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SENSOR PLATFORM OF INDUSTRIAL TOMOGRAPHY FOR DIAGNOSTICS AND CONTROL OF TECHNOLOGICAL PROCESSES

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Abstract: *This article presents an industrial tomography platform for diagnosing and controlling technological processes. The system has been prepared in such a way that it is possible to add individual sensors that cooperate with the system of an intelligent cyber-physical platform with an open architecture. In addition, it is possible to configure and cooperate with external systems freely. As part of the experimental work, a platform has been developed that allows individual subsystems and external customer systems to work together. The cyber-physical system, a new generation of digital systems, focuses mainly on the complex interaction and integration between cyberspace and the physical world. A cyber-physical system consists of highly integrated computing, communication, control and physical elements. It focuses mainly on the complex interaction and integration between cyberspace and the physical world.*

Keywords: electrical capacitance tomography, cyber-physical systems, sensors, electrical impedance tomography

PLATFORMA SENSOROWA TOMOGRAFII PRZEMYSŁOWEJ DO DIAGNOSTYKI I STEROWANIA PROCESAMI TECHNOLOGICZNYMI

Streszczenie. *W artykule przedstawiono przemysłową platformę tomograficzną wykorzystywaną do diagnostyki i sterowania procesami technologicznymi. Aplikacja pozwala na dodawanie poszczególnych czujników współpracujących z systemem inteligentnej platformy cyber-fizycznej o otwartej architekturze, a dodatkowo możliwa była dowolna konfiguracja i współpraca z systemami zewnętrznymi. W ramach prac eksperymentalnych opracowano platformę, która umożliwia współpracę poszczególnych podsystemów i zewnętrznych systemów klienta. System cyberfizyczny, koncentruje się głównie na złożonej interakcji i integracji między cyberprzestrzenią a światem fizycznym. System cyberfizyczny składa się z wysoce zintegrowanych elementów obliczeniowych, komunikacyjnych, kontrolnych i fizycznych. Rozwiązanie koncentruje się głównie na złożonej interakcji i integracji między cyberprzestrzenią a światem fizycznym.*

Słowa kluczowe: tomografia pojemnościowa, systemy cyber-fizyczne, sensory, tomografia impedancyjna

1. General principles of the system

The portal allows the user to manage the data collected on the server by reading current or historical data. Sensor data is sent to the database and can be viewed and read anytime. Individual sensors can be added to the system and communicate using MQTT, OPC, and Kafka. The system continuously displays data from sensors measuring various physical quantities.

It is a system that allows building a platform for Industry 4.0 by combining the system with smart sensors [1, 2, 7, 12, 17]. Furthermore, a unique solution is using industrial tomography with appropriate algorithms to analyse and diagnose technological processes.

The networking of intelligent sensors, many advantages can bring many benefits to industrial environments, such as the combination of information and operational technologies. Although operational technologies include hardware and software systems that control processes on the shop floor, they have generally not been integrated into a network or wider information system. This connection allows computer components to communicate directly with other machines and central servers, exchanging information via the computer network.

It will also reduce the number of operations required; improve performance and resource utilisation; minimise the life cycle cost of the asset; speed up decision-making; buy and sell products as services, expand business opportunities and enable new business models to emerge for manufacturing. Therefore, the requirements for emerging factories that form global networks of assets, storage systems and manufacturing processes in cyber-physical systems are key issues.

Cyber-physical systems make it possible to increase the level of effectiveness and efficiency in industrial value creation through the amount of real-time information on technical processes [5, 13, 18]. To fully exploit cyber-physical systems, the information gathered should include the knowledge of the personnel. Often this knowledge is only available informally, and the problem is formalising it. However, due to the high value of this knowledge, systematic collection, categorisation, and mapping methods should be introduced. Furthermore, the availability of this knowledge can be used to develop operational guidelines, which are an essential part of decision support systems.

An example might be the repair of a faulty machine. The first time a fault occurs, the troubleshooting process should be documented so that if it occurs again, there are guidelines for action, and each troubleshooter can benefit from the effect of the learning curve. However, the system-based capturing, categorising and mapping of hidden knowledge requires additional employee effort. Therefore, it is necessary to explain the overall added value based on the availability of action guidelines after the development and implementation of a decision support system [19, 20, 21].

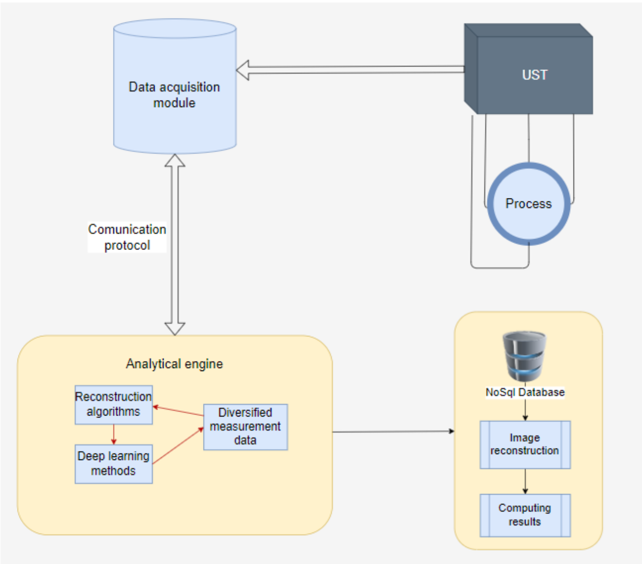

Fig. 1. Model of a sensor platform with an analytical system

In industrial research, it is often necessary to carry out measurements that cannot be carried out using non-destructive methods without interfering with the inside of the tested object. The presented system consists of a network of intelligent sensors using wired and wireless communication, which allows the acquisition of data from various sources, directly or indirectly, related to the production process (figure 1).

Sensors and measuring devices are connected to the communication interface whose task is to read the signal from the selected sensor, process it into a consistent form and then send the read and processed data to the acquisition module (figures 2, 3 and 4). The algorithm was trained using learning data obtained by computer simulation from real models to solve the inverse problem. In addition, the conductivity values of individual pixels of the output vector made it possible to obtain images of the interior of the tested objects.

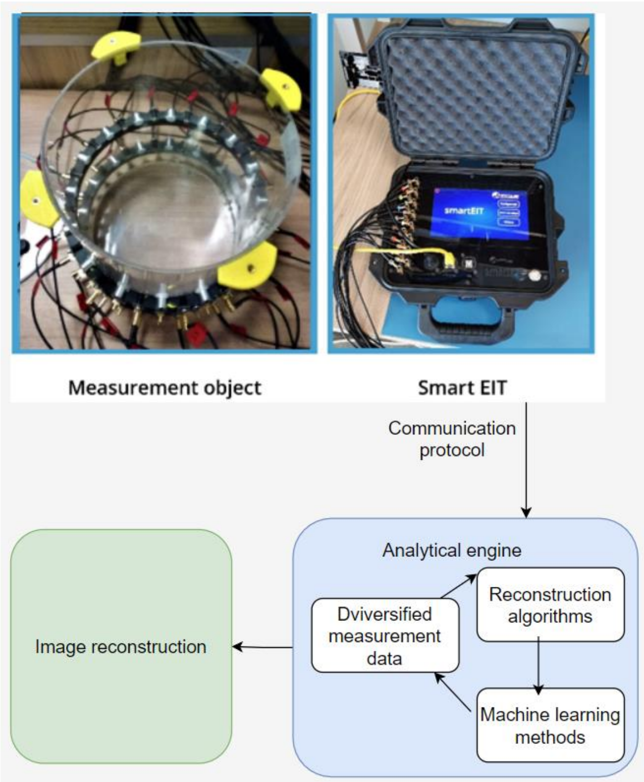

Fig. 2. Measurement system with a model of data transmission, collection and analysis

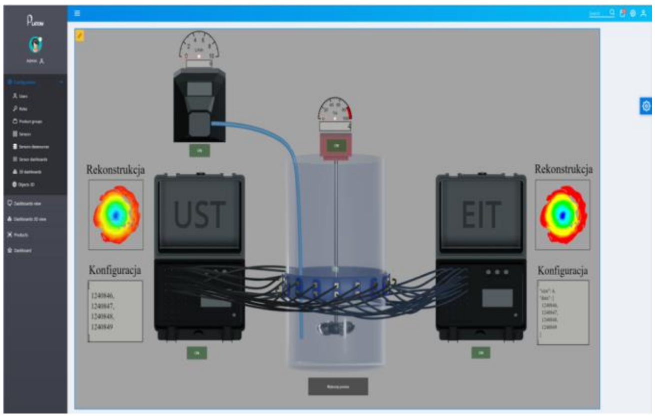

Fig. 3. Digital twin – simulation

The research presented focuses on electrical impedance tomography (EIT), a non-invasive imaging technique that visualises the dynamic distribution of electrical conductivity within the test object. In this method, the sensitivity of EIT solutions to measurement, numerical and model errors requires adapting model parameters to specific cases. In the traditional approach, studies performed with EIT tomography are computationally resource-intensive, resulting in complexity. Therefore, the best solutions are sought to reduce the computational effort by finding suitable algorithms to improve the quality of the measurements. The authors used the logistic regression method to reconstruct tomographic images.

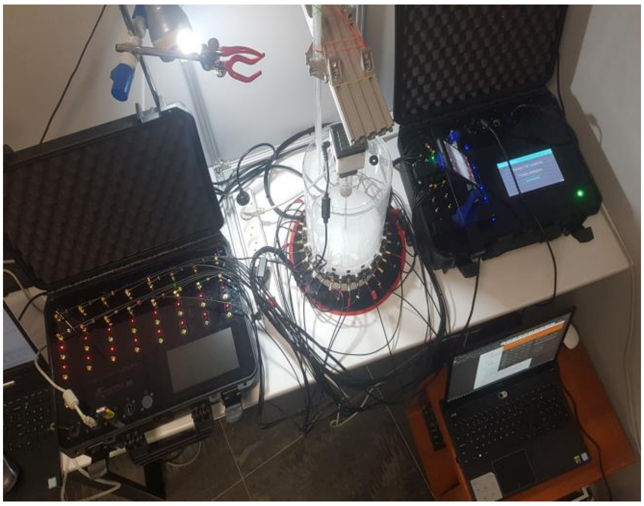

Fig. 4. Digital twin – real model

A cloud computing model (PLATOM Cloud) has been developed. The system design is based on containers with the possibility of deploying them in the cloud. Using containers makes it possible to use the public and private clouds at the location specified by the customer. The model is based on virtualisation and resource aggregation. The starting point for the developed concept of communication protocols of the PLATOM platform is a general architecture model that considers the data flow between five basic types of components, i.e. measurement, control and service components, including central, computational, timestamp, GUI and data. The control architecture and data communication platform technology has been developed. Measurement and control, and service components have been incorporated into the PLATOM platform. Measurement and control components are devices with dedicated software designed to collect data from measurement devices used to monitor the state of the process (tomograph, camera, flow meter, etc.) and to set values of settings on active devices of the process (inverters, control valves, etc.).

On the other hand, service components are responsible for implementing individual PLATOM platform services and are not directly connected to the process measurement and control devices. Instead, they operate as elements of the PLATOM Cloud in the form of software modules on dedicated server computers. The following functionalities/modules are implemented within these components: repository, computing module, database module for storage and distribution, central module and GUI modules. The diagram in the figure (figure 5) illustrates the platform concept with the division into measurement and control components and service components with the indication of the data transmission direction.

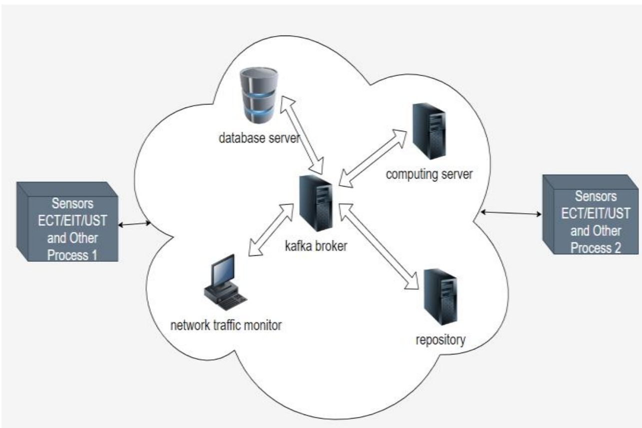

Fig. 5. Schematic diagram of the built computational cloud

2. System development

The preparation of the system was divided into several tasks. The main challenge of this phase was to develop 3D and 4D (time-resolved) imaging models and techniques for industrial crystallisation and fermentation processes using process tomography techniques.

In the first task, mathematical investigations were carried out using existing software tools for modelling the crystallisation process, enabling the selection of a technologically optimal algorithm for visualising the process in terms of ultrasonic, electrical and capacitive tomography measurements. In the next task, the research focused on developing mathematical models of the fermentation process and selecting an optimal technological algorithm for the visualisation of the process in ultrasonic, electrical and capacitive tomography measurements. In the third task, several analyses were conducted by applying mathematical models describing time-resolved tomographic measurements and visualising the results obtained in industrial batch crystallisation and fermentation processes. The next task allowed the development of new technology for tomographic measurements using ultrasonic tomography (UST) to control and seriation batch crystallisation processes [8–11]. This task required the development of hardware solutions and appropriate algorithmic tools. As part of the task, several works were carried out to develop tools for modelling the crystallisation process taking into account reaction kinetics and crystal particle growth through a population equilibrium model. The hardware solutions developed made it possible to increase the efficiency of ultrasonic wave penetration into crystal suspensions in terms of reflection and transmission tomography methods. Measurement cards were also developed for cooperation with probes of different ultrasonic wave frequencies. A method of effectively placing active elements (ultrasonic transmitters) on the rim of the vessel (reactor) where the crystallisation process occurred was also developed. At the same time, a model for spatially resolved and time-resolved (3D and 4D) measurement of crystal size and density using tomographic data reconstruction has been developed. The work carried out as part of the task also included the development of a new concept for adaptive control of homogeneous crystal growth by ultrasonic activation. A number of crystallisation measurements were carried out to test the concept of continuous and time-resolved measurements. The crystallisation measurements were carried out at different reactant dosing rates and at different substrate mixing rates. The collected results of the task directly contributed to creating a demonstration set for the measurement of batch crystallisation processes using process tomography techniques.

The implementation of the next task focused on developing new technology for tomographic measurements using capacitive (ECT) and resistive (ERT) tomography techniques to control and manage the biogas fermentation process. The work carried out in this task included the development of tools for modelling the fermentation process, considering mixing methods, including pneumatic mixing. Work also involved increasing the efficiency of tomographic imaging by simultaneously applying capacitive and resistive tomography techniques. Similar to ultrasound tomography, models have been developed for the efficient placement of measurement electrodes and their mutual positioning. It is particularly important for 3D and 4D measurements. In addition, time-resolved measurements were carried out to investigate the possibility of improving the efficiency of the fermentation process using process tomography techniques. All the research, tests and simulations carried out, combined with the hardware components developed, led to the development a demonstration measurement setup. In the next task, process measurements were performed with the developed demonstration workstations to verify the results of numerical simulations with the developed solution elements in the context of application in industrial installations. In the last task, assumptions were developed for algorithms of reconstruction and visualisation of process tomography images were developed [3, 23-26, 28].

The platform consists of special tanks for carrying out the crystallisation. The tanks are equipped with special holders that allow the mutual arrangement of the transducers to be changed and the measurement system to be adapted to the crystallisation process to be analysed. The platform allows ultrasonic tomography measurements in both transmission and reflection modes of ultrasonic waves. Furthermore, the hardware platform can work with transducers of different frequencies.

Measurements are made in 32 channels. 3D and 4D measurements are possible for both techniques. The results obtained can be directly visualised on the measuring device. Due to the high speed of measurement data acquisition and the development of new image reconstruction techniques, it is possible to obtain images in less than 250 ms. During the crystallisation process, the crystals formed to change the physical properties of the medium. As the number of crystals increases, the density of the medium changes. Density changes increase the speed of propagation of ultrasonic waves. Based on these changes and the known size of the container, the crystal density can be spatially measured throughout the process. The developed models were used to design the crystallisation process. Within the fermentation process, using a novel method of simultaneous measurement of resistive and capacitive tomography for analysis and control allowed the detection of heterogeneities. As the measurements were made at high speed, it was possible to control the stirrer by implementing FPGAs. The measurements carried out showed that the delay or reaction time between the detection of inhomogeneities and the operation of the agitator is less than 1 ms, which fully meets the parameters specified in the milestone. As with ultrasound tomography, a demonstration platform was developed to analyse fermentation processes. The demonstration platform also required the development of reliable software to control the measurements and reconstruct the huge amount of tomographic data (as the acquisition speed increases, so do the amount of data).

3. Measurement

3.1. EIT measurement system

The designed tomograph uses EIT technology to study the cross-sections of closed spaces. The spatial distribution of the impedance can be determined, and the internal structure of the medium can be visualised by measuring the voltages on electrodes directly adjacent to the medium. Thanks to the built-in microcomputer, it is possible to carry out EIT measurements and view the reconstructions based on them. It also has a network interface for data transfer to an external server. The tomograph measures voltages by switching channels according to the polar method. First, multiplexers connect the EXC and GND outputs to two opposite electrodes. A current flows, the intensity of which is programmed to a set value. Then the signal input is successively connected to the remaining electrodes on which the voltage to GND is measured. After 14 measurements, the measurement information is disconnected, the forcing electrodes are switched to the next pair, and the cycle is repeated. The 224 (16x14) results were converted into 192 (16x12) values of the voltages between the measuring electrodes. The image reconstruction algorithm then transforms the results.

3.2. Logistic regression

When creating a reconstruction in EIT, we need to answer the question of which finite elements belong to inclusion in the field of view. We define a logistic regression model to create the reconstruction for each finite element. Let (Ω, F, P) be a probability space, and for the finite element, we define a random variable Y with discrete distribution, where $Y{:}\,\Omega \rightarrow \{0,1\}$. In the presented approach, if the finite element belongs to inclusion, we put on the realisation of random variable Y is equal to 1 (i.e. y = 1); otherwise, 0. The main objective is to determine whether the finite element belongs to inclusion based on signal $x \in \boldsymbol{R}^m$ obtained from sensors. For this purpose, we must define a classifier $f{:}\boldsymbol{R}^m \rightarrow \{0,1\}$). In this paper, logistic regression has been used to create a classifier. The logistic regression model is used to estimate the binomial (or multinomial) distribution of the response variable Y based on the realisation of the input variables $X{:} \in \boldsymbol{R}^m$ (in other words, we determine $P(Y = y|X)$, where $y \in \{0,1\}$).In the literature $P(Y = 1|X)$ value denotes the success probability, but $P(Y = 0|X)$ – defeat probability [14, 16-17, 27].

3.3. Results

A measurement system consisting of a SmartEIT tomograph and a measurement object with 16 sensors was used (Fig. 6). The image reconstructions are shown in figure 7, where three variants of the algorithms were compared, comparing the images obtained by the methods Logistic with Elasticnet [6], Logistic with Db12 wavelet [4], Logistic with Sym9 wavelet [21] were compared. Table 1 corresponds to figure 5 and presents a comparative analysis of the reconstructions obtained. Based on the indicators: Accuracy, Sensitivity, Specificity, PPV, NPV, Detection Rate, and Level. Basic properties of the first model describing the view area. Number of electrodes: 16, type of electrodes: linear, number of nodes: 1338, number of finite elements: 2502. In this case, the decomposition level j = 2 was used for wavelet analysis.

Table 1. Summary of reconstruction of pattern presented in figure 7

Methods	Elastic net	Db12	Sym9
Accuracy	0.957	0.950	0.946
Sensitivity	0.609	0.646	0.589
Specificity	0.995	0.982	0.985
PPV	0.925	0.797	0.803
NPV	0.959	0.963	0.957
Detection Rate	0.059	0.063	0.057
Level	0.50	0.30	0.27

Fig. 6. Measuring system using the SmartEIT electric impedance tomograph

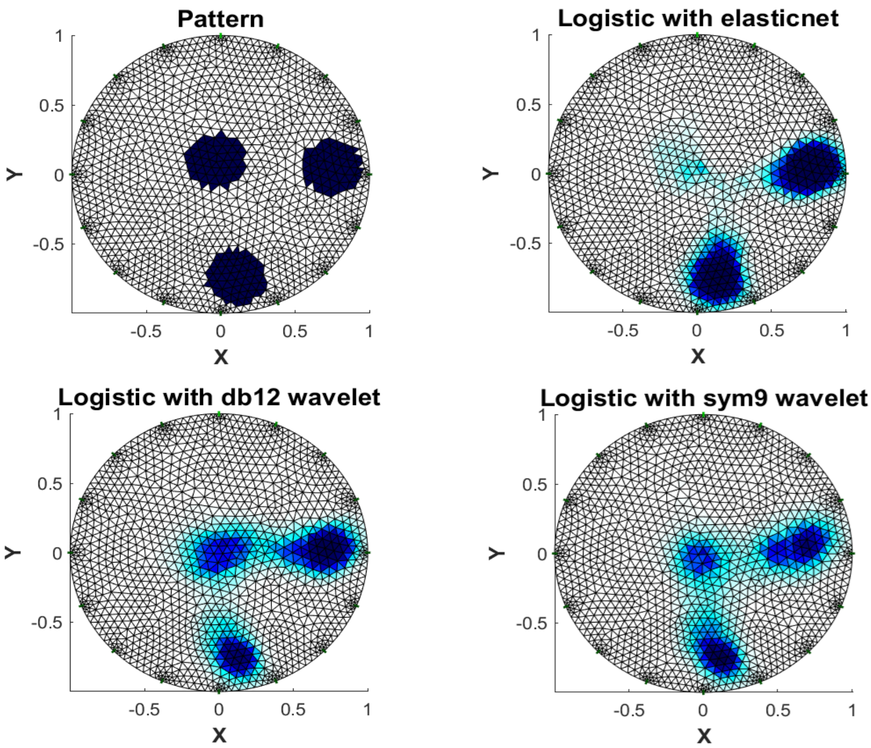

Fig. 7. Image reconstruction – 16 sensors, three objects: Pattern, Logistic with Elasticnet, Logistic with Db12 wavelet, Logistic with Sym9 wavelet

4. Conclusions

An industrial tomography platform used for process diagnostics and control has been developed. Adding additional sensors to the platform, which work together, is possible. It allows individual subsystems and external customer systems to work together and focus on developing algorithms and models for image analysis and reconstruction. All the presented algorithms were found suitable for practical applications in industrial tomography. Furthermore, the proposed research results contain essential information that may contribute to accelerating machine learning methods in industrial tomography.

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