Video Camera and Sensor Status Monitoring System in IoT Environments

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***Abstract*—Recent progress in Ambient Intelligence (AmI) technology leads to many proposals of sensing systems in the physical, informational, and social worlds. Such systems focus primarily on the sensed data retrieval, including advanced cases of Internet of Things (IoT) sensors and video capture. Operation of a sensor is subject to faults, anomalies, and outliers. In this work-in-progress paper, we consider the problem of tracking the operation of a video camera or environment sensor to recognize deviations from the expected function. The recognition is based on neural network and context analysis. We implemented a module that makes a sensor smart in terms of operation status recognition and its self-understanding. Our demo shows the applicability of the module in IoT monitoring systems.**

I. Introduction

Digitalization of all spheres of human life is progressing based on the emerging technologies of Artificial Intelligence (AI) and Internet of Things (IoT), e.g., see [1]. Digital services are constructed using devices of an IoT environment with Ambient Intelligence (AmI) [2]. AmI makes the environment sensitive to current situation and context (e.g., presence of people). A sensing system is needed to implement this AmI property. Many proposals exist for sensing in the physical, informational, and social worlds.

In an IoT monitoring system, a sensor operates in real-time providing fast sensed data for event-driven recognition [3]. An advanced case of a sensor is video cameras and IoT sensors that can produce volumetric data for edge analytics [4]. Note that such sensors are key players in Big Data.

Existing systems focus primarily on the sensed data retrieval. Nevertheless, another problem occurs since the operation of a sensor is subject to faults, anomalies, and outliers [5]. In this work-in-progress paper, we consider the problem of tracking the operation of a video camera or environment sensor to recognize deviations from the expected function.

The problem is essentially important for industrial IoT monitoring systems, e.g., monitoring of production equipment [6] or video surveillance systems [4]. Tracking of sensor operation leads to recognition of sensor status. In the solution demonstrated in this paper, the recognition is based on neural networks. This study continues our previous work on real-time smart sensorics in IoT environments [3], [4], [6]–[9].

The rest of the paper is organized as follows. Section II introduces the problem of tracking the sensor operation to recognize deviations. Section III presents our implemented module for tracking and recognizing the sensor status. Section IV demonstrates the applicability of our module for use in IoT monitoring systems.

II. Tracking the Sensor Operation

The sensor operation needs tracking to recognize deviations from the expected function. Deviations occur due to faults, anomalies, outliers, and other incorrections [5]. Sensors for physical parameters (e.g., vibration, current, temperature, rotation speed) regularly fail due to impacts from the physical environment. Cameras provide low quality images due to contamination of the camera lens or due to network data transfer problems. The quality of the sensed data is also reduced due to low computational power of sensors as IoT edge devices.

Tracking of sensor operation status is needed in real-time. The status forms a part of context within which the sensor can act as smart IoT object [2], [10]. The availability of sensors being able to

- self-monitor its latest status,
- self-adapt own operation to continue correct work,
- self-heal the status to the expected function,
- self-report the status to the interested parties,

would be a key step towards the reliability and intelligence of IoT technologies [11], [12].

The following two options are available for running the self-computing algorithms that perform incorrectness recognition, prognostics, and drive adaptation and healing (i.e., the smart function of the IoT device).

1) Built-in: Directly on the sensing device that performs both sensing and processing.
2) Delegated: Distantly on a remote device that makes monitoring of the sensing device.

To identify a sensor with incorrect behavior, additional information can be exploited. Such information is retrieved from other sensors, e.g., see [13]. Let us consider an example of a node for production equipment utilized in factory department [6]. The node has an electric motor; the activity of the motor is monitored. Monitoring uses three sensors: current, temperature, and vibration. Thus, the system can determine the operation state of the node for each sensor separately. Example behavior is shown in Fig. 1. The node heats up, vibrates, and current is applied to the motor. Analysis of changes in the

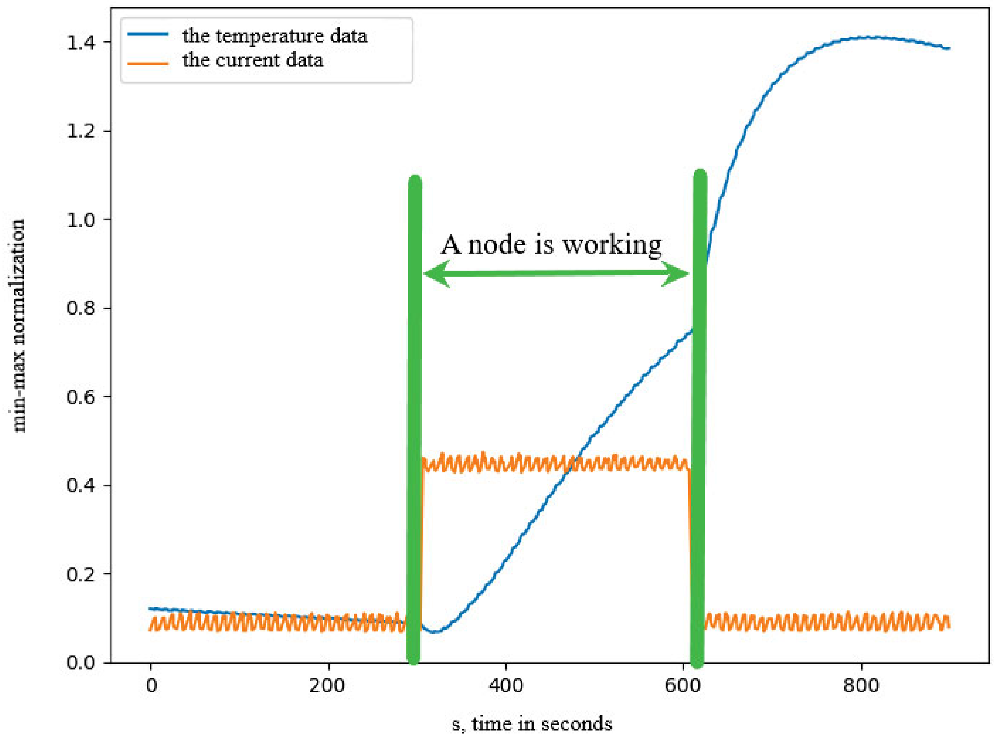

Fig. 1. Temperature and current sensors monitor a node of production equipment

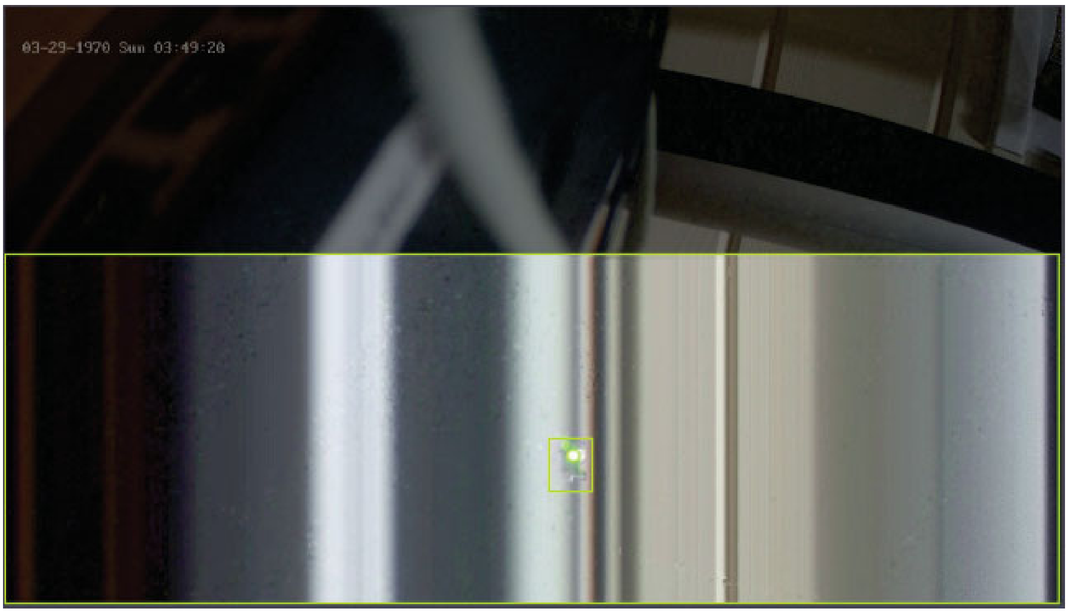

Fig. 2. Camera: example video artifacts

current provides additional information on whether vibrations have appeared or whether the temperature is changing.

Operation of a video camera has situations when timely intervention is necessary to restore the function. For example, the protective glass of a camcorder or camera lens become dirty outdoors or in a dusty workplace. To track the operation

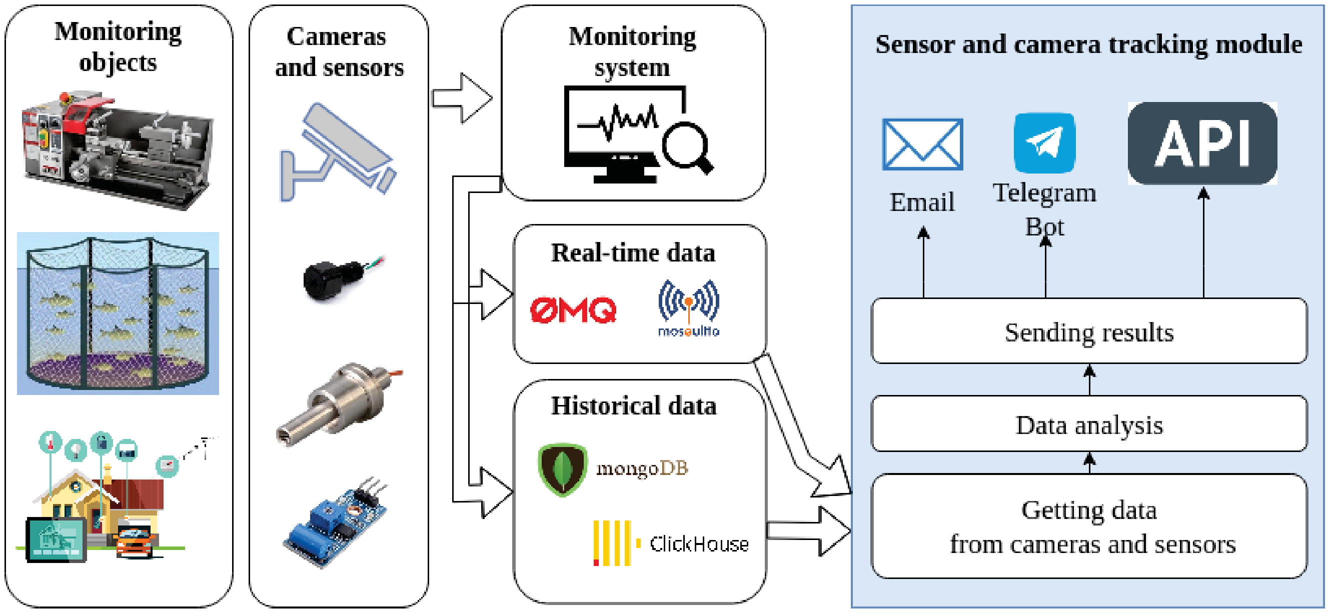

Fig. 3. Service architecture

status, frames in video stream are analyzed to detect distortions. Example video artefacts are shown in Fig. 2. Distortions in video capture occur due to contamination of the protective glass or due to data losses in network transfer from the camera to the server.

The two examples above show possible deviation of a sensor from the expected function. When a deviation is detected, it can be further analyzed. For instance, notifications can be sent to responsible personnel using various communication channels (e.g., email, chat, phone call, signal to situational center).

III. Implementation Notes

In our previous work, we showed that deviation recognition can use statistical metrics [8] and analysis with neural networks [7]. To track sensor readings, the system needs to accumulate data, to determine the time intervals at which the sensors worked properly or improperly, to apply algorithms finding various properties in the readings, and to draw conclusions about the status of the sensor operation.

Our model of sensed data processing from sensors of physical parameters is presented in [9]. The model can be easily extended with a smart function to recognize deviations in the sensed data flow.

Our implementation for tracking a video stream includes frames receival (from a given camera) and frame data processing (using a neural network). Communication with camera is implemented using the ZeroMQ library. This high-performance asynchronous messaging library (also denoted a ZMQ, 0MQ) aims at distributed and parallel computing. The reasons for using ZeroMQ for Machine-to-Machine (M2M) communication in industrial IoT applications are discussed, e.g., in [9], [14].

The library implements a message queue that can function without a dedicated message broker. To receive frames, a connection is made through ZeroMQ. The module parses the frame, writes the result to the MongoDB database, and then notifies the frame collection module that the module has processed the frame.

Processing the frames from a video camera is implemented using OpenCV. The frame is sent using ZeroMQ for further recognition. The implementation of frame transfer using ZeroMQ is intended for further scaling of modules for monitoring. Recognition of deviated frames uses the YoLoV4 neural network. The use of YoLo (You only Look once) and OpenCV is recommended for real-time tracking, e.g., see [15]. We performed pre-training using a dataset, which includes images with noises highlighted on them. The data markup was carried out using the Roboflow service. The software implementation is in Python3.

The architecture of the proposed module is shown in Fig. 3. The module receives information about a sensor to monitor and track. Multiple sensors can be monitored by one module. The module reads the sensor data, depending on the settings, from one of the following databases: Clickhouse, PostgreSQL, MySQL, or through the MQTT message broker. Based on the analysis of the readings of various sensors, the module generates events that are stored in MongoDB. These events can be accessed via the specialized API (Application Programming Interface).

IV. Discussion

The developed module can be used to automatically monitor the operation of sensors, including video capture with cameras. The module can be integrated to any monitoring systems that supports ZeroMQ library, MQTT message broker, Clickhouse or MongoDB databases.

The progress in video sensorics leads to appearance of more and more sources of video data in IoT environments. Video data are becoming topical for use in various analytics. Often data are collected for long time periods and without human control and intervention. External factor can lead to decreasing the data quality, to data losses, or even to data corruption. In such applications, the automatic control becomes important. A typical case is Northern territories where climate conditions influence the sensor operation.

To maintain the quality of the sensed data, it is necessary to automatically evaluate the data in real time. In particular, video stream is an interesting subject to the evaluation [3]. The following problems are associated with frames received from a camera.

- Damaged image in the process of transmission over communication channels.
- Damaged or dirty camera lens and contamination.

Recognition of operation deviation from the expected function leads to generation of events important in the monitoring. As a result, the users and other interested parties receive real-time notification about possible problems in the sensor operation. Then decisions are made on how to fix the recognized problem.

V. Conclusion

This work-in-progress paper considered the problem of tracking the operation of a camera (video capture) or environment sensor (physical parameters) to recognize deviations of the sensor operation from the expected function. The recognition uses well-known data mining algorithms (statistics and neural networks). The architecture is based on efficient IoT technologies for M2M communication as well as for data collecting and processing. The implemented module for tracking the operation status makes a sensor smart, i.e., having self-understanding properties. Our demo shows the applicability of the module in IoT monitoring systems, especially for use in sparsely populated areas and with rare human intervention (e.g., the case of Northern territories).

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