give the operator in-depth knowledge of the problem. The combination and integration of both have the potential to support this even further.

In this paper, the focus is on the integration of the knowledge-based systems (KBS) [5], AI, and AR in new technology, (see Fig. 1 for schematic representation) that can be used as a tool for supporting troubleshooting. The role of the KBS is

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to incorporate the expert's knowledge, and the supporting information necessary for complex maintenance tasks on the operator side [5]. Then AI, in particular machine learning (ML)/deep learning (DL), is used to extract and analyze the desired information. Eventually, this technology element supports the operator by screening failure diagnosis and possible repair instruction. To close the information loop between KBS and AI, and hence contextualize and visualize context- and user-dependent information, the AR element is utilized. The three modules together define a dynamic reference map required to perform automatic fault diagnosis. In this way, all elements are related and connected, and hence will be an important starting point for troubleshooting.

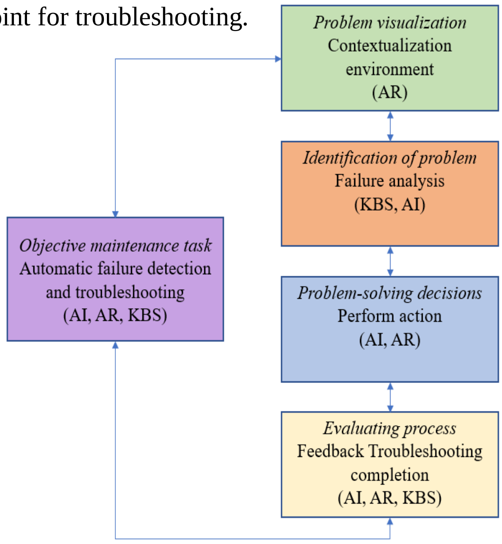

Fig. 1. Relations between KBS, AI, and AR.

The paper is organized as follows: a brief introduction to the KBS, AR and AI for troubleshooting is given in section 2. The technology foundation of the dynamic reference map and all its modules required to map the environment to the troubleshooting procedure is described. In section 3 a case study is analyzed as an early-stage demonstrator. Finally, section 4 concludes the paper and outlines topics for future research.

2. New dynamic reference map

The newly proposed dynamic reference map connecting KBS, AI, and AR modules for automatic fault detection is depicted in Fig. 2 by adapting the KBS architecture presented in [5].

2.1. Initializing reference map

The map starts with the AR user interface that simply ensures efficient communication with the user through menus while having a clear graphical user interface that contextualizes, visualizes, and provides real-time information to the operator. This interface is then coupled to an automated data acquisition facility which transfers real-time data captured by the operator, its problem-solving expertise, and/or other information sources to an AI module. Since AI is capable enough to recognize, classify and predict the expected health state of a machine, this module is also referred to as an inference control engine [6]. This module acts as the brain of the system that uses the rule interpreter to execute a forward chaining algorithm and selects a methodology for reasoning. Next to the acquisition data, the control engine also uses data available in the information inference source, where the knowledge needed for understanding maintenance, in the form of manuals, figures, videos, and documents is stored. Finally, the decision rule module is detecting if additional data are required. Hence, the inference control engine uses input data and decision rules to automatically diagnose a failure and identify the corresponding maintenance tasks with the help of the appropriate ML/DL model. Failure diagnostics are then reported to the user interface and the operator is provided with maintenance tasks required to resolve the fault.

2.2. Technology foundation

The novelty of this research is based on combining AR spatial mapping with the processing power of AI while visualizing the results directly in AR. Data is collected from the KBS to supply supportive information. When these modules are connected, one may trace whether the operator understands the real-time information or not, by comparing performed activities with the suggested or expected activities. Similarly, monitoring of maintenance activities, as well as capturing of outcomes becomes possible. These data can be further used to improve the AI system for future maintenance activities. Eventually, connecting KBS, AI, and AR releases the contribution of human labor and automatically recognizes the health state of a machine.

2.2.1. KBS module

Maintenance operators are mostly experts in the field and have specific domain knowledge that consists of experience, expertise, judgement, and the knowledge about methods required to solve complex maintenance problems.

Capturing and formalizing the previously described knowledge is the main focus within the information inference stage, which applies logical rules to the knowledge base to deduce the new information that can directly be used in maintenance operations [7]. When maintenance procedures are standardized, reliability prediction information can

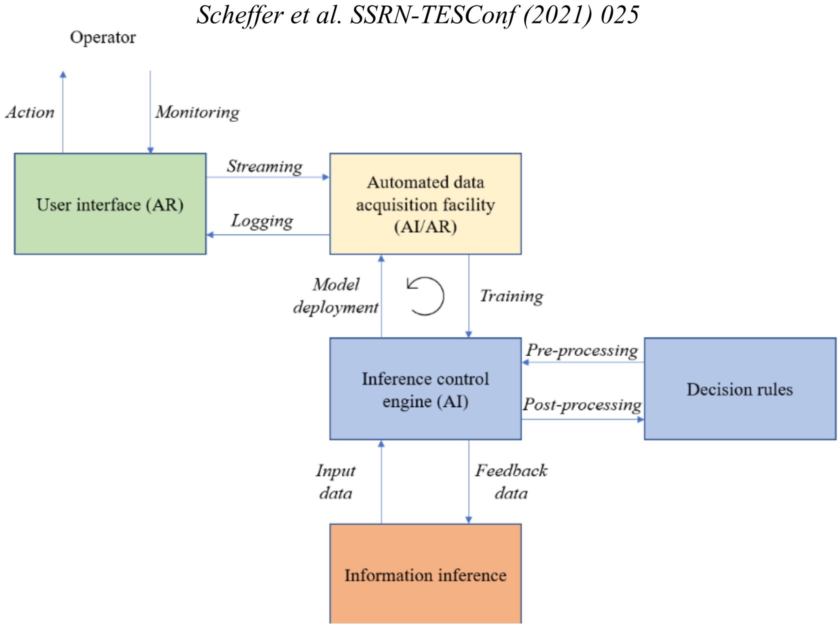

Fig. 2. Dynamic reference map.

be collected and used as input data for the information inference. From the standardized procedures, requirements and boundary conditions can be set. However, when procedures are standardized, the support given to the operator will not be dynamic. Therefore, the information inference requires the user to continuously feed the system with new data. When a service task or fault diagnosis is resolved, the operator must replenish the information inference with new information. Hence, this new information supports the maintenance procedure in establishing new strategies.

To conclude, the information inference must be synthesized after every task performed by the troubleshooting tool.

2.2.2. AR module

The AR module in the proposed dynamic reference map can successfully assist maintenance operators in improving their overall productivity by corresponding automatic object recognitions and inspection of the machine or its parts. Similarly, maintenance tasks can be visualized and screened according to the failure diagnostics. This is achieved by visualization and contextualization of data stored in an intelligent data acquisition facility, a link to the AI module, that couples the maintenance instructions, the maintenance information systems, and the environment together. Data captured in the intelligent acquisition facility help the operator diagnosing faults correctly, by e.g. showing only the appropriate information which is normally not visible without AR. Therefore, the readability of text instructions in AR should be sufficient and simplified. Furthermore, the use of visual elements is partially encouraged [8] by translating as many text instructions to (2D or 3D) graphic symbols, if possible. When maintenance information is supplied properly to the operator and feedback on data acquired, proper failure diagnosis and repair can be guaranteed. However, to make use of AR solutions in different applications, the new authoring manuals for automatic failure diagnosis have to be within Industry 4.0 principles [9]. This offers structured and real-time communication by using automated augmentation of message elements and improves efficiency in terms of time and error reduction. Next to this, standardized communication between cyber-physical systems, the operators, and the environment is desired. Similarly, the performance data collected during diagnosing and repairing operations, have to be marked, tracked and captured for further improvements of the system. Hence, the AR module has to provide a digital and contextualized version of technical documentation, exchange real-time information, and be highly flexible. To achieve this, the specific hardware-software choice for the AR module has to be made based on the user and maintenance requirements [10]. Any hardware solution that interacts with human senses (e.g. tablets, Head Mounted Displays (HMD), hand-held devices, projectors, and headphones) can be an option. Based on the desired quality, resolution and environment conditions, these can be marker-less or marker-based AR systems [9]. The decisions on when, how and which type of AR can be used highly depends on the clarity of existing information on the operation application, specific maintenance tasks, and the end-user [11]. This decision can be made throughout the development and use phase since standardized communication allows multiple AR solutions to fit the system, and to be changed over time.

2.2.3. AI module

Over the years, an increasing amount of data is gathered from machines leading to more useable diagnosis results. To automatically learn features given the input monitoring data and hence recognize the health state of machines [6], one can use the inference control engine (AI module). Inference control engines can be classified into four categories: (1) rule-based reasoning, (2) fuzzy-logic-based reasoning, (3) ML/DL-based reasoning, and (4) case-based reasoning [6]. In the case of ML/DL reasoning, the correct workflow in intelligent maintenance operations and adequateness of decision rules highly depend on the accuracy and prediction of ML/DL models [12]. To diagnose failures of the tracked equipment and/or component, the appropriate ML/DL model, as well as, the dataset of sufficient size and quality have to be identified. Therefore, sensible decisions on the collected data type and handling are required. For example in predictive maintenance based on ML/DL approach, large datasets are required. This is often not feasible as the data are often not available in the public domain [12], or not collected at all. Although real-time data is preferred over laboratory data, the latter ones are more often used due to their availability. The main challenge is, however, these datasets do not contain the disturbing features or records of subcomponents of the machine [12].

The choice and optimality of a suitable ML/DL model on the other hand depend on the chosen AR module, which is to be complemented by AI. In general, ML/DL models are used for image classification and object detection given the data collected by the AR module [4]. Image classification, as a predecessor to object detection, recognizes the scene and labels it to the corresponding class. Furthermore, object detection is used to recognize the objects in the scene by for example bounding box method or similar. Besides the mentioned AI applications in AR, the inference control engine also captures the performed tasks.

To develop a decision-making engine, DL can be deployed for big data scenarios. ML/DL-based diagnosis procedures consist of two steps: (1) big data collection and (2) automatic diagnosis [6]. Once the dataset is collected, the manually extracted data features [6] are mapped to the corresponding failure class via classical ML models [3]. However, this type of modelling requires complicated features engineering in contrast to the DL approach. Following this, the main objective of the inference control engine is to identify the optimal supervised, semi-supervised or unsupervised ML/DL model within a defined computational timeframe. Utilizing the results from the ML algorithm requires special interpretations [4] that depend on the characteristics of the dataset, the chosen algorithm, parameter setting, and the expected output [4].

For effective maintenance interventions, discernment in the model's interpretability, explainability, and accuracy is of the utmost importance. Hence, the model verification and validation have to be analyzed according to the preset objectives.

Finally, the outcome of the inference control engine provides machine diagnostics for the operator. Consequently, when combining KBS, AI, and AR, a new maintenance strategy can be established to support the operator.

3. Real application troubleshooting

To enhance the knowledge and understanding of the process behind the reference map, a case study is executed. To validate the dynamic reference map, the proposed process is implemented in an early-stage demonstrator. Eventually, a questionnaire is employed to reflect on the case study.

3.1. Case study

The case study comprises automatic failure detection, which combines KBS, AI, and AR for troubleshooting. The case has been selected based on the data given by diagnosis experts from a machine manufacturing company. These modular machines produce lay-flat photobooks and other premium print-on-demand products.

The company provided over 20 hours of interviews to identify current processes and solutions in the classification of well-produced book blocks. Based on the interviews, a Failure Mode and Effects Analysis (FMEA) is performed and revealed that the book spine is mostly printed incorrectly [13]. More specifically, when the moving table and the rotating drum are not aligned, the book spines are not produced correctly.

A book spine is classified as good or bad, and is bad if: (1) the book spine is uniformly leaning, (2) the book spine is one-sided leaning, (3) the book spine has a bulbous shape, or (4) the book spine has a hollow shape.

3.2. Early-stage demonstrator

The troubleshooting demonstrator comprises three main components: (1) an information inference to store the transferred data, (2) an HMD for the operator with an AR application using the HoloLens 2, and (3) the AI intelligent control engine. The system overview, along with the software and hardware is presented in Fig. 3.

For the information inference, interviews are performed with operators. Besides this, operating manuals, maintenance instructions, notes, videos, images, and CAD files of the machine are structured and stored. As the access to the real-time data from the machine was not available, images of badly produced book blocks are collected.

To identify the appropriate maintenance task, the image of the book block has to be classified appropriately. To achieve this, the convolutional neural networks (CNN) are offline trained on a balanced dataset of bad and good book spines and further used for online classification.

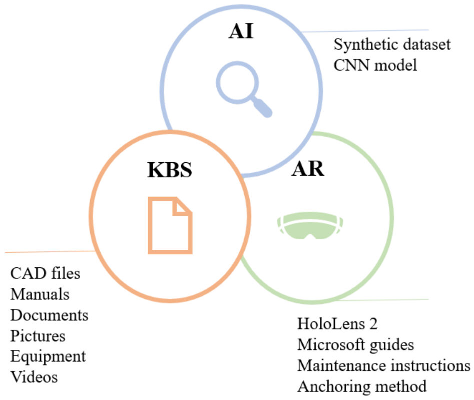

Fig. 3. System overview.

Due to the limited dataset, 100 images of real book blocks are augmented by a synthetic virtually emulated dataset. This results in a dataset consisting of 1000 images of both bad and good produced books which can be classified into the five aforementioned classes.

Once the CNN model is trained, it is used on the real-time data coming from the camera stream of AR. The inference engine classifies the seen book block images by identification of the book spine problem. Images are recognized, analyzed, and then used for predicting the correct label. Thus, the algorithm classifies whether the book spine is correct, uniformly leaning, one-sided leaning, hollow, or bulbous shaped. The predicted labels are then projected to the HMD.

Once the book block is classified, the corresponding result, as well as maintenance activity, is visualized on HMD based on the maintenance requirements. Maintenance of the considered machine is a standard operation performed by the operator. It is an operation of high occurrence and of very low variance in terms of time and maintenance failure rate. However, the machine itself is subject to degradation and hence may lead to the new maintenance operation. According to this, the maintenance (manual) instructions are generated in the information inference system, translated into the digital system, and anchored by a marker-based technology. To visualize the maintenance instructions on the HMD, Microsoft Guides is utilized. This application shows clear instructions while still being able to use custom pictures, videos, text, and 3D models.

In short, a DL algorithm can classify good and wrong book spines, label the specific failure, and display the results on the HMD. Hereafter, the maintenance steps used to solve the issue causing the book spine problem are visualized on the HMD.

3.3. Feedback on the proposed process

The proposed dynamic map is validated by questionnaires. Expert and non-expert operators' feedback is gathered, recorded, and compared. In total, six participants took part in validating the process. Participants were selected based on their level of expertise ranging from no previous experience to good knowledge about the HMD.

All participants were asked to detect, inspect, and recognize a wrongly produced book spine. Hereafter, the DL algorithm and HMD are used to provide failure information and the corresponding maintenance task to the operator.

The goal of this validation process is to identify (1) the usefulness of the reference map, (2) the problem-solving capabilities of an automatic failure diagnosis tool, (3) the reduction of diagnosis failures, and (4) the effect on maintenance operations in terms of time. To score the previous statements, participants were asked about their experience and the level of satisfaction related to the aforementioned four goals. Statements are ranked between 1-5 in which the score varies from strongly disagree to strongly agree. Table 1 presents the results of the validation session.

Table 1. Validation session automatic failure detection.

Validated item	Average score
Usefulness	3.5
Problem identification capability	4
Time	4.2
Failure reduction	4

As the collected dataset is limited, the corresponding statistical analysis is not provided. Instead, the information gathered during this experiment is used to make the first qualitative estimation of integrated KBS, AI, and AR structure and elements.

The data reveal that the majority of the participants were excited about using the troubleshooting demonstrator. Finding failures was easier when using automatic failure analysis by AI, and the use of AR guidance made the maintenance instruction clearer. Hence, the errors in the process were significantly reduced, and non-expert users felt confident when using the new technology. In addition, the experiment has validated the DL model used for the classification of both good and bad book spines. However, the classification procedure of the book itself was not as smooth as expected. Due to special features of the training dataset, the correct distance between the book and the HoloLens 2 was difficult to find so that the algorithm could recognize the book block and properly classify its state. To improve this, more attention should be paid to image classification in the future.

4. Conclusion

In this work, a dynamic reference map of all the modules required to perform automatic fault diagnosis is presented. The reference map describes the connection between KBS, AR, and AI in an existing maintenance system. The AI module is integrated as a computational system that automatically classifies and identifies failures. The AR module assists the operator in solving the previously identified failure. Thus, the given proposal draws a holistic view of integrating different modules to support the operator in his maintenance work, i.e. to supplement maintenance operations and contribute to knowledge enhancement by utilizing this troubleshooting tool.

A case study revealed that the dynamic reference map is rather accurate when relating KBS, AI, and AR to maintenance systems. Although most user reactions to the proposed solution for troubleshooting were positive, more attention needs to be paid to its direct application. This research has impact on organization’s data infrastructure, i.e. data capturing and management. The AR module is connected to a centralized AI system for real-time data streaming. Identifying data processing techniques and developing centralized information management systems is required. Follow-up research is needed to develop the ML/DL algorithm with in-depth network and dataset specification. CNN promises efficient offline training of a balanced synthetic dataset, however this dataset should be replaced by a dataset containing real images for online training and classification.

The current study is focused on image classification and performing maintenance on a physical component. Exploring the usefulness of this method in a different setting, such as maintaining digital systems, is also worthwhile. Thereby, adapting the algorithm to a big environment. Similarly, the dynamic reference map should be explored more thoroughly in different AI, and AR-model environments. While the current research is focused on image classification, the next step is to include object recognition and detection.

In the future, this research should extend to creating a self-learning system that captures and transfers data to improve its capabilities. Thereby, a self-learning automatic fault diagnosis solution can be created that supports operators in their complex maintenance activities.

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References

[1] Xu Z, Saleh JH. Machine learning for reliability engineering and safety applications: review of current status and future opportunities. Reliab Eng Syst Saf. 2021;211:107530.

[2] Nguyen KTP, Medjaher K. A new dynamic predictive maintenance framework using deep learning for failure prognostics. Reliab Eng Syst Saf. 2019;188:251–62.

[3] Joung BG, Lee WJ, Huang A, Sutherland JW. Development and application of a method for real time motor fault detection. Procedia Manuf. 2020;49:94–8.

[4] Sahu CK, Young C, Rai R. Artificial intelligence (AI) in augmented reality (AR) - assisted manufacturing applications: a review. Int J Prod Res. 2020;1–57.

[5] Ahmed A, Masri N, Sultan YA, Akkila AN, Almasri A, Mahmoud AY, et al. Knowledge-Based Systems Survey. Int J Acad Eng Res. 2019;3(7):1–22.

[6] Lei Y, Yang B, Jiang X, Jia F, Li N, Nandi AK. Applications of machine learning to machine fault diagnosis: a review and roadmap. Mech Syst Signal Process. 2020;138:106587.

[7] Rivera CA, Poza J, Ugalde G, Almandoz G. Industrial design of electric machines supported with knowledge-based engineering systems. Appl Sci. 2021;11(1):1–25.

[8] Gattullo M, Scurati GW, Fiorentino M, Uva AE, Ferrise F, Bordegoni M. Towards augmented reality manuals for industry 4.0: a methodology. Robot Comput Integr Manuf. 2019;56:276–86.

[9] del Amo IF, Erkoyuncu J, Vrabič R, Frayssinet R, Vazquez C, Roy R. Structured authoring for AR-based communication to enhance efficiency in remote diagnosis for complex equipment. Adv Eng Informatics. 2020;45:101096.

[10] Palmarini R, Erkoyuncu JA, Roy R. An innovative process to select Augmented Reality (AR) technology for maintenance. Procedia CIRP. 2017;59:23–8.

[11] del Amo IF, Erkoyuncu JA, Roy R, Wilding S. Augmented Reality in Maintenance: an information-centred design framework. Procedia Manuf. 2018;19:148–55.

[12] Lee WJ, Wu H, Yun H, Kim H, Jun MBG, Sutherland JW. Predictive maintenance of machine tool systems using artificial intelligence techniques applied to machine condition data. Procedia CIRP. 2019;80:506–11.

[13] Limmen N. Bridging artificial intelligence and augmented reality for creating a maintenance and troubleshooting tool. Master thesis. 2021.