A Mixed Fog/Edge/AIoT/Robotics Education Approach based on Tripled Learning

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Abstract. The article describes a triple learning approach to educational process using a specialized three-level training robotics platform to train professionals in the higher education system, which includes software and hardware for the sequential study of general intelligence related AI, such as Internet of Things, Cloud Computing, Robotics, and more. The described solution is based on Fog/Edge/AIoT stack and allows to build both set of laboratory works and complex completed projects in the context of the concept of tripled learning, as well as to carry out research projects. The platform described is modular and contains several levels of difficulty for optimal configuration according to the course syllabus. The usage of an Artificial Intelligence approach with remote data preprocessing (at edge level) can significantly reduce the computing and time resources and complexity, as well as refuse centralized storage of the entire array of data, which brings the processing of data much closer to online mode. The proposed platform allows improving the quality of the educational process, to increase its orientation to practical experience and to reflect the current state of AI synergy through Fog/Edg/Cloud with IoT.

Keywords: AIoT, Fog, Edge computing, Robotics, Cloud, Tripled Learning.

1 Introduction

The educational process for teaching an engineer in scientific information technology using modern software and hardware is high complicated and must be in permanent progress [1]. The development of IT, like other evolutionary processes, can be characterized by spiralling growth. First of all, a return to saved solutions, but to a higher technological level. The principle of operation is a mainframe with an extended system of terminals for operators. Merged factual terminals have gradually grown and evolved into "smart" terminals, using personal computers (PCs). Autonomous PCs have become integrated into networks, with the development of which the Internet has become a self-contained phenomenon. Accordingly, the dominance of the client-server architecture can be considered to some extent

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equivalent to the "mainframe" transposed to a higher technological level. Gradually, individual servers began to merge into clusters, and a cloud-based distributed computing system developed, and the Internet began to integrate a huge number of peripherals, the Internet of Things (IoT).

The ever-increasing amounts of information, including high-resolution video streams from a variety of surveillance cameras, and, consequently, the need to process them in near real-time, have led another developmental spiral to delegate some computing capabilities to the Cloud level.

The emergence of Edge/Fog computing [2] and the emergence of "smart" IoT - AIoT is a result of the synergy of IoT and artificial intelligence (AI).

At the same time, there is a rapid evolutionary development of a fundamentally new concept for human civilization - creation of robots endowed with certain artificial intelligence, oriented mainly in narrow spheres, such as:

- orientation and autonomous movement in different terrains,
- the performance of specific technological functions and other activities that do not require high level of ownership.

The next stage of development is the emergence of "full" artificial intelligence - Strong Artificial Intelligence, known as Strong AI in English sources [3], or full AI [4] or Artificial General Intelligence (AGI) [5].

The purpose of the article is to describe the principles of blended learning using a robotic platform and artificial intelligence on the Internet of Things.

2 The educational robotic platform

It is suggested to use a specialized training platform to train professionals in the higher education system, which includes software and hardware for the sequential study of general intelligence related AI (AI), such as Internet of Things, Cloud Computing, Robotics, and more.

The described solution allows to build both complex laboratory works and complete completed projects in the context of the concept of tripled learning [6], as well as to carry out research projects. The platform described is modular and contains several levels of difficulty for optimal configuration according to the course syllabus.

The first level is a versatile standalone T-Bot mobile platform based on the popular Arduino training microcontroller with distance, motion and color sensors.It is also possible to use a more powerful microcontroller from the STM32 line. This level has already been successfully implemented in the educational process during the three years of study in the course “Algorithmization and Programming. Part 1” of the first year of study at the Department of Artificial Intelligence of the Lviv National Polytechnic University. Photo of this hardware presented on Fig.1

The second level is structurally placed above the first and is responsible for more intelligent capabilities such as image recognition, object analysis and communication with the Cloud. Technically, this layer is a Raspberry Pi 3/4 microcomputer with a video/web camera and OpenCV or OpenVINO. The main task class is machine learning, that is, the computation of pre-trained and optimized neural networks, usually using Keras with TensorFlow. Because the Raspberry Pi's computing resources are not enough to fully support artificial intelligence tasks, particularly when moving from cloud to Edge/Fog Computing, the next component of this layer is a separate, dedicated neural network-oriented USB module.

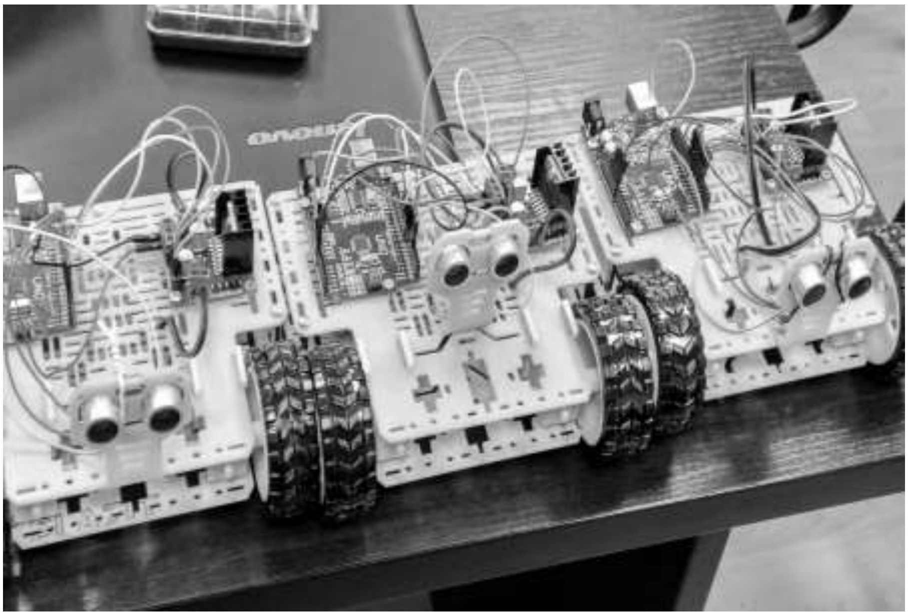

Fig. 1. Appearance of the first-level T-Here robotics-training platform with Arduino and ultrasonic rangefinder.

Examples of this approach are Intel's Myriad ™ X VPU [7] - the third generation and the most advanced VPU from Movidius ™, Intel, or the Google Edge Coral Accelerator [8]. Intel's Myriad ™ X VPU for the first time in its class features the Neural Compute Engine, a specialized hardware accelerator for deep neural networks. The combination of 16 powerful SHAVE cores with intelligent memory makes Myriad X a leader in the use of deep neural networks and computer vision software. Google Edge Coral Machine Accelerator - Edge TPU ASIC developed by Google. Provides high performance machine learning (ML) for TensorFlow Lite models.

The third level is the extension of the described two-tier platform for robotics tasks and provides both laboratory work in an appropriate course and opportunities for research in the fields of robotics, artificial intelligence and the Internet of Things. The Robot Operating System (ROS/ROS2) open source software framework is a software framework that provides a suite of libraries of software and tools for programming robotic systems of varying complexity and contains a wide range of applications, from drivers to state-of-the-art algorithms and powerful developer tools.

In addition to software, this level involves the use of various actuators and sensors, which are typical in robotics tasks. One of the benefits of ROS is the ability to both pre-simulate robotic systems in a Gazebo virtual environment and run on real hardware.

3 From Cloud to Edge/Fog/AIoT

Modern artificial intelligence and IoT technologies are closely linked and complementary. The classic topology of IoT solutions involves the analytical processing of information on the Cloud side and, by analysing data obtained from many sources of information, produces a synergistic effect of Artificial Intelligence on the Internet of Things (AIoT).

The downside, as mentioned above, is today's cloud-based data analytics. Collecting huge amounts of data from thousands or millions of peripherals requires not only the continued growth of Cloud computing resources, but also high-speed and broadband communication channels. Since the performance of the neural networks in machine learning tasks depends not least on the quality of the data received, it also causes an increase in data transmission.

One way to solve this problem is to deploy artificial intelligence at the earliest stages of information transfer, using the concept of moving from Cloud computing to Fog computing [9].

In other words, Edge devices become "smart" and capable of performing a wide range of typical artificial intelligence tasks, including machine learning (ML) and deep learning (DL), on their own high-performance neural network-oriented hardware, without sending them to the Cloud. Results are no longer sending a raw data to the Cloud, but rather as structured metadata. For example, instead of continuous high-definition video streaming, only the results of detected events or objects with the appropriate description are sent to the Cloud, and this process is not continuous, but only as certain changes in the observed space are detected, ie from time to time.

Obviously, this approach can significantly reduce the requirements for data channels, cloud-computing resources and provides a number of additional benefits, such as the ability to improve AIoT peripherals without making changes to the system architecture as a whole. At the same time, the released cloud resources will allow more efficient processing of structured metadata and decision-making. Because AIoT/Edge/Fog technologies are in active development and development, there are different approaches both to architecture as a whole and to sectioning into separate logical and structural layers. One of the most appropriate is to take the conditional section vertically from the peripherals through the "smart fog" (Fog) to the cloud level. Other authors find this approach somewhat simplistic and use two-dimensional views with detail and a complex interconnection system.

According to Mukherjee et al [10], Aazam and Huh [11] and Muntjir and others [12], the Edge/Fog architecture of computation consists of six layers:

1. **Physical and virtualization:** virtual sensors and their virtual network; physical sensors, devices, their wireless network;
2. **Monitoring:** activity, capacity, resources, reactions (responses) and services;
3. **Pre-processing of data:** analysis, filtering, reconstruction and restoration, cleaning;
4. **Temporary storage:** data dissemination, replication and de-duplication; virtualization of storage space and devices (NAS, FC, ISCSI, etc.);
5. **Security:** encoding / decoding, privacy, integrity;
6. **Transportation:** Uploading prepared and secure data to cloud services.The physical and virtualization layer includes different types of nodes such as physical nodes, virtual nodes, and virtual sensor networks. These units are managed and maintained according to their types and maintenance requirements.

The monitoring level monitors the use of resources, the presence of sensors, and the monitoring of Edge / Fog nodes and network elements. It keeps track of all the tasks performed by the nodes in a given layer, monitoring how energy consumption and computing time are monitored, which node performs what task, at what time, and what it will require in the next moment.

The performance and status of all applications and services deployed in the infrastructure depends largely on the effectiveness of the monitoring. The pre-processing layer performs the task of managing the data. The data collected is analysed, filtered and cleared of unnecessary information and noise. Pre-processed data is stored at the temporary storage level. Once the prepared data is transferred to the cloud, it no longer needs to be stored locally and can be removed from temporary storage. At the security level, encryption / decryption of data takes effect. In addition, data integrity prevents unauthorized interference and measures are in place to protect data from tampering.

Finally, in the transport layer, the pre-processed data is loaded into the cloud for further analysis. Only a fraction of the data collected is downloaded to the cloud for efficient energy use. In other words, a gateway device that connects the IoT to the cloud processes the data before sending it to the cloud. This type of gateway is also called the smart gateway.

Data collected from network sensors and IoT devices is transmitted through smart gateways to the cloud. The resulting data is stored and used by the cloud to create relevant services and services for users. Given the resource constraints, communication protocols for Edge/Fog computing should be efficient and easy to set up. The use of a microservice approach with remote data preprocessing (at edge level) can significantly reduce the use of computing and time resources, as well as avoid centralized storage of the entire data set, which brings the processing of data much closer to online mode.

Next level of scalability is thinking about Fog/Edge computing from robotics point of view. As an example of mobile IoT scenarios, in robotic deployments, computationally intensive tasks such as run time mapping may be performed on peer robots or smart gateways. Most of these computational tasks involve running optimization algorithms inside compute nodes at run time and taking rapid decisions based on results. In [13], authors incorporate optimization libraries within the Robot Operating System (ROS) deployed on robotic sensor-actuators. Using the ROS based simulation environment Gazebo, they demonstrate case-study scenarios for runtime optimization. Instead of Intel Movidius with Raspberry Pi existing other similar solutions. For example, in [14] a framework of such an edge computing system is presented for robotic applications. The system consists of a recent machine learning platform (Jetson TX2) integrated within a heterogeneous robotic environment of UAVs and mobile robots operated through robot operating system (ROS).

4 Implementation of the concept of tripled learning

Vertically oriented, architecture is presented in Fig. 3, proposed in [14], which describes Edge / Fog / Cloud in terms of distributed computing of the Internet of Things.

Thus, the use of a microservice approach with remote preprocessing (at edge level) can significantly reduce the use of computing and time resources, as well as to avoid centralized storage of the entire data set, which brings the processing of data much closer to online mode.

General architecture of modern Edge/Fog/Cloud can be represented [13] as in

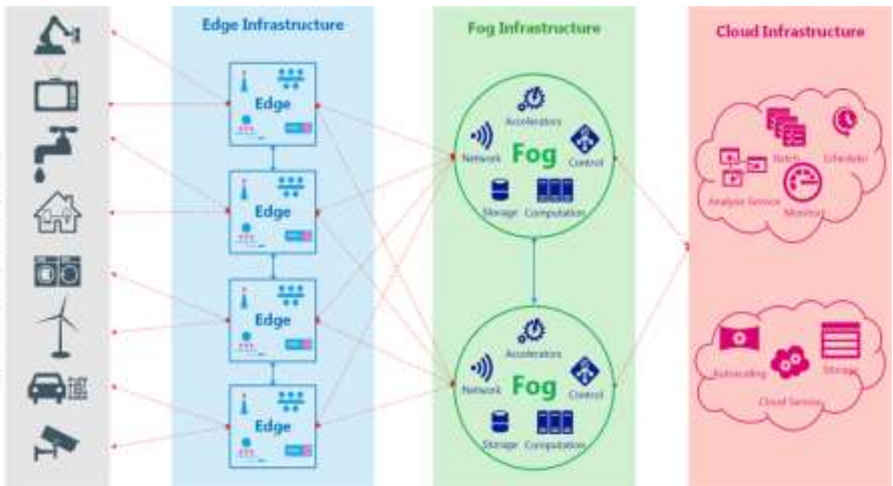

Fig. 2.

Fig. 2. The horizontal edge-fog-cloud architecture

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Modern civilization is constantly on the lookout for effective ways of learning, particularly in the face of rapid progress. In addition to traditional or "classic" methods, such as lectures and workshops, there is also an online version of it as e-learning and blended learning. In [6, 15], the term blended learning was introduced for the first time, or triple learning as a combination of three different complementary approaches:

1. Offline or "traditional" training that includes lectures, hands-on and / or lab work according to the "classic" approach.
2. Self-study online on one or more pre-selected free online course (MOOC) courses, selected by the lecturer according to the subject matter.
3. Team work on own projects with the possibility of involving third-party mentors and experts for evaluation.

All three components are strongly interrelated and run concurrently within a specific training course. According to the proposed structure of triple learning, which is already practiced in separate courses, third-party independent experts noted the increase in the effectiveness of training and awakening of creative potential among students. For three years, we have successfully implemented the proposed triple training as part of the Algorithm and Programming course. Part One "for first year students of the Artificial Intelligence Specialty.

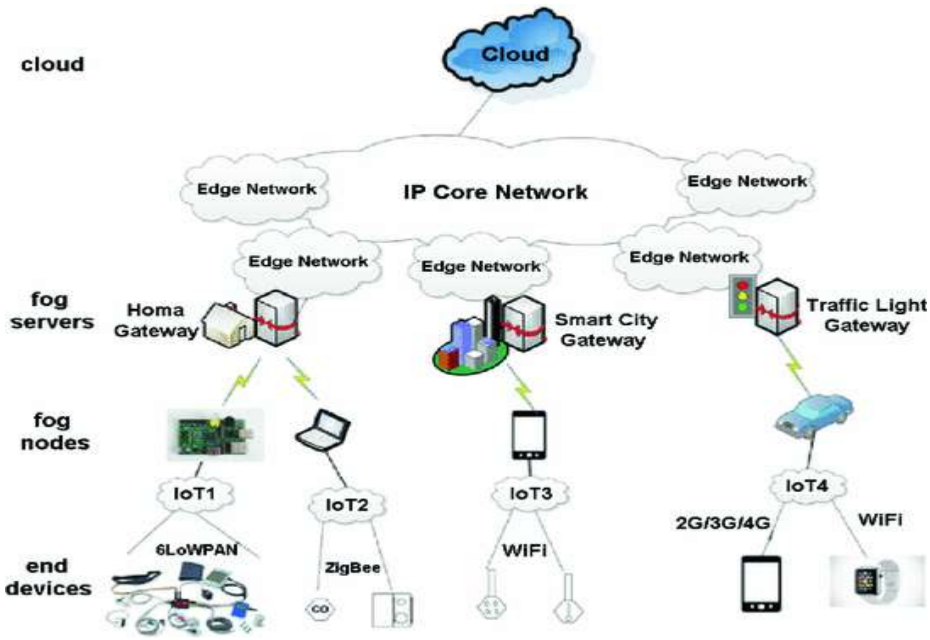

Fig. 3. Vertical edge-fog-cloud architecture

This course is designed to learn the basics of C/C++ programming with examples of using different algorithms. The basics of different basic concepts and concepts of IT, such as operating systems, networks, Internet, client-server technologies, elements of modern web development, project management process, Cloud computing, Internet of Things, artificial intelligence, robotics, etc., are also presented in an overview. The focus is on learning C/C ++ programming.

As a second component, for self-study, expert analysis of a number of different online courses was conducted to select the best one according to the subject of this course. The result is the internationally recognized online course "Introduction to Computer Science. CS50" from Harvard University.

The third part is teamwork on different projects during the semester. As a result, for three consecutive years, more than 120 first-year students are consistently formed from 30 to 40 teams working together on self-selected topics, drafting projects during the semester under the guidance of a lecturer, presenting them at an interim defence and completing a presentation with an independent panel of experts invited from various IT companies.

This practice made it possible to extend the concept of tripled learning to the next academic years as well. Current projects provide opportunities for development in subsequent courses and mentoring support from undergraduates. The next is the introduction of a similar approach to the level of training in the training courses in cloud technology, the Internet of Things, robotics with a common unifying approach to machine learning within artificial intelligence.

The proposed robotic platform provides the technical capabilities for a quality implementation of the concept of tripled learning in a crosscutting perspective, that is, with the gradual, permanent development and development of projects from simpler to more sophisticated as well as the continuation of student projects to the level of research.

Thus, in the first year students use a ready-made robotic system with the specified encoders and capacities for programming a narrow class of tasks - movement along the trajectory, exit from the maze and so on. In the second year, depending on the type of project, students add additional sensors, and form a front-end and back-end part to control the robotics part. In the third year, students can add to the specified Raspberry Pi 3/4 platforms with camera and OpenCV / OpenVINO while using the Myriad ™ X VPU with a trained neural network. An example of this project is a mobile robotics platform for detecting the movement of an object indoors. In addition, in the fourth year, students take the AIoT part while studying the Cloud Computing and Introduction to Robotics courses.

5 Conclusions

The article describes a three-level training robotics platform for use in the educational process when performing laboratory work, developing course projects and in the research process.

Significantly new in the work is the creation of a universal modular solution with complementary components, the ability to apply at different levels of qualification and modify according to current needs.

At the same time, the proposed platform is an organic part of the modern spiral of development of information processes and systems and allows improving the quality of the educational process, to increase its orientation to practical experience and to reflect the current state of AI synergy through Edge/Fog/Cloud with IoT.

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