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Tomographic Ultrasonic Sensors in Industrial Applications

***Abstract**. The work presents the results of research on the use of tomographic ultrasonic sensors to analyse industrial processes using dedicated measuring devices, image reconstruction algorithms and cyber-physical system.*

***Streszczenie.** W pracy przedstawiono wyniki badań nad wykorzystaniem tomograficznych czujników ultradźwiękowych do analizy procesów przemysłowych z zastosowaniem dedykowanych urządzeń pomiarowych, algorytmów rekonstrukcji obrazu oraz systemu cyber-fizycznego. (**Tomograficzne czujniki ultradźwiękowe w zastosowaniach przemysłowych**).*

Keywords: ultrasound tomography; sensors; cyber-physical system; Industry 4.0.
Słowa kluczowe: tomografia ultradźwiękowa; czujniki; system cyber-fizycznego, Przemysł 4.0.

Introduction

Cyber-Physical Systems (CPS) is a concept of systems with strictly integrated computational, physical and communication processes. In contrast to advanced systems, CPS create a unified structure for modelling and implementing complex systems as a whole. The presented concept of Cyber Intelligent Enterprise consists directly in the application of the CPS vision in the field of enterprise systems, the Internet of Things (IoT) and the semantic network. The tight integration of physical devices and business processes gives new possibilities and increases the efficiency of the enterprise [1]. Systems of cooperating computing units that are in in-tense connection with the surrounding physical world and its current processes provide and use simultaneously data access and data access services available on the Internet. They can be part of the fourth industrial revolution, often labelled as Industry 4.0. Cyber-physical production systems (CPPS) are based on the latest developments in the fields of information technology, electronics, information and communication technologies. Autonomy, cooperation, optimization, integration of analytical approaches and simulations is related to the operation of sensor networks, large amounts of data and the search, analysis and interpretation of information with particular emphasis on security aspects [2]. The hybrid NC control system for an automatic line based on CPS technology uses a variety of techniques, such as sensors, intelligent computing and heterogeneous network integration [3].

The implementation of a system combining real industrial environments with a virtual copy of components is presented in [4]. Intelligent hardware and software are needed to build a smart factory. These include broadband devices, intelligent machine controllers, analytical systems for large data sets, and integrated information applications. With the advent of new technologies such as IoT, Cloud Computing, Big Data, Artificial Intelligence - intelligent machines and products can communicate with each other and negotiate configuration changes to flexibly produce many types of products. Data can be collected from smart devices and sent to the cloud. This gives feedback and coordination based on large data analysis to optimize system performance. Self-organizing reconfiguration and communication based on large amounts of data de-fines the framework and mechanism of operation of an intelligent factory in industry 4.0 [5]. Agent-based intelligent production applications are the right solution to the problem of production planning and scheduling because production companies can include many different elements such as planning, monitoring and control of production processes. Agent-based deployment lets you define workflow and track production logic. In the automation of production systems for parallel control, multi-agent technologies can be used, using cloud computing and service-oriented architecture (SOA) to share production resources [6].

Tomographic imaging of objects creates a unique opportunity to discover the complexity of the structure without having to damage the object [7]. In industrial processes, there is a growing demand for information on how internal flows behave in devices such as pipelines, reactors and tanks. Observations should be made non-invasively using tomographic equipment. Conventional measuring instruments may be unsuitable for difficult internal process conditions or their presence may interfere with the process.

Process tomography involves manipulating data obtained from remote sensors to obtain accurate quantitative information from inaccessible locations [8]. Tomographic monitoring streamlines processes and their design, enabling real-time imaging of boundaries between different components using non-invasive sensors [9-11]. Information on substance properties, vector flow velocity or component concentration in process tanks and pipelines can be determined from the images obtained by installing sensors around the object to be imaged. Image data can be analysed online or collected for later use to launch a process control strategy or to develop models describing individual processes. Online monitoring and diagnosis of tomographic data streams can be integrated into automated decision systems for industrial applications. By using computer monitoring methods, you can solve very complex problems. Current tomographic systems provide limited support for computer intelligence methods, given the limited space and relatively long computation time that is required to process data by embedded algorithms. The monitored object is a tomographically instrumented part of the production plant, in which the tomographic device collects data thanks to transducers. Transducers are placed on the surface of the tested object (e.g. tank) and emit and receive ultrasonic signals in a non-invasive manner. The device sends raw data to the cloud computing system, where the reverse problem is solved (image reconstruction). The last effect is the use of a deterministic algorithm, optimization methods and machine learning to classify the state of the monitored object [12-30].

Ultrasound Tomography System

Many measurements can be made using ultrasound without the risk of damage or irradiation of the test objects. Measurement of such parameters as signal transition time, damping factor and its frequency derivative allows, after appropriate reconstruction transformations, imaging of the internal structure of the medium under study, as well as such flow parameters as, for example, its instantaneous speed or average velocity profile.

The ultrasonic tomograph consists of active measuring transducers controlled by an external module via a Controller Area Network (CAN bus). CAN bus is a robust vehicle bus standard designed to allow microcontrollers and other devices to communicate with each other's applications without a host computer. Active transducers are divided into digital and analogue parts. The digital part is responsible for sending ready measurement results to the tomography controller via the bus. The analog part has been adapted to work with a piezoelectric transducer operating at 48 kHz. The active transducer can act as both an ultrasonic signal receiver and as a transmitter.

The main tomography controller is responsible for managing the measuring sequence, setting the active transducers in transmit / receive mode and recording the results taken from other transducers. The transducers are designed so that they can be placed very close to each other. Power lines, communication buses and interrupt lines necessary for proper measurement of time from sending to receiving the signal on other transducers were carried out using RJ-12 cables. The concept of ultrasound tomography construction assumes the construction of a system of active measuring transducers controlled by an external module via CAN bus. Active transducers are divided into digital and analogue parts. The digital part of the transducer is responsible for sending ready measurement results to the tomography controller via the bus. Figure 1 show measurement models for process tomography based on ultrasound tomography. The model of analysis and control of the crystallization and fermentation process is shown in Figure 2.

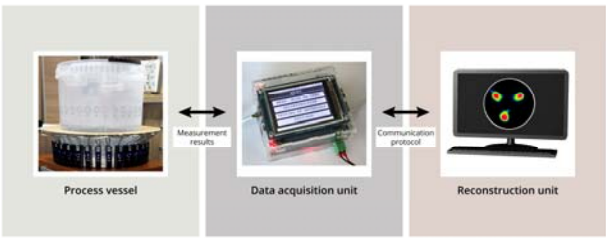

Fig.1. Measurement model for ultrasound tomography

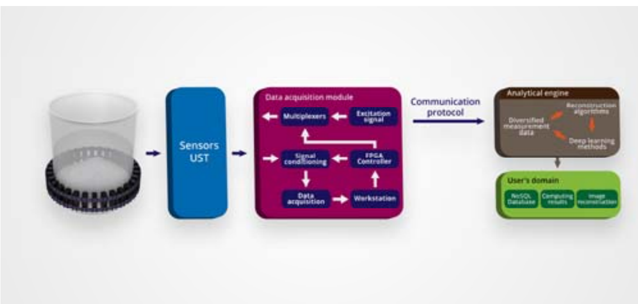

Fig.2. Monitoring, analysis and control processes in the test tank by tomographic methods

Deterministic Measurement Model

At Research and Development Centre Netrix S.A. a liquid environment measuring station for ultrasound tomography was prepared. Ultrasound tomography enables the analysis of processes taking place in the facility without interfering with the production, analysis or detection of obstacles, defects and various anomalies. The presented measuring system has a specially designed measuring structure including transducers. Thanks to this, the cyber-physical system is an innovative solution, especially effective in the analysis and control of industrial processes.

The transducers are designed so that they can be placed very close to each other. Power cables, communication bus and interrupt lines necessary for the correct implementation of time measurement from the moment of sending the signal to receive from other transducers were made using RJ-12 cables. The device housing is laser cut from acrylic glass. A printed circuit board (PCB) assembly inside the housing is done by inserting a ready-made plate with a soldered ultrasonic transducer and fix it with plastic screws.

Under the ultrasonic transducer there is a flexible rubber pad, which allows it to move, thanks to which it can adapt to the curvature of the examined object. The transducers are installed on the tested object through flexible strips threaded through the holes located in the upper part of the housing. Each transducer is assigned a number from 1 to 32. The transducer number is assigned based on the microcontroller's serial number. Therefore, after registering all serial numbers, you can update the transducer software with the same batch file. Measurement of the time of transition of the ultrasonic wave from one transducer to another was achieved by connecting all transducers to an additional communication line.

When the low state appears on this line, all transducers except for the transmitting transducer start the time measurement and end it after receiving the ultrasonic wave. Then each receiving transducer sends the measurement result to the tomograph controller. Based on information about which transducer was the transducer and which transducer sent the result, the measurement value is saved in the appropriate cell of the measurement matrix. The analog signal is processed using an A/C converter or comparator with a programmable threshold. Due to better accuracy in the current version, the measurements are sampled, and the exact time of appearance of the acoustic wave is determined on the basis of samples. This method is much more accurate, but unfortunately requires more processing power than the processor, which means that the measurement takes longer than in commonly used methods.

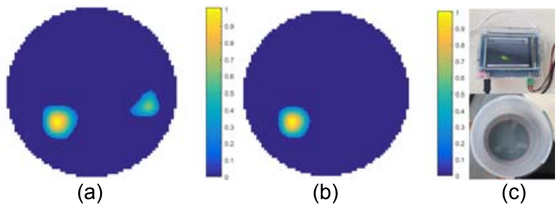

Fig.3. Examples of reconstruction using ultrasound tomography for 20 measuring points with 48 kHz transducers: (a) image reconstruction for 2 objects, (b) image reconstruction for 1 object, (c) tomographic system

The main controller of the tomograph is responsible for managing the measurement sequence, setting the active transducers into transmit / receive mode, and saving the results on an SD card. This is an early version that will be further improved with additional features:

- the ability to change the gain on individual transducers,
- the ability to send results via a USB port to external imaging devices,
- display graphics illustrating changes in the values of individual cells of the results matrix.

Figure 3 shows image reconstruction made by RayIntegration method with a communication system.

Machine Learning Measurement Model

To transform ultrasonic measurements into a tomographic image, an artificial neural network (ANN) of the multilayer perceptron type preceded by an autoencoder was used (Fig. 4). The neural network used during the research had the following structure:

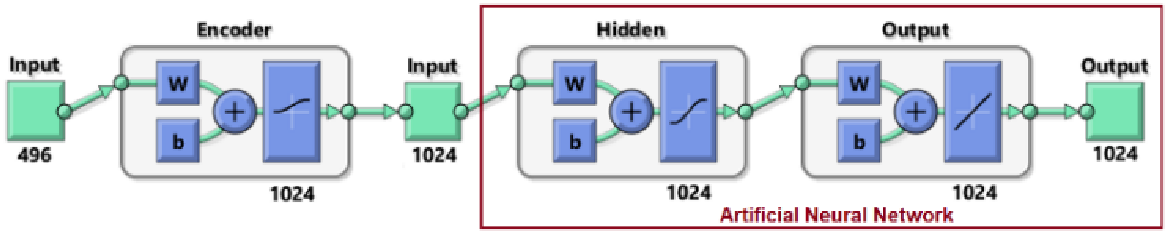

Fig.4. ANN with autoencoder structure

The task of the autoencoder is to improve the image quality by reducing measurement noise. In the presented case, the measuring vector constituting the ANN input consists of 496 measurements. Each measurement reflects the time at which the sound wave travels the distance between the individual transducers. Each of the 32 transducers located around the container walls can both emit and receive ultrasonic signals.

If there are no inclusions on the sound wave path, the time the sound wave travels over a given distance is the shortest. Before starting measurements, the system performs a reference measurement in an object-free environment. The appearance of objects inside the tank disturbs (reduces) the speed of sound, thus increasing the time recorded between individual transducers. This allows you to specify the location and size of the objects. The test object is a physical model of an industrial tank reactor. During the tests, a container filled with tap water was used. Various objects were hidden in water and ultrasound measurements were carried out to detect them. Knowledge of the location and dimensions, as well as the number of all inclusions corresponding to each measurement, enabled the development of a simulation algorithm that generated 20,000 learning cases (measurements and pattern images) used to train ANN.

Conclusions

The RayIntegration algorithm gives good reconstructions, but the condition for obtaining them is a precise calibration of the devices made before each series of measurements. This is troublesome because the calibration is performed on an empty tank. In laboratory conditions, calibration is not difficult, but in industrial conditions, frequent calibration can be difficult.

ANN does not require such frequent calibration - which is its advantage. ANN has been enriched with an autoencoder for denoising the input data. In the presented research ultrasound tomography was used to identify hidden inclusions in a tank filled with water. The input vector contained 496 measurements, which were characterized by a certain level of noise. The noise was caused by errors and inaccuracies in the measuring equipment, as well as interference in the way the data was transmitted between the components of the measuring system. Research has shown that using ANN in combination with an autoencoder, the reconstruction images are of good quality. It was found that sparse encoder placed before ANN inputs significantly improves the quality of measurement data. Furthermore, the use of the encoder equipped with a sufficiently large number of neurons allows the transformation of an under completed problem into an over completed one, which significantly improves the reconstruction results. The research has confirmed that the use of rare autoencoders can significantly improve tomographic imaging performance. As a result, the ultrasound tomography method, which is still not very popular, can be successfully used in the process industry.

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