Sensor Fault Diagnosis for Precision Agriculture

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***Index Terms*—Sensor fault detection, IoT, fuzzy logic, fuzzy classification**

I. Introduction

Sensors are an integral part of IoT systems. They collect data about the surrounding environment. These data can be used for monitoring the environment, but also to infer human or actuator-based actions. Any inference is therefore not only dependent on the availability of data, but also on the data quality. A faulty sensor, i.e. one reporting incorrect data could have detrimental effects on an IoT system [1]. For example, in precision agriculture, IoT systems are deployed within a crop field or greenhouse. They include sensors to monitor environmental data like soil moisture or temperature and water pumps for irrigation. The behavior of the water pumps can be automated based on the sensor readings e.g. triggering irrigation if the soil is dry. However, faulty high soil moisture values may lead to wilting crops. Hence, to ensure a well-operating IoT system, faulty sensors have to be detected and replaced. The talk will give an overview over sensor fault diagnosis and presents our experiences in our Precision Agriculture testbed [2].

Classification of Faults

Different categorizations of sensor faults exist (see for example [1], [3]). Li et al. divide sensor faults into *incipient* and *abrupt* failures [1]. Abrupt failures result in complete failure of the sensor such that no data is collected or sent. The reason may be a broken sensor or sensor board, a broken network connection or a discharged battery. These types of faults can be easily detected by a monitoring system.

In contrast, incipient failures are caused by an abnormal sensor status in which incorrect data is sent. Incipient failures can be further distinguished and include similar fault classes like proposed by Zou et al. as so-called soft failures such as drift, bias, stuck fault, accuracy decline, and spike fault [3].

Classification of Sensor Faults Detection

A simple approach for identifying faulty sensors is redundancy: using multiple sensors of the same type. Then, a faulty sensor can be identified by its measurements differing from the majority. However, this approach increases costs, maintenance and system complexity. In a different approach, detection of a faulty sensor is based on historic data of the sensor or knowledge about the sensor's behavior [1], [3].

Research for detecting faulty sensors is ongoing and there exists no agreed classification yet. Here, we follow Li et al. [1] and distinguish model-, knowledge- and data-based approaches. A **model-based** approach consists of a mathematical model, which describes the system behavior. The values obtained by the sensor are compared to those predicted by the model. However, developing a model that can accurately describe the behavior of sensors is complicated in practice, especially if different types of sensors are used. This approach is suited for extreme challenging projects for example within spacecraft control systems [4].

Knowledge-based approaches are characterized by an expert system. The expert system consists of a knowledge and a rule base and a reasoning mechanism. The expert's knowledge about the system forms the knowledge base. Based on the reasoning mechanism, knowledge-based systems are divided into rule-based or fuzzy inference systems. Rule-based systems require specific binary (true/false) rules that can be hard to obtain for complex systems. In a fuzzy inference system, the *weak* knowledge about the modeled system is formulated using fuzzy logic. A rule-based system has been applied in a setting with greenhouse environmental sensors [5], and also fuzzy inference systems have been used in a variety of settings [6]–[8].

The **data-based** approach is the most current of the three. From large amounts of labeled data, a classifier is obtained by training. Possible approaches include neural networks of varying complexity, and also support vector machines [9], [10]. However, large data requirements and necessary (re)-training in data-based methods is time- and resource consuming.

II. Precision Agriculture Testbed

To evaluate and demonstrate the benefits of the semantic-based approach of the MYNO project [11], a precision agriculture testbed was set up at the University of Potsdam [2]. The testbed contains a Raspberry Pi 3B as an edge component, and several microcontroller boards which monitor and water a group of plants. Communication is done over WiFi. The Raspberry Pi runs the MYNO components: an MQTT-broker and the NETCONF-MQTT bridge as well as a NETCONF-client, which provides a user-interface. The user-interface displays current sensor values and allows user input to control actuators and set up automations. The microcontroller boards

are based on the low-priced ESP32 NodeMCU Module.
Multiple sensors are used per board since each board monitors a number of plants. Additionally, multiple sensors of the same type are used in proximity to compare their readings to confirm our fault detection diagnosis. The following sensors are used per board:

- 3 different soil moisture sensors (discussed below)
- a temperature, humidity and air pressure sensor combined in a GY-BME280 module
- a GY-302 BH1750 light sensor
- a touch-free capacitance sensor to detect the water level within the water reservoir (one board only)

The following actuators are deployed:

- a 9V mini water pump (one board only)
- a RGB LED module as a simple actuator to test board responsiveness

Observed Sensor Faults

Running our testbed since summer 2021, we did not observe most of the aforementioned sensor fault classes known from literature. In our case, we noticed most faults in soil moisture sensors. Abrupt faults were limited to a single light sensor and full sensor boards. All other faults were incipient failures of soil moisture sensors. We observed soil moisture sensors reporting incorrect, almost constant values. Motivated by this, we attached a database to collect all sensor values from March to May 2023. During this period we noticed the following faults in our system:

- Sensor board fault, two times: hard fault, unresponsive sensor board
- Soil moisture sensor fault, 10+ times:
  - intermittent largely differences between measurements (spike fault in [3])
  - permanently constant measurement values (stuck fault in [3], possibly with prior drift)

From the incipient faults mentioned in literature we did not observe accuracy decline or bias. The soil moisture sensors faults are caused by sensor deterioration over time. In the most severe cases, electronic parts were eventually exposed to the environment, i.e. water, leading to corrosion. It is assumed that this is due to the materials used and the manufacturing process.
We employed three different sensors that use two different ways of measuring soil moisture. A resistive soil moisture sensor by AZ-Delivery ($\approx$ 3€) and capacitive soil moisture sensors by AZ-Delivery ($\approx$ 2€) and BeFlE ($\approx$ 13€).
In resistive soil moisture sensors, the electrodes are exposed to the environment by design and their sensitivity to electrolytic corrosion has been identified [12], [13]. Corrosion and erroneous measurement values occurred within one week of deployment. A corroded sensor reported constant values of 0% soil moisture. Capacitive soil moisture sensors try to circumvent this problem by employing a different technique. They determine the dielectric constant of the soil, which changes depending on the water content [14]. Capacitive soil moisture sensors do not expose electronic parts to the environment directly. However, we noticed corrosion in many of the capacitive sensors by AZ-Delivery as well, albeit after weeks or months. The protective layer of the sensor was bloated and partly broken off. We assume that this is due to water-intake as the protective layers are only pressed and glued together, leaving an open edge. Corroded sensors of this type report a constant 0% or high values of soil moisture. The BeFlE sensor included a "durable protective layer" [15] similar to epoxy resin in appearance. However, this protective layer developed small blisters over time. If blisters are present, the sensor reports low-varying high values of soil moisture.

Fuzzy-Logic based Detection of Faulty Soil Moisture Sensors

While abrupt failures are easily detected by MYNO's monitoring component, incipient failures remained a challenge. Since it is hard to find a mathematical model and on the other hand a data-based approach seems not to be sustainable (regarding different sensor types), we developed a Fuzzy-Logic based Sensor Fault Detection. The Fuzzy-Logic approach is in a sense a mixture of the model- and data-based approach. It does require some *fuzzy* knowledge about the system at hand. Therefore, we inspected collected previous data and formulated a set of *fuzzy rules* based on the following observations:

- If the pump has been triggered, the moisture must rise significantly.
- Over three days, the soil moisture must decrease by a value of $m \in \mathcal{N}$, where $x \leq m \leq y$ percent, where x and y are positive thresholds. This holds unless the pump is activated. The thresholds x and y depend on the manufacturer's specifications for sensor variability and the specific environment itself.
- If the pump has not been triggered, the moisture must not increase much more than the sensor variability.

The inputs are the water pump states and the difference between the current and old soil moisture values, whereas the output is the diagnosis that indicates fault and non-fault states.

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