Artificial Intelligence-based Module Type Package-compatible Smart Sensors in the Process Industry

Laura M. Neuendorf*, Valentin Khaydarov, Christiane Schlander, Tobias Kock, Joshua Fischer, Leon Urbas, and Norbert Kockmann

DOI: 10.1002/cite.202300047

Supporting Information available online

Image analysis presents a set of powerful methods to receive additional information about multiphase processes. It enables the development of advanced applications for process monitoring and optimization or, so-called, soft sensors. However, the integration of advanced smart sensor systems based on image analysis into the process control system presents a complex task. To address this challenge, a modular automation concept offers a standardized interface to integrate modules. This paper presents an integration profile as a service specification that allows a plug-and-measure integration of smart visual sensors into modular plants. To verify the concept, we applied it to three different use cases. At the end, we discuss open challenges in the integration of complex analysis systems with multidimensional data streams into modular plants.

Keywords: Artificial intelligence, Complex data streams, Computer vision, Image processing, Modular automation, Module type package

Received: March 10, 2023; *revised:* June 28, 2023; *accepted:* July 20, 2023

1 Introduction

Highly volatile market dynamics, long-term uncertainties in supply chains and increased demand for individualized products are presenting critical challenges in the chemical and, especially, pharmaceutical, and special chemistry industries [1]. Modular automation and the module type package (MTP) are key technologies to address them by ensuring high flexibility of the production facilities [2]. Predesigned self-contained process equipment assemblies (PEA) are connected to a modular plant and integrated into the process control system or, so-called, process orchestration layer (POL). At any time, PEAs can be rearranged and used in another production line. Thus, great flexibility is provided. This paradigm requires an access to a high variety of modules that are ready to integration. So far research and development in the field of modular automation was mainly focused on process-related modules such as dosing units, stirred tank units, or tempering modules.

Although recent advances in image analysis empowered by machine learning provide new opportunities to use data to generate models for advanced process monitoring [3, 4]; there are only single developments in the integration of smart sensor systems into modular plants [5].

In this paper, we present a concept of a smart image analysis module for advanced process monitoring. In the first section of the paper, we provide a literature review on modular automation as well as artificial intelligence (AI) focusing on computer vision applications in the chemical industry. The second section presents the developed service concept for the camera module with a detailed description of services, procedures, and parameters. Then, we present three reference use cases that are used to evaluate our concept. The last section presents a conclusion and discussion on new challenges to the MTP interface derived from the considered use cases.

[1]Laura M. Neuendorf https://orcid.org/0000-0001-6593-1752 (laura.neuendorf@tu-dortmund.de), [2]Dr. rer. nat. Valentin Khaydarov, [3]Christiane Schlander, [2]Tobias Kock, [3]Joshua Fischer, [2]Prof. Dr.-Ing. Leon Urbas, [1]Prof. Dr.-Ing. Norbert Kockmann

[1]TU Dortmund University, Department of Biochemical and Chemical engineering, Laboratory of Equipment Design, Emil-Figge-Straße 68, 44227 Dortmund, Germany.

[2]TU Dresden University, Process-to-Order Lab, Helmholtzstraße 16, 01069 Dresden, Germany.

[3]Merck Electronics KGaA EL-OTE, Frankfurter Straße 250, 64293 Darmstadt, Germany.

2 State of the Art

In this section, we give a brief review of modular automation and the development of modules. After that, the topic of AI in the chemical industry is considered.

2.1 Modular Automation

Modular automation offers promising technologies for the process and chemical industry. It meets the requirements for greater flexibility and a shorter development cycle for production facilities by dividing the process plant into self-contained production units or PEA. A key concept of modular automation is the MTP. It represents a standardized and manufacturer-independent description of the automation interface of PEAs and endows their plug-and-produce capability [6, 7].

The functionality of the PEA is defined in the form of services [8]. Each service encapsulates a self-contained function with a standardized state-based interface. Variants of the service execution are presented as procedures that together share one state-based control in the service. Services and procedures can be parameterized using configuration and procedure parameters. Besides that, the procedures have input, output, and report values. The latter is used to provide the POL sensor readings on the plant level for further data historicization. A comprehensive state-of-the-art on modular automation can be found in the book of Tauchnitz et al. [9].

Services and procedures together with their parameters and variables compose a service specification that is the most important component of every PEA since it defines the module's functionality. The process of designing the service specification is a complex engineering process that connects process and equipment knowledge with the requirements from the side of the end user [10, 11].

The developed service specification and description of the automation interface are supposed to present requirements for developing concrete PEAs of this type. This type-based approach for the engineering of modular plants (proposed in [12]) not only accelerates the PEA engineering process by giving PEA manufacturers the template and the automation interface description, but it also drastically increases flexibility. The module within the plant can be replaced by another module of the same type but from another manufacturer without significant changes in the orchestration. The type-based approach expects that there is a set of abstract module types that share the same functionality. BioPhorum organization proposed such a unified profile for a stirred tank unit [13]. The profile describes the set of services with their functionality, procedures, parameters, and variables. Authors of [14] are developing a standardized MTP-profile for water electrolysis modules. Although visual sensors or other advanced sensing systems are a common equipment in chemical industries, no unified service specification has been developed for them by now.

2.2 Artificial Intelligence

There is considerable excitement in the chemical industry about advances in data-driven computational methods and the associated expectations for machine learning (ML) and AI. The increase in available data and computational power have made ML an attractive way to generate understanding and predictions from historical information, and it is making inroads into the process industry. Typically, ML refers to a process that converts experience or training data into expertise in the form of an algorithm that performs some tasks [15]. A wide variety of tasks such as active learning applications for recognizing steps in chemical batch production are covered by AI applications in the chemical industry [16].

Also, computer vision for tasks of process monitoring in the chemical industry is on the rise. As the processes benefit from improved supervision thus more precise process control becomes possible [17–19]. Image processing applications range from classification tasks to object localization and instance segmentation tasks, where multiple objects need to be found within an image.

For example, in the field of segmentation of grains for digitized grinding tools to measure abrasion and thus determine their remaining life span [20]. Another use case in the chemical industry is the usage of Boston Dynamic's dog-like robot Spot for reading analog gauges at industrial facilities or for thermal anomaly detection [21]. Moreover, in the field of quality control deep learning is being used for defect detection to improve performance and reduce quality inspection costs by process automation [22].

3 Service Concept

Once an abstract, unified service design has been completed, the PEA hardware can be adapted to specific process conditions by using appropriate equipment. Although the use cases considered further utilize different hardware components, the service specification and automation interface (MTP) remain the same. This way the requirements of flexibility and short integration time of modular plants can be fulfilled.

To develop an abstract service concept the required functionalities were first evaluated within a series of workshops. "Service" is a concept derived from the VDI guideline VDI 2776 [6] that describes abstracted process functions.

The smart sensor should be able to acquire, process and archive relevant data. In addition, hardware-specific functionalities are defined which can be utilized if needed and the required hardware is available, e.g., adjustable illumination or a pan and tilt head to move the camera. Ongoing from this, relevant services are specified as shown in Tab. 1.

The service *Raw-data acquisition* is developed to enable the PEA to capture images or obtain other types of input data and prepare them for further processing, e.g., cropping

Table 1. Description of the developed services and their respective parameters.

Parameter	Parameter Type	Input/ Output	Description
Service: Raw_data_acquisition			
Shutter_speed_setpoint	AnaServparam	In	Sets the shutter speed
Resolution_setpoint	AnaServparam	In	Sets the captured image resolution
ROI_x0	AnaServparam	In	Variables to cut off the image to important regions
ROI_y0	AnaServparam	In	
ROI_x_delta	AnaServparam	In	
ROI_y_delta	AnaServparam	In	
Gain_setpoint	AnaServparam	In	Sets the gain applied to the captured image
Auto_brightness_setpoint	AnaServparam	In	Enables or disables automatic brightness adjusting
Time_interval_setpoint	If 0 the camera takes images as a sequence as fast as possible	In	Only relevant for continuous capturing. Defines the frequent of recorded images (zero means continuous Video)
Shutter_Speed_feedback	AnaView	Out	Feedback value about the current shutter speed
Resolution_feedback	AnaView	Out	Feedback value about the current image resolution
Gain_feedback	AnaView	Out	Feedback value about the currently applied gain
Auto_Brightness_feedback	AnaView	Out	Feedback about the applied automatic brightness
Webserver_endpoint	StringView	Out	Shows the web address of the captured image stream
Service: Raw_data_archiving			
Data_sink	StringServParam	In	Specifies where the captured images are stored
Data_format	StringServParam	In	Specifies in which format the images are stored
Status message	StringView	Out	Status message to inform, e.g., about low remaining memory
Service: Data processing			
Model_ID	DIntServParam	In	Identifier which model should be used to process the captured images
Result	AnaView	Out	Result of the model after processing the last image
Confidence_interval	AnaView	Out	Confidence of the model when available
Status message	StringView	Out	Status message, e.g., for displaying relevant parameters or processing times
Service: Camera Positioning			
X_setpoint	AnaServParam	In	Input to move the camera it can be either absolute/ relative coordinates or absolute/ relative angles, describing the rotation of the camera around all three axes
Y_setpoint	AnaServParam	In	
Z_setpoint	AnaServParam	In	
Position ID	DIntServParam	In	Input to move the camera to a previously saved position
X_current	AnaView	Out	Current absolute coordinates or angles of the camera
Y_current	AnaView	Out	
Z_current	AnaView	Out	
Service: Configuration Mode			
Configuration_ID	DIntServParam	In	Input to load a predefined configuration
Current_Configuration_ID	DIntView	Out	Displays the currently active configuration ID

an im-**Table 1.** Continued.

Parameter	Parameter Type	Input/ Output	Description
Service: Illumination			
Wavelength_setpoint	AnaServParam	In	Sets the emitted light color as wavelength
Intensity_setpoint	AnaServParam	In	Sets the light intensity
Frequency_setpoint	AnaServParam	In	Sets the blinking frequency
Duration_setpoint	AnaServParam	In	Sets the time on cycle time
Intensity_feedback	AnaView	Out	Feedback about the current light intensity
Light_trigger	BinProcessValueIn	In	Used to switch the light on and off by an external source
Service: Lens			
Focus_setpoint	AnaServParam	In	Defines the focus point or sets it to autofocus
Iris_setpoint	AnaServParam	In	Define the iris set point or sets it to auto
Focus_feedback	AnaView	Out	Feedback about the current focus
Iris_feedback	AnaView	Out	Feedback about the current iris

age around the important region. The data acquisition service covers the data acquisition functionality of the PEA. The service has three procedures to enable the camera's different operating modes to take continuous/single or trigger-based images. Also, different procedure parameters are implemented to allow configuring the image resolution, region of interest (ROI), brightness, gain, and image capturing frequency. As report values the current values of the above-listed parameters are available for reporting purposes. Additionally, a web server endpoint is published as a string variable. Thus, the image from the camera in the real-time can be translated over a network for visualization or other purposes.

The service *Raw-data acquisition* presents a core service of the module. Images captured during its execution are available for other services and can also enable their execution. For example, while another service *Data processing* is running, the internal processing loop will be executed each time a new image is taken within the service *Raw-data acquisition*. Thus, the image processing routine can be synchronized with image acquisition.

Data processing processes the acquired data using a selected image analysis technique or deployed model. The service consists of two procedures that rely on the output data types, regression and classification. The regression model returns a continuous value, while the classification model outputs an enumeration value. As a procedure parameter, the user specifies a model ID that decides which of the available models should be inferred. As described above, each time the service *Data acquisition* is triggered, the data analysis routine is executed. Adding, modifying or removing of models is done outside the normal operation and therefore not part of this service.

Data archiving is designed to save the generated input and output data. The data archiving service is not defined as a main functionality of the PEA. The service enables the PEA to archive the obtained frames in a defined format to a variable data sink. The service depends on the data acquisition service to obtain images. If the service is running and new frames are detected an internal variable is set to true and if the frame is successfully archived, it is set to false. When a new frame is captured by the acquisition service the variable is set to true again. This archiving does not replace the documentation done by the POL because only the pictures and associated parameters are saved and not all service states and parameters. The service is furthermore intended to obtain training images for AI models under conditions as close to the real use case as possible.

Data configuration service is intended as a function to set up specific sensor parameters, camera models etc. which are not implemented in the data acquisition service. Additionally, when in execute it allows the modification and/or removal of AI models by accessing them with their ID.

Illumination enables the PEA to influence the lighting conditions to obtain images as good as possible. The illumination service is dedicated to the illumination functionality of the PEA. It contains three procedures to realize continuous, interval-based, or trigger-based illumination. Furthermore, it enables the user to define the wavelength and the intensity. It also delivers feedback on the current intensity. This service has to be adjusted in its functions depending on the used illumination hardware and the existing interfaces.

Camera movement to enable the PEA to move the camera to a different location inside the laboratory setup. It has three procedures, the first one is capable to move the device to absolute position coordinates by taking them as procedure parameters. The second procedure uses relative position inputs to change the position-based on the actual one. The third procedure deals with more advanced position changes, to find the desired position either by using saved coordinates or by orienting on markers on the plant, e.g., QR codes.

Lens control to define optical parameters like focus or aperture. As the name suggests the camera *lens* service should manage the parameters of the optical lens in front of the camera. There are two modes depending on whether the camera model and lens can be accessed via a digital interface or have to be set up manually. The service only has one procedure which sets the relevant parameters, such as the (auto) focus set point.

Once an abstract, unified service design has been developed, the PEA hardware can be adapted to specific process conditions by using appropriate equipment. The here considered use cases utilize different hardware components, but the automation interface (MTP) remains the same for all PEAs of this PEA type. This way the requirements of flexibility and short integration time of modular plants can be fulfilled.

The core smart sensor PEA functions are covered by the data acquisition, the data archiving, and the data processing service. Starting from them the function of the smart sensor PEA can be enhanced with further services when needed.

4 Reference Use Cases

The developed service concept is now applied to three independent use cases in which the MTP-capable soft sensor enhances different existing fully automated plants.

4.1 Process Development Supported by Monitoring (Merck)

In industry, modular development allows highly flexible plants. On the automation layer, this modularity could be realized using MTP and POL. To achieve the goal of the proposed concept, Merck developed a PEA which can be integrated into the existing POL Zenon Logic from Copa Data. The main benefits of this module are monitoring, image acquisition, and user-specific applications in chemical fume hoods. Therefore, the PEA consists of a smart camera Iris GTR5000c from Matrox, a TURCK programmable logic controller (PLC), and additional elements for adjusting position, focus, and lighting. The structure of the communication between the different elements is illustrated in Fig. 1. The state logic of MTP is loaded into the PLC, which communicates with the POL via MTP protocol. The MTP interface is created according to the VDE/VDI standards with the open-source software CodeSys and the installed library MTPLib from SiSa. Modbus/TCP is used to communicate between the PLC and the smart camera. The smart camera is able to perform AI classification or image analysis methods, depending on the current application. The file-sharing system Samba and additional access rights allow images to be saved on the POL server, with the currently stored images assigned to the MTP log. For live monitoring, the smart camera provides a web server from which the POL retrieves the current image and displays it on the POL's human machine interface (HMI). A sketch of the HMI is shown in Fig. 1. The attached elements liquid lens EL-16-40-TC-VIS-5D-C from Optotune and light are controlled via serial interface RS232 and via Input/Output (IO). Between the liquid lens and PLC there is an additional lens controller TR-CL 180 from Gardasoft. Along with the electrically controllable elements, other manually controllable elements such as an objective lens and an adjustable arm for positioning the camera are also attached.

The PEA consists of three services *RawDataAcquisition, RawDataArchiving,* and *DataProcessing. RawDataAcquisition* includes two procedures *FreeRun* and *SnapShot. FreeRun* starts the live monitoring of the smart camera, *SnapShot* acquires one image and shows it on the HMI of the POL. In addition, this service provides settings for exposure time, focus, and illumination via procedure parameters. Since the modules receive an IP address via DHCP, the configuration parameter CamIP can be set to establish the Modbus connection between PLC and smart camera. The service *RawDataArchiving* has two procedures *SingleSave* and *IntervalSave. SingleSave* stores one actual image, *IntervalSave* stores multiple images with time-adjustable intervals. A procedure parameter allows the user to specify the path where the images are saved on the POL server. The *DataProcessing* service controls the currently used method for image analysis or AI classification. The methods run on the smart camera in the Matrox Design Assistant (MDA)

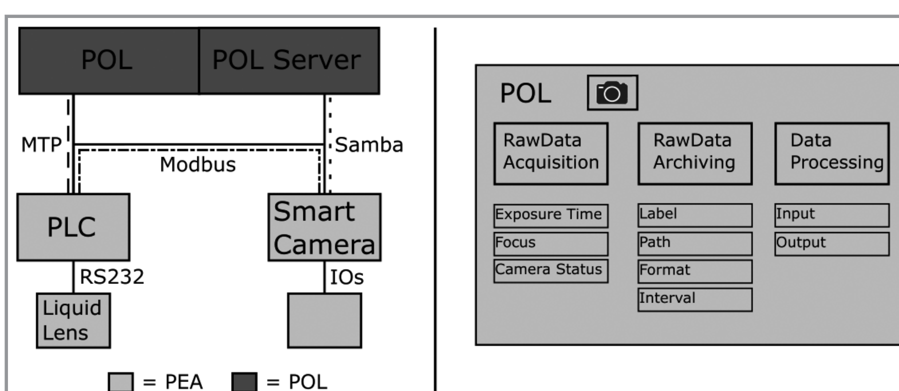

Figure 1. Left: Camera module setup at Merck. Right: Sketch of the POL HMI. The camera icon symbolizes the button for opening the live monitoring.

software. MDA has already integrated image analysis functions and supports trained AI classifications, which can be used for several applications.

4.2 Hydrodynamics Supervision in a Solvent Extraction Process (TU Dortmund University)

Continuous process supervision is of great interest for nearly any (bio-)chemical process. In our laboratory, an artificial intelligence-based optical sensor was developed to monitor a solvent extraction process. A DN32 extraction column, depicted in Fig. 2, was used [17, 23, 24].

By using image-based sensors more insights into the hydrodynamics of the extraction process are obtained [27]. By detecting droplets and calculating their average size, supervision of whether the process is running in the ideal hydrodynamic state is performed. Even overlapping droplets can be detected by the neural net. An image showing one example of the process is evaluated in 0.2 s per image. Therefore, Nvidia RTX5000 GPU on an Intel® Xeon® W-2155 CPU with 10 cores at 3.30 GHz is used. By improving the knowledge of the ongoing process further online process control can be applied.

The droplet detection AI algorithm was implemented into a PEA as follows. The setup of the PEA consists of two services, *Data acquisition* and *Data processing*, with one procedure each (see Fig. 3).

The service *Data acquisition* with its procedure *Free run* realizes the PEA functionality to acquire a data stream of images from the connected camera. The procedure parameter *data source* allows for selecting the camera or alternatively a folder with images. The procedure parameter *Region of Interest* enables cropping of the original image by inputting the required coordinates, Image Crop Origin X/Y Direction, and the image cropped width and cropped height coordinates. The service writes the corresponding cropped images to an internal variable as a NumPy array. In addition, a binary flag is set to indicate the generation of a new image.

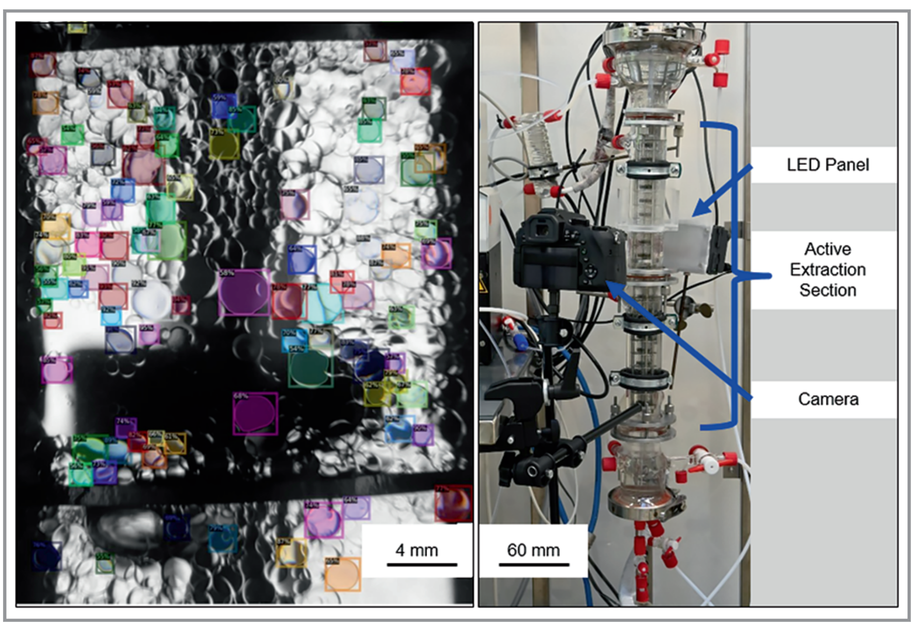

Figure 2. Image analysis in a stirred solvent extraction column. Left: Visualization of detected droplets by the AI algorithm. Right: DN32 solvent extraction column setup with camera setup [17, 25, 26].

The service *Data processing* with its procedure *drop size detection* is dedicated to analyzing the image using the neural net Mask-RCNN [28]. The AI algorithm takes the new images and outputs the average drop size and the bounding boxes of all the droplets found [27]. The masked overlaid image is written on the web server and is thus available for the operator. The average drop size is written to the report value *average drop size*.

Ongoing from the defined service architecture the realization of the PEA with the already developed AI algorithm took around four to six hours of work. For the implementation of the PEA dedicated logic defined in VDI/VDE-2658 the open-source Python package MTPPy was used. [29]

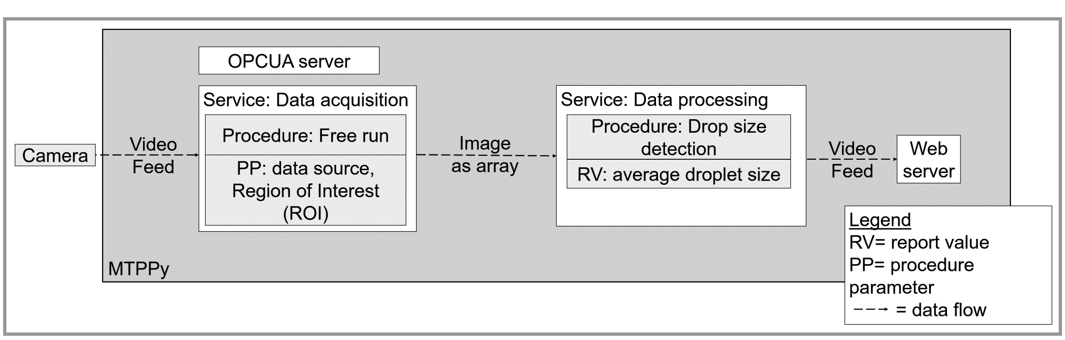

Figure 3. Extraction drop size detection PEA.

4.3 Flow Regime Classification in Bioreactor (TU Dresden University)

Monitoring of flow regimes in aerated stirred tanks is an important task to ensure optimal aeration conditions. Low impeller speed results in a lack of energy for sufficient bubble dispersion or so-called flooding. On the other hand, if the agitator speed is over-controlled and the completely dispersed flow regime occurs, excessive energy consumption would lead to unfavorable operational costs. Therefore, it is advisable to operate a reactor within the loaded flow regime, that presents a good balance between aeration performance and energy consumption [30]. One of the promising non-invasive online approaches to estimate the flow regime is the use of image data and a deep learning model as proposed by Kröger et al. in [19] The approach is schematically presented in Fig. 4.

During the model development and deployment following challenges occurred:

- The position of the camera impacts the model performance. Each time the camera sensor is used, its position should be the same as during the acquisition of training data to achieve the best model performance. The use of data augmentation can help to make the trained model more invariant regarding small camera position changes.
- The camera parameters such as shutter speed, gain, and gamma define the quality of data. Those parameters need to be adjustable by the operator to ensure high data quality.
- The collection of data for training should be synchronized with the plant operation cycle to collect only data that are relevant for model training.

The above-mentioned challenges were addressed by applying the presented approach of a smart camera with corresponding services and equipment. The final setup of the camera module is depicted in Fig. 5.

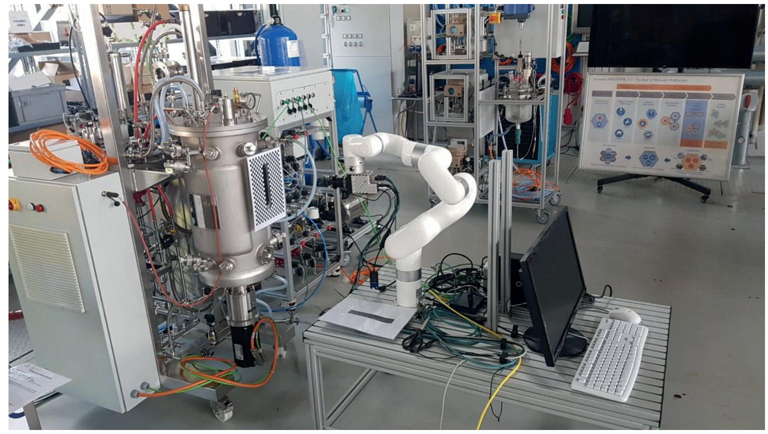

Figure 5. Camera module setup at TU Dresden: the smart camera is mounted in the robot arm to enable precise positioning and repeatability.

We used a smart camera VAX-50C.I.NVX (Baumer) with an integrated NVidia Jetson Xavier board (6-core Nvidia Carmel ARM with 384 CUDA cores and 8 GB RAM), where software for camera and position control, data collection, model serving, and MTP interface run. The camera is mounted in a robot arm xArm 5 (ufactory) to ensure repeatable camera positioning.

The service *Camera position* provides this functionality using an Aruco marker for the precise alignment of the camera to be orthogonal to the plane of the reactor's window. Then, given a desired angle on the horizontal plane and a distance between the camera and the window, the robot arm moves the camera to the given position. The position is then also provided as additional metadata to the taken image. This allows to consider the camera position in data analysis.

To set the camera parameters, the service *Data acquisition* has corresponding configuration and procedure parameters. Available Python API (NeoAPI by Baumer) for the smart camera allows to programmatically change the

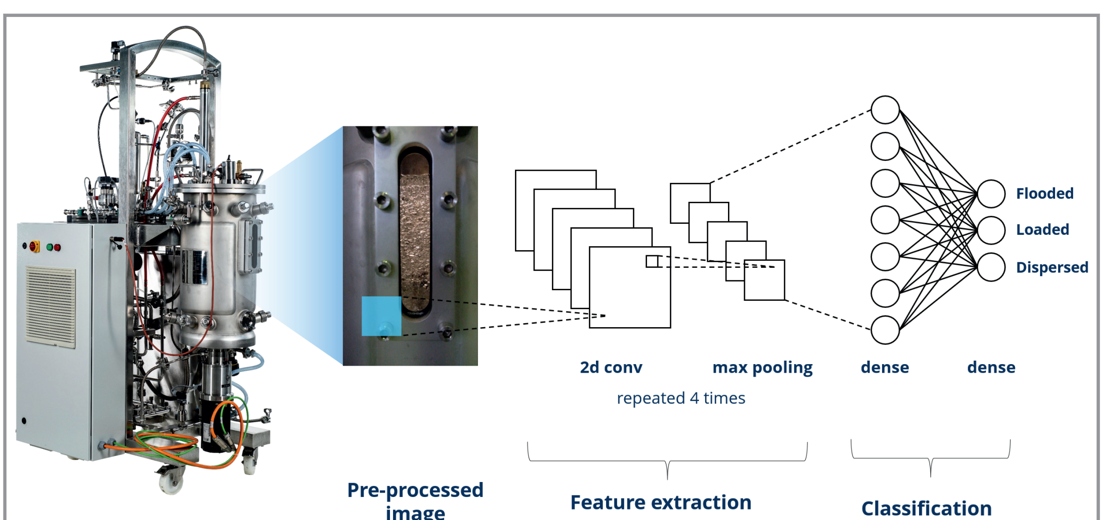

Figure 4. Flow regime classification using image data and convolutional neural network.

camera parameters. The same API is also used to take images and provide them as NumPy arrays for model inference within the *Data processing* service or/and data collection within *Data archiving*.

The services *Illumination* and *Objective/Lens control* are not implemented. The lightning conditions stays constant thanks to the use of non-transparent shielding fabric. The used lens has been set manually once and requires no changes. Since MTP standard is natively not compatible with two-dimensional arrays, we used image streaming over HTTP to have a web-based image visualization for the operator. The same stream can be integrated into a POL using the iFrame technology. Deployment of the camera as MTP-compatible module significantly reduced the overall effort of the model development and module usage. Moreover, the camera module is now not bound to a certain application but can be repurposed to work with another reactor after the model replacement.

5 Conclusion and Outlook

In this paper, we presented the unified service specification with loosely coupled seven services. This specification provides a comprehensive scope of the possible functionality of a smart camera sensor for a wide range of applications. To verify that we considered three significantly different use cases, where the presented service concept was implemented. The concept was also proven to be equipment and solution independent.

Development and evaluation of the use cases indicated a drawback in the MTP information model. While most of the sensors and actuators installed in a plant provide and consume scalar values, image data are two- or three-dimensional arrays depending on the number of color channels. Such multidimensional data format is not compatible with the current version of MTP and, therefore, additional channels for archiving or visualization purposes were used as an alternative solution. To allow a native integration of image data into POL, corresponding data assembly types need to be introduced into the MTP standard.

Supporting Information

Supporting Information for this article can be found under DOI: https://doi.org/10.1002/cite.202300047.

Acknowledgment

We are grateful for the financial support of BMWK (German Federal Ministry of Economic Affairs and Climate Action, Support codes 01MK20014O, 01MK20014S, and 01MK20014T). Open access funding enabled and organized by Projekt DEAL.

Abbreviations

AI	Artificial intelligence
API	Active programming interface
DHCP	Dynamic host configuration protocol
HMI	Human machine interface
I/O	Input/Output
IP	Internet protocol
MDA	Matrox design assistant
MTP	Module type package
PEA	Process equipment assembly
PLC	Programmable logic controller
POL	Process orchestration layer

References

[1] *Modulbasierte Produktion in der Prozessindustrie - Auswirkungen auf die Automation im Umfeld von Industrie 4.0: Empfehlungen des AK Modulare Automation zur NE148 der Namur*, ZVEI – Zentralverband Elektrotechnik und Elektronikindustrie e. V., Frankfurt/Main **2015**.

[2] J. Bernshausen, A. Haller, H. Bloch, M. Hoernicke, S. Hensel, A. Menschner, A. Stutz, M. Maurmaier, T. Holm, C. Schäfer, L. Urbas, U. Christmann, C. Fleischer-Trebes, F. Stenger, *atp* **2019**, *61 (1–2)*, 56–69. DOI: https://doi.org/10.17560/atp.v61i1-2.2400

[3] A. Voulodimos, N. Doulamis, A. Doulamis, E. Protopapadakis, *Comput. Intell. Neurosci.* **2018**, *2018*, 7068349. DOI: https://doi.org/10.1155/2018/7068349

[4] M. Gärtler, V. Khaydarov, B. Klöpper, L. Urbas, *Chem. Ing. Tech.* **2021**, *93 (12)*, 2063–2080. DOI: https://doi.org/10.1002/cite.202100134

[5] V. Khaydarov, S. Heinze, M. Graube, A. Knupfer, M. Knespel, S. Merkelbach, L. Urbas, in *2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, IEEE, Piscataway, NJ **2020**.

[6] VDI 2776 Blatt 1:2020-11, *Verfahrenstechnische Anlagen – Modulare Anlagen - Grundlagen und Planung*, Beuth Verlag, Berlin **2020**.

[7] VDI/VDE/NAMUR 2658 Blatt 1:2019-10, *Automatisierungstechnisches Engineering modularer Anlagen in der Prozessindustrie*, Beuth Verlag, Berlin **2019**.

[8] VDI/VDE/NAMUR 2658 Blatt 4:2022-10, *Automatisierungstechnisches Engineering modularer Anlagen in der Prozessindustrie*, Beuth Verlag, Berlin **2020**.

[9] *MTP Automation of Modular Plants* (Ed: T. Tauchnitz), 1st ed., Vulkan-Verlag, Essen **2022**.

[10] H. Bloch, S. Hensel, M. Hoernicke, K. Stark, A. Menschner, A. Fay, L. Urbas, T. Knohl, J. Bernshausen, *Procedia CIRP* **2018**, *72*, 1088–1093. DOI: https://doi.org/10.1016/j.procir.2018.03.037

[11] A. Homay, M. de Sousa, A. Zoitl, M. Wollschlaeger, in *2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, IEEE, Piscataway, NJ **2020**.

[12] J. Lorenz, A. Klose, I. Viedt, J. Mädler, V. Khaydarov, L. Urbas, in *Automation 2022*, VDI Verlag, Dusseldorf **2022**.

[13] R. Polley et al., *Automated Facility Plug-And-Play - Stirred Tank Unit Interface Specification*, Biohorum, Sheffield **2021**. www.biophorum.com/download/automated-facility-stirred-tank-unit-interface-specification (Accessed on February 27, 2023)

[14] L. Bittorf, L. Beisswenger, D. Erdmann, J. Lorenz, A. Klose, H. Lange, L. Urbas, A. Markaj, A. Fay, in *2022 IEEE 27th*

International Conference on Emerging Technologies and Factory Automation (ETFA), IEEE, Piscataway, NJ **2022**.
[15] L. H. Chiang, B. Braun, Z. Wang, I. Castillo, *AIChE J.* **2022**, *68 (6)*, e17644. DOI: https://doi.org/10.1002/aic.17644
[16] A. Ahmad, C. Song, R. Tan, M. Gartler, B. Klopper, in *2022 IEEE 27th International Conference on Emerging Technologies and Factory Automation (ETFA)*, IEEE, Piscataway, NJ **2022**.
[17] L. M. Neuendorf, F. Z. Baygi, P. Kolloch, N. Kockmann, *ACS Eng. Au* **2022**, *2 (4)*, 369–377. DOI: https://doi.org/10.1021/acsengineeringau.2c00014
[18] N. Blum, V. Krespach, G. Zapp, C. Oehse, S. Rehfeldt, H. Klein, *Chem. Ing. Tech.* **2021**, *93 (12)*, 1937–1948. DOI: https://doi.org/10.1002/cite.202100094
[19] C. Kröger, V. Khaydarov, L. Urbas, in *32nd European Symposium on Computer Aided Process Engineering* (Eds: L. Montastruc, S. Negny), Computer Aided Chemical Engineering Series, Vol. 51, Elsevier, Amsterdam **2022**.
[20] P. Wiederkehr, F. Finkeldey, T. Merhofe, *CIRP Ann.* **2021**, *70 (1)*, 297–300. DOI: https://doi.org/10.1016/j.cirp.2021.04.051
[21] S. C. Nandakumar, S. Harper, D. Mitchell, J. Blanche, T. Lim, I. Yamamoto, D. Flynn, *Bio-inspired Multi-robot Autonomy*, arXiv:2203.07718, **2022**. DOI: https://doi.org/10.48550/arXiv.2203.07718 arXiv:2203.07718
[22] J. Villalba-Diez, D. Schmidt, R. Gevers, J. Ordieres-Meré, M. Buchwitz, W. Wellbrock, *Sensors* **2019**, *19 (18)*, 3987. DOI: https://doi.org/10.3390/s19183987
[23] A. Holbach, E. Çalışkan, H.-S. Lee, N. Kockmann, *Chem. Eng. Process.* **2014**, *80*, 21–28. DOI: https://doi.org/10.1016/j.cep.2014.03.013
[24] L. Hohmann, S. K. Kurt, S. Soboll, N. Kockmann, *J. Flow Chem.* **2016**, *6 (3)*, 181–190. DOI: https://doi.org/10.1556/1846.2016.00024
[25] S. Soboll, I. Hagemann, N. Kockmann, *Chem. Ing. Tech* **2017**, *89 (12)*, 1611–1618. DOI: https://doi.org/10.1002/cite.201700031
[26] S. Soboll, N. Kockmann, *Chem. Eng. Technol.* **2018**, *41 (9)*, 1847–1856. DOI: https://doi.org/10.1002/ceat.201800283
[27] L. Neuendorf, P. Müller, C. Bergeest, N. Kockmann, A. Meijer, C. Schlander, Künstliche Intelligenz (KI)-basierte optische Sensorik für flüssig-flüssig Systeme, in *16. Dresdner Sensor-Symposium 2022*, AMA Service GmbH, Wunstorf **2022**. DOI: https://doi.org/10.5162/16dss2022/P50
[28] K. He, G. Gkioxari, P. Dollár, R. Girshick, *Mask R-CNN*, arXiv.1703.06870, **2017**. DOI: https://doi.org/10.48550/arXiv.1703.06870
[29] V. Khaydarov, L. Neuendorf, T. Kock, N. Kockmann, L. Urbas, in *2022 IEEE 27th International Conference on Emerging Technologies and Factory Automation (ETFA)*, IEEE, Piscataway, NJ **2022**.
[30] M. Warmoeskerken, *Gas-liquid dispersing characteristics of turbine agitators*, Doctoral thesis, TU Delft **1986**.

