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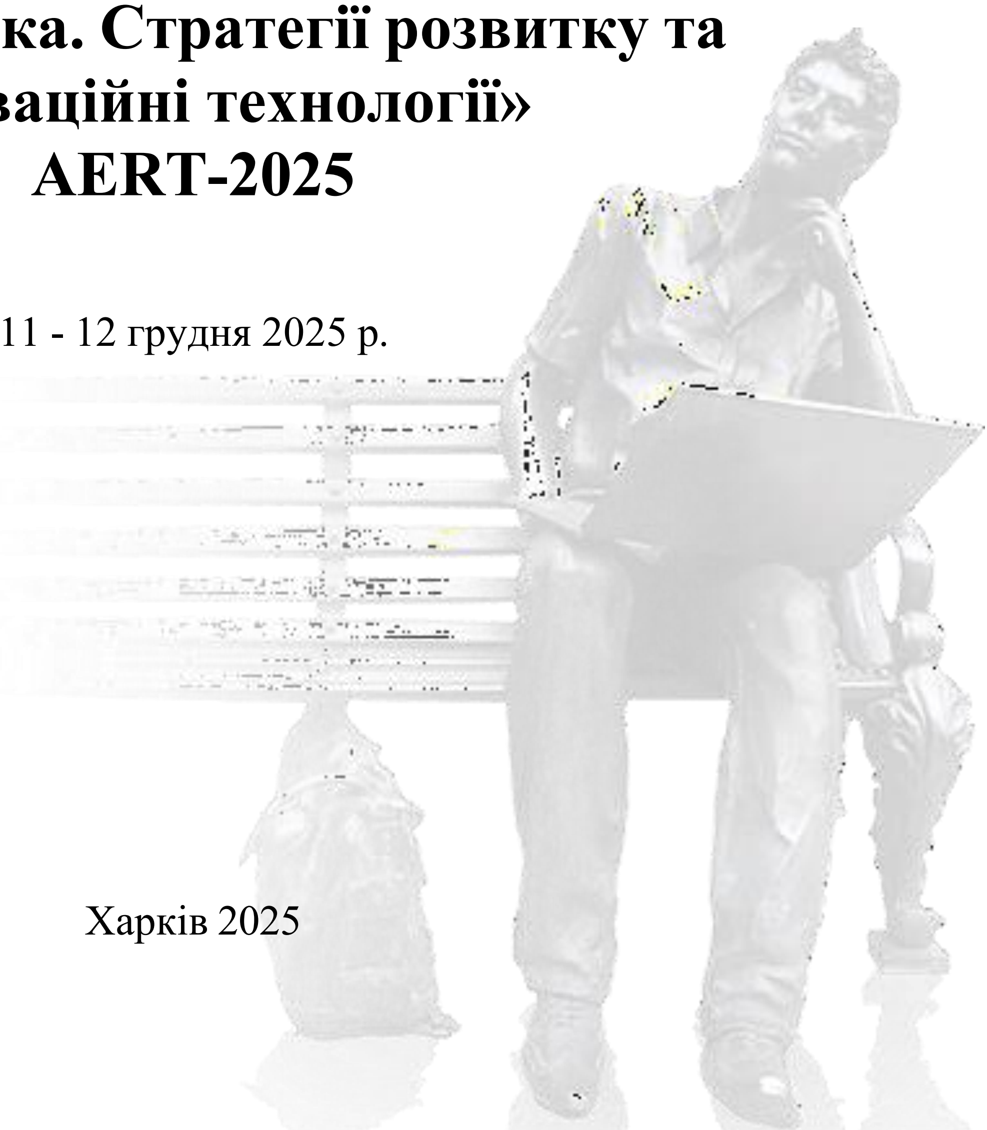

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ARTIFICIAL INTELLIGENCE AND DIGITAL TWINS

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Abstract. Robots and AI-based software can be expensive, delaying adoption in some industries. In addition, AI tools are not always ready for mission-critical applications because there are not enough data sets to train them. One of the important factors in the development of cyber-physical systems is the use of digital twin technology. As embedded vision systems, sensors, and AI pipelines become increasingly complex, digital twins will continue to be the testing ground where the robotic accounting of the future are created today.

Keywords: digital twins, artificial intelligence, robotics, data.

Introduction. Digital twins are quickly becoming a key tool in developing and implementing artificial intelligence in robotics. While previously limited to aerospace or high-budget automotive projects with significant use of simulation, they are represented by highly accurate, real-time virtual models that can significantly simplify the implementation of sensory systems.

Digital twins provide a fast, secure, and scalable tool for training and optimizing AI models for developers of embedded machine vision systems, sensors, and AI applications. Worldwide, this convergence of the physical and virtual worlds enables machines to see, think, and act more accurately.

Traditional approaches to implementing AI systems have always been too expensive, slow, and limited by production constraints. The challenges are not only hardware-related, but also real-world conditions. In addition, extreme scenarios are often challenging to capture or replicate in the real world.

Digital twins are changing the status quo. By simulating a manufacturing process or system on a computer, engineers can subject a model to thousands of tests for different environmental conditions, manufacturing processes, materials, technologies, or natural anomalies. These tools speed up model training and enable more intelligent decision-making by allowing engineers to test scenarios that would be difficult, expensive, or impossible to perform in the real world.

Moreover, because the data are collected in a known, controlled environment, the results are guaranteed to be accurate. These data significantly reduce the need for human correction, an expensive and time-consuming aspect of supervised machine learning.

Implementing AI based on digital twins

Some leading vehicle manufacturers are partnering with electronics industry leaders to integrate digital twin technology with AI-based robotics, particularly in smart manufacturing and logistics.

These digital twins simulate robotic manipulators and autonomous transportation systems, and train AI-based vision models to process assembly data, recognize parts, and recognize obstacles in the workspace. Training embedded vision systems in the simulation cycle will increase the production efficiency and reduce integration errors in real-world conditions.

Manufacturing uses 3D scanning of factory floors to create digital twins automatically. This map includes complete semantic object segmentation and composition geometry, which are critical for training AI vision models that must interact with congested, complex industrial spaces (Fig).

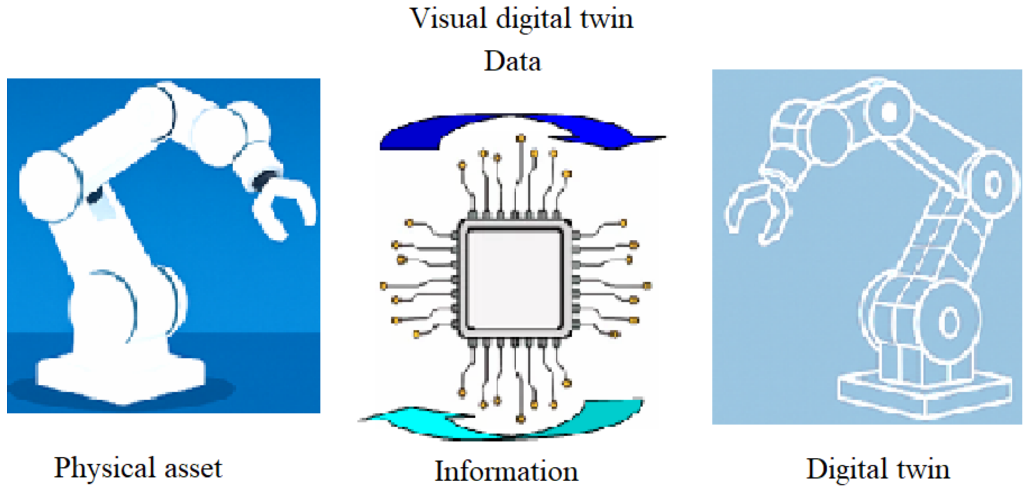

Fig. Generalized framework for implementing AI based on digital twins

Synthetic data as the basis of AI

Synthetic data were recently seen as a workaround for the lack of real-world data sets. But today, it is becoming the basis for developing AI systems for vision analysis in digital twin applications. The special feature of synthetic data is the ability to scale and evolve. It allows for dynamic randomization of domains, allowing models to learn the visual features of the system under a wider distribution of conditions.

Synthetic data generated by AI based on samples. It takes a real dataset as input and is used to train a generative AI model. The model learns the original data's structure, patterns, and statistical properties, and then generates entirely new data points that reflect those properties. The result is synthetic data that closely mirror the original dataset regarding utility and behavior but contains no personal information.

Real data, in contrast, are created without reference to real data. They rely on predefined rules, randomness, or patterns. Because they lack real-world context and complexity, mock data often fail to capture the statistical nuances needed for complex use cases such as model training or analytics.

A recent development uses AI-generated mock data, which is made possible due to large language models. This approach does not rely on a sampled dataset, but instead uses query-based generation to produce data that conforms to structural or semantic patterns. While it can be more flexible and realistic than rule-based dummy data, it still lacks the statistical underpinnings that sample-based synthetic data provides.

There is also an important distinction between structured and unstructured synthetic data. Unstructured synthetic data includes images, audio, or video, which are common in fields such as computer vision or speech recognition. Structured synthetic data, on the other hand, refers to tabular data with defined relationships between values, such as financial transactions, medical records, or time-series behavioral data. This data type is widely used in enterprise systems and is particularly valuable for developing artificial intelligence and analytics.

Developers can simulate changes in the time of day, sensor condition, component form factor, or camera positioning, all without having to touch the equipment. Moreover, failure modes can be intentionally induced, training AI systems to respond to unlikely but critical edge cases. Conducting such tests on a physical object directly on the production line is very difficult, if not impossible.

Embedded vision in manufacturing

Integrating embedded machine vision systems into a digital twin simulation environment offers significant advantages from an engineering perspective. Using virtual cameras and simulated image streams, developers can prototype AI algorithms directly on virtual versions of embedded hardware, such as FPGAs, ASICs, PLDs, or MCUs.

When these embedded systems are combined with continuously operating actuators, such as levers or coordinate systems, that provide high precision and repeatability, the resulting synthetic data becomes even more valuable. The precise mechanical behavior ensures that the AI vision model can learn from consistent motion similar to real-world motion, which is crucial for object detection, sorting, or micro-assembly tasks.

It opens the way to in-loop hardware simulation in conjunction with AI vision, where engineers can evaluate the performance of their system under real-time constraints. An engineer can simulate latency, frame rate limitations, and sensor noise without the physical object.

The promise of digital twins is not just convenience, but also productivity. AI systems trained in these environments are more reliable, adaptable, and ultimately more valuable to the industries implementing them.

Digital twins allow robots to adapt to unfamiliar environments by learning in virtual environments, replicating their physical counterparts. These simulations allow engineers to test the limits and optimize collaborative tasks in real time. AI can learn collectively across industries by integrating digital twins with IoT sensor data and feedback on system performance.

Sensor integration for reliable defect detection

Quality control is an important but often inefficient part of the manufacturing process. Machine vision can help by automating some or all of the defect detection operations, but it cannot provide improvements on its own.

Engineers must understand and improve the machine vision inspection process for the technology to deliver the desired results. Like artificial intelligence technologies, machine vision is just a tool. How well it works depends on how well the end users can use it. With that in mind, there are several critical steps to integrating machine vision systems into defect detection.

The first step in the machine vision inspection process is determining what qualifies as a defect. AI is not as flexible or capable of nuanced thinking as humans, so it needs specific guidance. Effective defect detection depends on understanding what acceptable products look like and what does not.

Next, it is necessary to determine the technology that meets the specific task of detecting defects or discrepancies.

One of the important factors that complicates the application of machine vision in digital twin technologies is lighting. All visual studies depend on light, so it is necessary to provide the right environment to increase the contrast of the object of identification and minimize the contrast of other elements.

The next step in the machine vision validation process is to build and train a machine learning model. The data fed into the system is the most important factor in this step. The key here is to have enough informative defect examples and acceptable data. All data should be in the same format as the machine vision system to analyze it in practice.

Implementing results into production

Therefore, machine vision, embedded vision systems, sensors, and AI pipelines can significantly improve the speed and accuracy of defect detection, provided that they are properly implemented. This is crucial to maximize the impact of this technology.

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