Edge-Centric Video Data Analytics for Smart Assistance Services in Industrial Systems

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***Abstract*—Video data analytics has now become essentially oriented on edge-centric computing in Internet of Things (IoT). In this paper, we consider such video services that provide analytics to smart assistance in industrial IoT systems. We identify the opportunities of industrial video data analytics. We present an edge-centric architecture for constructing smart assistance services. Based on this architecture, we implemented several pilot services that demonstrate the opportunities of industrial video data analytics. The services are deployed and experimented in a real enterprise for monitoring industrial production equipment (technical state and its evolution, ongoing production processes, equipment operating conditions).**

Keywords*–*Video data analytics; Internet of Things; Smart Assistance Services; Edge-Centric Computing.

I. INTRODUCTION

Internet of Things (IoT) supports the development of smart environments, where the key element is a smart service [1]. The service intelligence is essentially based on data analytics. In the case of video data, a smart service provides video surveillance and visual interactivity with the user [2]. Such a service provides analytical information about the object under monitoring [3].

Video data analytics has now become essentially oriented on edge-centric computing in the Internet of Things (IoT) [4], [5]. In this paper, we consider services that provide video data analytics to smart assistance in industrial IoT systems. Our Industrial Partner to deploy and experiment with the services is Petrozavodskmash, which is a branch of AEM-technology JSC in the Petrozavodsk city (Republic of Karelia, Russia). The company is one of the largest machine-building enterprises based on the following industries: foundry, welding, and mechanical assembly production.

The challanging problem is performing video data processing on edge devices, which are of low capacity and computing power [1]. In this paper, we show that a solution to this problem moves industrial video data analytics to the next level with respect to the "real-time assistance" property of the smart services. We consider an edge-centric architecture for constructing such smart assistance services in Industrial IoT (IIoT) systems.

Based on this architecture, we implemented several pilot services to demonstrate the opportunities for industrial video data analytics.

- Monitoring mechanical components of equipment to detect deviations in machine operations;
- Operator presence in the area to control production processes;
- Screen image text analysis from the Computer Numerical Control (CNC) display monitor to detect errors.

The services are deployed and experimented for monitoring industrial production equipment (technical state and its evolution, ongoing production processes, equipment operating conditions).

The rest of the paper is organized as follows. Section II considers existing methods and example services in edge-centric video data analytics. Section III identifies the opportunities of video data analytics based on the needs of our Industrial Partner. Section IV presents our edge-centric architecture for constructing smart assistance services. Finally, Section V concludes the paper.

II. RELATED WORK

The current focus on edge-centric in IoT systems supports high efficiency and throughput of the processed information [6], as well as provides additional opportunities for connecting multiple devices. Edge-centric allows us to organize decentralized computing on multiple edge devices, using limited resources between participants in the space. Many systems use mobile devices at the edge [7], which allows for more efficient distribution between devices. The organization of such a computation model makes it possible to reduce the computation time of the most complex algorithms that require a large resource of time for preprocessing and analysis.

Many solutions integrate existing IoT concepts into more comprehensively organized structures. A particular example is the combination of several video surveillance devices into a common video system behind a complex object: the smart home. Smart homes are combined into smart cities [8], which makes it possible to control systems such as ecology, security, safety, and health of citizens on a global level. Modern monitoring systems are able to diagnose the working condition of machines in real-time. This allows for early detection of deviations and breakdowns that occur with equipment during active production [9]. As monitoring tools, sensors, or sensor networks is mainly used to measure various indicators of the current state of machines (e.g., current consumption, temperature, accelerometer values). Such sensors are installed in the internal system of the equipment or are connected separately from the equipment.

During the operation, machines generate vibrations which result in the deterioration of machine tools eventually causing failure of some subsystems or the machine itself [10]. The vibration signatures analysis can be used to detect the nature

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and extent of any damage in machines and components or any maintenance decisions related to the machine. However, modern industrial monitoring systems mainly use sensors to detect a large number of defects. Thus, the breakage verification criterion is based solely on sensor readings. The use of video services makes it possible to expand the empirical picture of the breakdown of machinery, even when a video camera is watching an object.

Thus, the closest solutions to the developed solution are the following scientific works: recognition of worker activity in a factory using convolutional neural networks [11], recognition of workers who are not wearing a safety helmet [12], error recognition based on text from CNC monitor [13].

III. Industrial Video Data Analytics

The Petrozavodskmash company is a machine-building enterprise with a huge database of machine tools working in various industries. We use our industrial partner to deploy and experiment with our pilot smart assistance services for monitoring industrial production equipment (technical state and its evolution, ongoing production processes, equipment operating conditions).

A. Methods

The key solution of the method is the use of edge computing, which includes well-known mathematical processing algorithms (for example, motion recognition on a video camera, image rendering, combining information video streams), semantic data mining (separation of relationships and relationships between streams) and performing calculations using several heterogeneous resources of video cameras and personal mobile devices available in the peripheral IoT environment on different mobile platforms.

Semantic integration will take place at the level of the IoT environment, using the available resources of the surrounding equipment to obtain data for observing objects. In particular, efficiency gains will be achieved through: connecting a large number of video cameras and processing on devices with low performance; the use of Artificial Intelligence (AI) technologies; calculating heterogeneous data analyzed on the basis of images from a video camera; using the Semantic Web and finding connections between video streams. Modern video data analysis systems for recognizing people, objects and zones, are described in [14].

The integration between smart video surveillance and IoT is described in [15]. The authors show how different objects, cameras, and sensors can process various pieces of information in the network. The authors propose an innovative topology paradigm that shows better communication between different video camera surveillance systems provided by IoT.

B. Multi-platform monitoring and computing

Multi-platform development of the mobile applications [16] refers to applications that can work both on mobile (Android, Apple) and desktop (PC, Windows) devices. One of the important advantages is the development of a distributed application that can run on several platforms at the same time, including adjusting to its interface depending on the mobile platform, screen resolution, orientation, and the user's own wishes. The main requirement is to create a combined desktop and Web application presented as a single development environment.

However, the most efficient implementation of multiplatform is to create a hybrid application [17] that runs on multiple platforms simultaneously. The simplest implementation method is to integrate applications into the user's Web browser that is used on each platform. Thus, the display of services will be implemented using their uniform representation for users in the form of an HTML page. All the user needs to do is have Internet access or a local router connection.

C. Edge analytics

An edge-centric parametric predictive analytics methodology is shown in [18]. The use of such a methodology uses predictive data analytics and ensures that only the information that is needed is transmitted. This point is especially important during analysis on the IoT edge, as video data is generally very large for processing and transmission, which creates a huge load on the server and network.

The main advantage is the extraction of the necessary video frames from the stream. Thus, processing incoming frames in real-time, although it will take up most of the processor time, will reduce the load on the network and the occupied space on the local data storage.

D. Heterogeneous data

Knowledge graphs can be used to implement edge analytics in some heterogeneous environments [4]. Since video analytics will be performed in real-time, various pieces of information will be received by users. Instead of the entire video stream, only keyframes that are meaningful to users will be used. Moreover, these frames will be preprocessed in advance and they will contain information that is important for solving a particular task (for example, determining the number of workers in the machine tool area). In addition, instead of frames, it can only be a text or graphic notification about the current state of the equipment. The most complete and advanced delivery option will be the use of graphs, charts, histograms with distribution over time.

Let us count the time between the incident and the operator's reaction. The system requires an average of 1 to 2 seconds to compute. Visible cases (defects) can be detected manually by a person within a few seconds or minutes. Invisible cases (which cannot be detected immediately) can be detected within hours or days. Manual viewing of all video recordings from cameras requires man-hours and also involves all the problems associated with the human factor.

The Video Event Representation Model is shown in Fig. 1. As an example, a service for recognizing people and calculating the distance to a person and equipment is used. The first video camera mounted on top of the machine area contains a video stream with people (machine operators) and also contains a video stream with the equipment. The second video camera is located at the level of human height and is necessary to recognize the helmets worn on the heads of operators (to comply with safety regulations). The third video camera is located at the level of the CNC monitor and is designed to recognize the error code that appears on the screen. Other IoT elements are also located next to the video cameras: an accelerometer, current clamp, temperature, tachometer (however, we will not discuss it at the level of the architecture). First, the connection to the database is initialized, from where the current information about the availability of

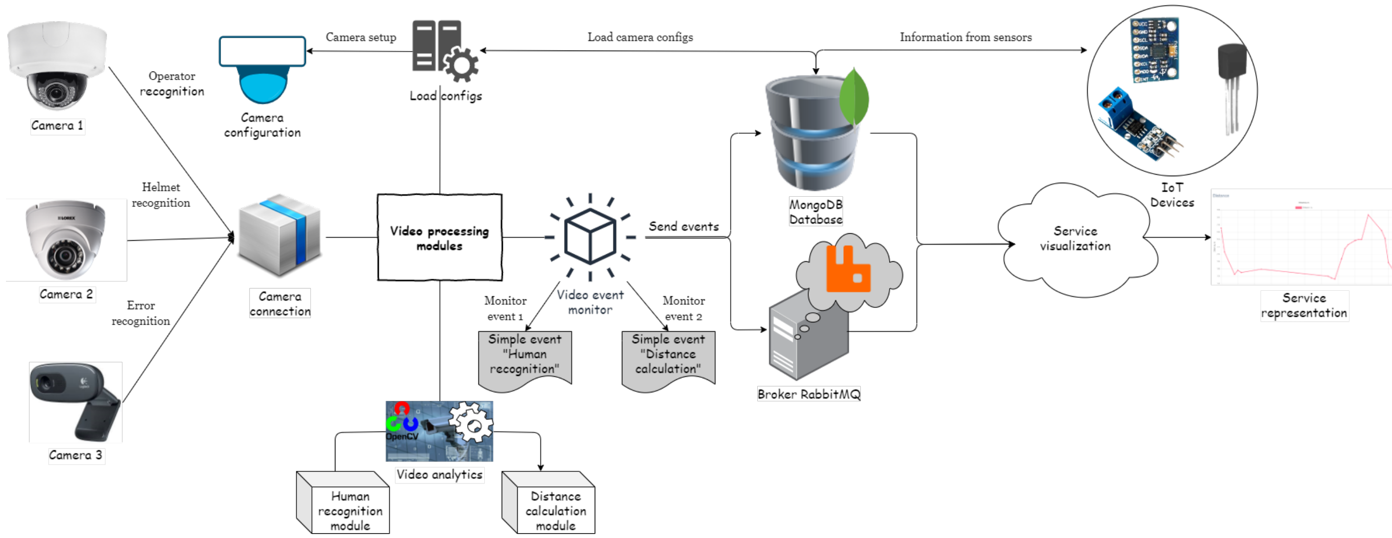

Figure 1. Video Event Representation Model

personnel in the area is taken, as well as the distance to the machinery. Cameras are connected to a router and transmit information to video processing modules. The video analytics modules (module for recognizing a person and calculating the distance) determine the presence of a person in the frame and also determine the distance to him by the silhouette of a person (it is assumed that the silhouette of a person in the frame is always fully visible). Further, events are generated using the monitor and sent to the MongoDB database, as well as to the RabbitMQ message broker. Further, the information is converted into the information necessary for users (building graphs and diagrams) and displayed in video services on the Web on end devices.

Each of the video cameras is used to provide the user with the specific information he needs. This allows the operator to receive real-time information about incidents involving people and machinery in the plant. Let us discuss the benefits of our solution. The applied architectural approach allows us to consider specific services from a practical point of view and deploy and use them in a specific enterprise. In particular, this approach is easy to understand and does not require a detailed explanation of the details. High performance is achieved through the use of automated recognition tools.

IV. Edge-Centric Video Data Analytics

The proposed architecture is based on the following properties:

- multiple video cameras to use, which provide various video data flows to be processed and analyzed;
- microservices to construct a dynamic system of services;
- edge-centric to implement an essential part of analytics locally (near the data sources).

In conditions of work in an unfavorable environment, a video surveillance camera protected from moisture and dust is used to obtain a video stream in real-time with its subsequent processing. The use of cameras that are not equipped with this protection requires the use of external protective boxes.

A. *Monitoring mechanical components of equipment to detect deviations in machine operations*

Consider the following objects for monitoring.

- Shock detection of moving parts of equipment [19].
- Detection of mounted rotary swivel head.
- Counterweight detection.

Monitoring the mechanical elements of the machine using video cameras allows us to automatically monitor the performance of the machine elements for the smooth operation of the machine. Elements that are attachments for the operation of the machine are tracked: counterweight and swivel head. For mounted elements, it is required to monitor: whether it is necessary to install, what is installed, whether it is installed correctly. External influences on the machine (impacts) are also monitored.

The use of the multi-platform allows the operator to control the correct operation of the machine, using a smartphone, without being at his work computer. The use of a smartphone allows us to increase efficiency and response to an event that has occurred since when an abnormality occurs, the operator processes all receive notifications in real-time.

Calculations are carried out on a central computer located near the machine. Computing near the machine helps to avoid the problem of transmitting large amounts of data over the network and to increase the processing speed.

The operator is provided with information about the rotary heads located on the storage rack, as well as the set angles of rotation of each of the heads. Depending on the head and the angle of rotation, a composite event is generated that notifies the operator whether the head is correctly or incorrectly positioned. The impacts of the moving parts of the machine are monitored and the information is transferred to the operator. The presence of the installed counterweight on the head is monitored. Depending on whether the counterweight is installed and the type of installed head, a composite event is generated about the requirement to install a counterweight to avoid incorrect operation of the machine.

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B. Operator monitoring in the area to control production processes

1) Operator memorization and identification by his external characteristics:
   - Work uniform recognition;
   - Helmet recognition;
   - Human and face recognition;
   - Operator identification to gain access to the machine area.
2) Determination of the presence of the operator in the danger zone of the equipment:
   - Operator recognition [5];
   - Equipment recognition [20];
   - Detection of current distance to operator, to equipment;
   - Operator is in the danger zone of the equipment based on distances.

Tracking the presence of the operator on the site allows us to ensure the safety of the work process and control access to the elements of the machine. Recognition of the work uniform and helmet allows to track that the worker is observing safety measures. Face recognition allows us to identify a person and check his competence to work with a specific machine. Determining the operator's presence in the hazardous area is a means of maintaining safety at the machine. Finding the distance between the operator and the elements of the machine allows us to determine the physical interaction with the machine.

The use of a multi-platform allows the operator to receive information on interaction with the machine without the necessary equipment on his smartphone and quickly prevent safety violations. The operator can view the list of current persons in the area of the machine for quick interaction with personnel.

Calculations are carried out on a central computer server, which is located near the machine. Fast data transfer and processing is ensured.

The operator receives a large number of basic events related to the presence of uniform elements, person identification, and distance determination. A composite event about the presence of the necessary uniform consists of the presence of a work uniform and a work helmet. Also, a composite event is the presence of a person in the danger zone without the necessary authority. This event consists of identifying persons, finding the distance, and information about the level of access and competence of a person.

C. Screen image text analysis from CNC display monitor to detect errors

Recognition of the CNC error code from the control panel screen allows us to receive errors that occurred during the operation of the machine in real-time without interfering with the operation of the system. The errors received are analyzed and the results are presented to the operator.

The use of a multi-platform allows us to interact with the system not only while at the work computer but also during absence from the workplace. The operator can receive information about the appeared and recognized the error in smartphone in the form of a PUSH notification, for a timely response and troubleshooting the equipment.

Computations for error recognition are carried out on an intermediate device when information is transmitted to the main computer server. Using the computing device directly next to the webcam will reduce the load on the central computing device.

The operator is presented with the last recognized error and history with time stamps. For each recognized error, a composite event is generated in which its description is shown with the methods for eliminating the error described in the official CNC manual. An event consisting of several errors is also a composite event. The operator is offered recommendations for their elimination, described by a person working with the machine. Providing the operator with analyzed data increases efficiency and reduces problem resolution time.

To deploy services, we need the installation of IP67, IP68 video cameras. The installation of protected cameras is required to prevent damage from dust and water exposure that can occur in a factory environment. The use of a twisted pair cable allows the camera to be powered via PoE (Power over Ethernet) and provides speeds up to 10 Mbps. A switch equipped with PoE ports is used for power supply. It is required to select the correct switch, since with a large number of connected cameras, the switch will not be able to provide enough power for all cameras.

D. Basic and composite events

The correct connection of all services to video devices for receiving data is provided by a user-defined config. The config includes network data for correct connection, authentication data for security, parameters of the received video stream, and the requirements for the video stream imposed by the service. The service results are saved in the MongoDB database.

Events:

- Events definition and specification: basic and composite events [21] [22].
- Composite events operators based on Snoop expressions.
- Table with examples of basic and composite events.

The event-driven data model allows us to organize interaction between software modules within the framework of a given application function. Software modules can be loosely coupled, i.e. to create a module, only the specification of the events to be processed with the rules for their inference is needed, which allows organizing a distributed microservice software infrastructure. Moreover, such a model allows us to combine heterogeneous data sources, forming a single consistent view with a high level of abstraction for a more accurate way of identifying events that occur.

An event in industrial equipment video monitoring systems is determined by a finite time interval at which some integral (indivisible) industrial phenomenon occurs, i.e. such a phenomenon either occurs entirely or does not occur at all. An industrial phenomenon occurs when the state is changed in the physical environment of an industrial enterprise. The environment is equipped with a video surveillance system that allows recording such events at a certain point in time.

In this case, an event occurring in the time interval between two consecutive points is considered to have occurred at the time of the endpoint of the interval.

At the initialization stage, it is necessary to describe the events that will be "tracked" based on video streams received from CCTV (Closed-circuit television) cameras. The following are suggested as basic rules: each video camera generates a separate video stream, which can contain many key elements (phenomena and anomalies) that make up a basic event. At the request of the developer, the underlying event can change depending on time, space, and context. The number of basic events from one video stream can be unlimited. Several video streams contain main events. Several major events make up a composite event (based on video streams $1 \ldots n$). A basic event depends on time, space, and context. Basic events can be independent and observed in different periods of time with different durations. Composite events can include several simple sequential or simultaneous basic events, as well as depend on other composite events. Composite events represent the end result, which can be presented in the form of a graph, diagram, text. The result, in turn, should be understandable and representative of the user.

Table I shows the composite events that result from the service. Composite events are made up of some basic and composite events functionality required by operators to service the machine.

The service for monitoring mechanical components monitors basic events: head type recognition, head rotation angle detection, shock detection. The composite head positioning event uses basic head type and angle detection events. For composite event tracking, the head type is determined based on its position in the storage rack and its external characteristics. The angle of rotation is tracked using visual elements on the head and displaceable when it is rotated. Tracking the correct positioning allows us to avoid breakdowns when installing the head on the machine since the machine does not check the current angle of rotation of the head and the installation is an automatic process of the machine and is little controlled by the operator. The tracking of counterweight installation depends on basic impact detection events and the type of head installed. Tracking the type of head installed allows us to know if a counterweight is needed on a given head. Impact tracking allows us to determine if the head is balanced. Installing a counterweight prevents incorrect machining of parts and is a necessary element for some machining heads.

The operator monitoring in the area of the machine monitors basic events: work uniform recognition, helmet recognition, human and face recognition, object distance detection. A composite event indicating that the operator is wearing appropriate clothing and protective equipment uses basic helmet and uniform recognition events. Every employee working in the plant must wear a special work uniform and be equipped with a helmet to protect the head. Wearing this uniform is required to comply with safety regulations and to save the life of employees. To track illegal access to the machine, human and face recognition events, object distance detection, as well as a database of employees with their competencies and access levels are used. Composing a composite event requires recognizing people's faces and distance to objects. If a person is in the service area, then his competence to work with this machine is checked. In a factory environment, with a large space and a large number of workers, it is required to control the level of access to equipment. It is required not to allow unqualified personnel to work with the machine without the participation of the machine operator. It is also required to track who at what time worked with the machine. The composite event of recognition of a person in a danger zone consists of human and face recognition, object distance detection. Recognition of a person and the distance to dangerous objects occurs, if the distance is less than a certain one, then the person is considered to be in the danger zone. An important element when working in a factory is compliance with safety measures; this can be solved by detecting a person in the hazardous area next to the machine in operation.

The screen image text analysis monitors a basic event - the appearance of error code on the screen. A composite event showing the operator a detailed description of the error consists of an error tracked on the screen and a database with a description of all available CNC errors. Obtaining a detailed description saves the operator from searching for information and provides information about the description and the method for resolving the error that has occurred. A composite event of related errors consists of several events of the occurrence of an error code at a time interval. It allows us to track errors that appear in a group for accurate identification of the malfunction and quick correction.

TABLE I. BASIC AND COMPOSITE EVENTS

Service	*Composite event*	*Basic event*	*Functionality*
Monitoring for position and movement of mechanical components	Correct head positioning	Head type recognition, head rotation angle detection	Prevention of breakage of parts of the head mounts, due to incorrect positioning of the head during its installation
	Counterweight Installation Requirements	Head type recognition, shock detection	Prevention of the appearance of defects on the object being processed by the machine, due to the appearance of vibration on the processing head
Monitoring for operator (human) presence in the area	Full uniform availability	Work uniform recognition, helmet recognition	Ensures the implementation of safety measures to protect the health of personnel
	Determining the access level	Human and face recognition, a database of employee qualifications and access levels, object distance detection	Prevention of access to personnel not qualified to operate the machine, to prevent damage due to poor quality maintenance
	Recognition of a person in a danger zone	Human and face recognition, object distance detection	Protection of personnel from being in hazardous areas where a person can be injured as a result of the operation of the machine
Monitoring for text messages observed on the equipment display	Error code with detailed description	Error code recognition, a database compiled from the official CNC error manual	Providing the operator with real-time error information, which will allow faster correction of errors and ensure the smooth operation of the machine
	Related errors	Recognition of error codes	Tracking error chains when a lot of errors appear, to accurately identify the problem and fix it as soon as possible

Table II shows the current capabilities of the service and possible improvements. Current capabilities refers to the capabilities that are currently provided by the installed services at the factory. Possible improvements refer to additional service capabilities that can be implemented to help workers and management.

TABLE II. SERVICE CABILITIES AND OPPORTUNITIES

Service	*Cabilities*	*Opportunities*
Monitoring mechanical components	Determining the angle of installation of the processing head and the type of installed head, as well as determining the installation of the counterweight	Recognition of the type of processing of parts in the working area
Operator presence in the area	Identification of a person in the danger zone and identification by face, the presence of a helmet and uniform	Tracking a worker's wearing a medical mask
Screen image text analysis	Error code recognition	Recognition of X Y Z coordinates published on the CNC screen

V. CONCLUSION

This paper discussed the service development problem of industrial video data analytics when services provide close to real-time assistance. We presented an edge-centric architecture for constructing such smart assistance services. Based on this architecture, we implemented several pilot services to demonstrate the opportunities of industrial video data analytics.

- Monitoring mechanical components of equipment to detect deviations in machine operations;
- Operator presence in the area to control production processes;
- Screen image text analysis from CNC display monitor to detect errors.

The services are deployed and experimented for monitoring industrial production equipment (technical state and its evolution, ongoing production processes, equipment operating conditions). Our early experiemnts show the high potential of edge-centric video data analitics for smart assistance in IIoT systems.

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