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Fundamental aspects in sensor network metrology

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ABSTRACT
Sensor networks have appeared on the 'radar' of metrology only recently and a rigorous treatment and metrological assessment have not been established yet. However, sensor networks as measuring systems underpin many developments in digital transformation, with applications ranging from regulated utility networks to low-cost Internet of Things (IoT). The metrological assessment of sensor networks necessitates a fundamental revision of calibration, uncertainty propagation and performance assessment and new approaches for information and data handling regarding the individual sensors and their interactions in the network to allow a systems metrology approach to be established. This contribution introduces some initial findings from recent research and gives an outlook into future developments.

Section: RESEARCH PAPER

Keywords: sensor network; measurement uncertainty; Internet of Things; co-calibration

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1. INTRODUCTION

Digital transformation includes the integration of digital technologies, such as software, communication and algorithms into products, processes, and services. A disruptive consequence is that these technologies are being used to generate completely new products, processes, and services.

The future digital world differs from today's situation substantially: digital exchange of data and information is becoming the standard; information is provided via cloud services in a machine-actionable way; digital infrastructures utilize information from calibration, self-diagnosis and other metadata communicated by individual measuring instruments; processes and services in the quality infrastructure are based on distributed databases and application programming interfaces (APIs).

One outcome of the transition to the digital world is that distributed measuring instruments and sensor networks are becoming more important than individual measuring instruments. Applications such as the Industrial Internet of Things (IIoT) and automated driving will belong to the first examples where the role of metrology is challenged. These challenges include methods for metrological traceable co-calibration and the metrological assessment of whole sensor networks in a systemic approach. For instance, the assessment of an autonomous vehicle measuring system requires a holistic perspective on the whole system instead of only the individual measuring elements.

Moreover, in the digital world, algorithms and software become as important as the actual measurements, and they will thus influence metrological traceability chains for measurands increasingly. In the digital age, artificial intelligence, sensor fusion and virtual measuring instruments will replace many of today's tools and principles. Their use will require a fundamental re-evaluation of the established methodologies for uncertainty evaluation and the assessment of algorithms. In the example of the autonomous vehicle, the assessment of the measuring system must take the algorithms into account, which analyse the data to take decisions.

Quality of measurement data, trustworthiness of measurement results and reliability of measuring instruments are as important in the digital world as before. Hence, metrology plays an important role also in the quality infrastructure in the digital age [1].

So far, metrology focuses on single measuring instruments and sensors. However, in a rapidly increasing number of applications networks of sensors are used to address measurement needs. Examples can be found in predictive maintenance of production machines in industry, urban air quality monitoring, and multi-modal human health assessment using wearables [2].

An important aspect that distinguishes sensor network applications from single sensor measurements is that rather than the individual sensors, the combined information from all sensors is the main object of interest. For instance, the combination of microphone data and vibration measurement in predictive maintenance provides more insights into the actual status of the monitored machine than the individual measurements alone [3]. A consequence of the focus on combined sensor data rather than individual sensors is that the definition of the quantity of interest, the measurand, is not straightforward. Moreover, the assessment of quality and reliability of the system is more complex and challenging than the individual sensors alone, e.g., in terms of calibration result. Such an assessment also has to take into account potential sensor failure or networking issues. This also includes consideration of energy consumption, localization of sensors in the network and network communication synchronization [4]

Let us consider again the above example of predictive maintenance. The combination of different sensor data is carried out in a data-driven approach, i.e., using machine learning methods. The target is a classification of the remaining lifetime of the machine being monitored. Thus, the purpose of the measuring sensor network and data analysis is clear, but the outcome – expected remaining lifetime – is not a physics-based combination of the involved measured quantities. Since the combination of all sensor data is of interest instead of the individual sensor readings, an assessment of the measurement performance should consider the sensor network as a complex (often distributed) measuring instrument. The metrological treatment of such sensor networks thus requires a novel approach – called "systems metrology". This approach includes the novel field of "sensor network metrology", which itself contains aspects such as, in-situ calibration and co-calibration, uncertainty evaluation for dynamic measurements and dynamically structured systems, semantic representation of metrological information, uncertainty-aware machine learning and explainable artificial intelligence applied to sensor networks. Most of these topics are still in a stage of early research and prototypical solutions.

This contribution introduces sensor network metrology aspects which were addressed in recent research projects. We outline the fundamental sensor network metrology aspects and discuss their combination into a coherent and consistent approach for a metrological treatment of sensor networks. Section 2 introduces general aspects of Internet of Things (IoT) type of sensor networks from the viewpoint of metrology. Section 3 addresses the digital representation of data and metrological information in sensor networks. Section 4 presents and discusses relevant uncertainty evaluation and propagation for processing of sensor network data. Section 5 discusses aspects related to the application of machine learning and artificial intelligence. Finally, Section 6 addresses the overall picture and gives an outlook to future developments.

2. METROLOGY AND THE INTERNET OF THINGS

In the concept of the Internet of Things (IoT), physical devices communicate with each other via web technologies, thus combining web technology with the physical world. With the rise of the IoT in Industry 4.0, Smart City, Smart Grids and more, the world of measurement is changing rapidly. As an example, the integration of measuring instruments in the IoT poses several specific requirements for the sensors itself, such as communicating via a digital interface, working reliably under a wide range of conditions, reporting on their health status upon request, and ideally, detecting and reporting adversarial conditions. These and other requirements have led to the development of so-called "smart sensors" [2]. These are measuring devices that contain some sort of pre-processing implementing the above features of the IoT. As the name "smart sensor" implies, the pre-processing is integrated together with the physical sensing element in one "package". However, this kind of pre-processing poses new requirements for the calibration of the measuring device because the pre-processing has to be taken into account in the calibration. Furthermore, measuring instruments which only provide pre-processed data usually don't fit well in today's calibration procedures and guidelines, because these assume access to the raw measurement data. A concrete challenge addressed in the project EMPIR Met4FoF[1] was the dynamic calibration of a digital-output sensor using an external time stamping, e.g., based on GPS and a custom-built microcontroller (µC) board [5]. The same approach was then used to demonstrate the extension of a digital sensor such that it communicates not only raw measurement values, but also provides information about the measurement units, uncertainty, and calibration in a machine-readable way [5]-[7]. In this way, the most basic requirement of a metrological treatment of a sensor network can be met: the provision of measurement uncertainty and other metrological information for the individual sensors. In the concept developed in the Met4FoF project this information is provided by the "smart" sensor itself. However, other information architectures are possible, too. For instance, in the BMBF FAMOUS project, a database approach combined with OPC-UA communication was considered instead. A similar approach is also considered in the project BMWK GEMIMEG-II. More details are given in Sections 3 and 4.

The concept of sensors providing self-information upon request in a standardized way is also a fundamental element of OPC-UA[2] (industrial interoperability standard), which is used mostly in industrial applications, but is increasingly adopted in other areas, too. For the metrological information communicated via OPC-UA to be machine-readable, it is necessary that the definition of a standard digital representation of units of measurement as well as commonly accepted data models for measured values are available. To this end, the digital SI (D-SI) data model developed in EMPIR SmartCom proposes an approach that is compatible with current guidelines and standards in metrology and calibration [6]. Other potential approaches for the digital representation of units of measurement and quantity kinds are the "Unified Code of Units of Measure"[3] (UCUM) or an ontology for units of measure

[1] https://www.ptb.de/empir2018/met4fof/home/
[2] https://opcfoundation.org/
[3] https://ucum.org/

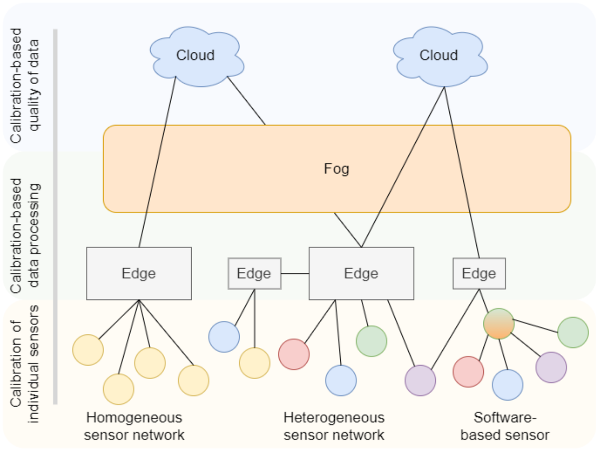

Figure 1 Calibration information in the different layers of the IoT architecture.

QUDT [8], [9] – each optimized for different data usage approaches. In principle, also combinations of these approaches are possible.

The concept of the IoT relies on a versatile and flexible combination of measuring instruments, the automated acquisition and processing of the measured data and the application of intelligent algorithms to derive conclusions or decisions. One consequence of this is that data analysis is typically carried out using data-driven machine learning. In contrast to mathematical models that rely on a physical understanding of the measured process, machine learning can be applied directly based on the sensors' output data. Thus, the need for calibration is not as obvious as for "traditional" measurements. However, calibrated measuring instruments in the IoT offer several benefits. For instance, calibrated sensors can serve as reference devices in the network to assess and improve data quality [10]; calibration of sensors enables the estimation of the measurand and thus, traceability [7], which itself is required to ensure the comparability of measurements between different sites and countries. Moreover, calibrated sensors improve the ability to explain the obtained output from the machine learning. That is, the calibration of a sensor enables direct interpretation based on the measurand whereas a non-calibrated sensors provides data streams which are only loosely related to the physical measured quantity. Moreover, the manufacturer's data sheet alone usually does not suffice as a source of information to assess the type B uncertainty components. Hence, calibration plays an important role in IoT and provides benefits on all data processing layers and a way to quantify the trust one can have in the measurement system (see Figure 1).

3. DIGITAL REPRESENTATION OF DATA AND INFORMATION IN SENSOR NETWORKS

In the digital world, measurement data must also be readable and understandable by machines. This implies that the information about the measuring instruments, the units of measurement and other accompanying metadata must be available in a format that can be used by software or an algorithm. For instance, the software may need to verify that the unit of measurements of a given data set is consistent with previous entries of a data base.

The machine readability of data and measurement information is of particular importance in sensor network

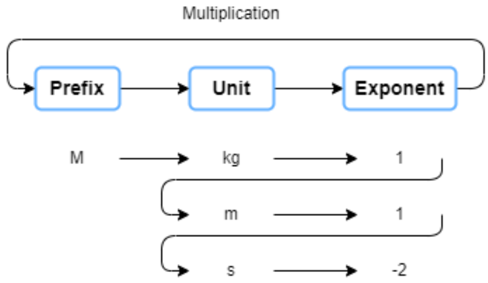

Figure 2 Example for an algorithmic representation of units of measurement, which can be used by a software

metrology. With hundreds of sensors measuring continuously, measurement data cannot be normalized and analysed manually, but requires a high level of automation. This, in turn, can only be achieved with machine-readable information. The machine readability begins with the description of the unit of measurement, for instance as shown in Figure 2. In the project EMPIR 17IND02 SmartCom, a data model and digital representation of units of measurement, called D-SI, have been proposed. On the CIPM level, the D-SI as well as UCUM and QUDT and other approaches to the digital representation of quantities and units of measurement are being discussed.

Another important element is the information about the individual measuring instruments. For instance, a machine-readable digital calibration certificate [11] could be provided by the sensor itself, e.g., using OPC-UA, or from another source, e.g., an internal quality management platform. If needed, this information could be further extended by other data which could affect the quality of measurement data [12].

Machine understandable representation of knowledge on information in sensor networks and its semantics can be modelled by means of (combinations of) ontologies. Several ontologies useful for sensor networks can be found within the semantic web community. These ontologies formalize the annotation of sensor data with spatial, temporal, and thematic metadata. Spatial metadata is particularly relevant for sensors distributed across a building or a country, or when mounted on a moving object like an automobile.

In the project FAMOUS a method to merge different kinds of metadata and ontologies along with the sensor measurement data was proposed [13]. The main idea of [13] is to split the self-description of a sensor into four aspects: (1) observation information, (2) general sensor description, (3) calibration information and (4) location information. Then, a sensor self-description can be achieved by combining existing ontologies that appropriately represent these aspects. In this way, one can build upon existing work and established principles and software tools. In the GEMIMEG-II project this development was extend to the integration of semantically described quality of data aspects [12].

4. MEASUREMENT UNCERTAINTY IN SENSOR NETWORK DATA PROCESSING

Measurement data in sensor networks is often heterogeneous, volatile, and time dependent. Moreover, sensor networks in IoT scenarios often contain low-cost measuring instruments based on MEMS sensor technology. Consequently, such sensor networks typically have a wide range of measurement data quality. Reliable data analysis for sensor networks thus requires taking data quality into account in a quantitative way.

An example of a fundamental property that can be considered as a quality metric is the measurement uncertainty. Other examples for parameters which may affect the quality of data in sensor networks are unstable network conditions, environmental interference, or malicious attacks. Moreover, in battery powered sensors, there is necessarily a trade-off between power-consumption and performance. Another common issue is drift, where sensor readings slowly deviate from the true value due to the degradation of the electronics [14]. One outcome from the GEMIMEG-II project is a framework for quality of data in sensor networks, expressed in terms of an ontology [12]. This can be expressed, for instance in an ontology [12]. In a joint effort by the projects FAMOUS and EMPIR Met4FoF it was demonstrated how an ontology of a sensor network could be utilized for an automated analysis [7], [13]. Moreover, together with the project EMPIR SmartCom a sensor network data set was enriched with machine-readable metadata to demonstrate the metrological support of the FAIR principles [15].

Usually, the sensors used in IoT applications are measuring continuously irrespective of how the measured values are used. Thus, for a reliable quantification of data quality it must be ensured that the sensor behaviour is well known for a wide range of measurement situations. This includes situations where the measurand, i.e., the sensor input signal, changes rapidly over time. Thus, sensor properties such as effective bandwidth, internal analogue-to-digital conversion, time stamping reliability, resonance behaviour need to be considered.

Data analysis in the IoT typically relies on and greatly benefits from modern machine learning methods, because of the complexity of the sensor network and the amount of data acquired. Uncertainty evaluation for machine learning is an important topic and considered in several research activities. However, this is only possible if the uncertainty associated with the machine learning input values is available. Hence, uncertainty for data pre-processing must be addressed as the initial step for an uncertainty-aware machine learning for IoT.

Measurements in the IoT are usually time dependent, and often even dynamic. Examples are air quality monitoring, traffic surveillance, production control or mobile health measurements. Thus, signal processing methods are regularly applied for data pre-processing in IoT scenarios. For instance, the discrete Fourier transform is often applied to extract magnitude and phase values from a measurement of vibration, which are then used in a subsequent machine learning method as features. Other examples for pre-processing are synchronising the time axis of sensors; interpolation of sensor data to account for missing values or non-equidistant sampling; low-pass filtering to reduce noise or other unwanted high-frequency components in the measured data. Another reason for the application of data pre-processing is the reduction of data dimensionality. This may be necessary simply due to storage or data transfer bandwidth limitations [3]. In the project EMPIR Met4FoF, the previously developed Python library PyDynamic [16] was extended to include the data pre-processing steps typically required in IoT. For each method, PyDynamic provides the propagation of uncertainties [16]. An important aspect in EMPIR Met4FoF and in FAMOUS was also the implementation of the methods in such a way that they can be applied online, i.e., during the measurement. For instance, the Discrete Wavelet Transform for uncertain input data was implemented using digital filters [17].

Another important aspect is the way of how the uncertainty propagation software is provided such that it is compatible with typical IoT architectures. In the project EMPIR Met4FoF, a so-called agent-based framework (ABF) was used. In an ABF, data processing steps are encapsulated in software modules, called "agents". These agents can run on different locations in the network, if necessary, and allow for a very flexible demand-driven data analysis. For instance, one agent may acquire the data from a sensor, hands it over to an interpolation agent, which then provides it to a Fourier transform agent. With each agent taking care of the proper uncertainty treatment, very flexible data analysis pipelines for sensor network metrology can be realised. Usually there is an existing data analysis framework in place, which needs to be extended to include measurement uncertainty treatment. As a result, a web-service approach was used in the project FAMOUS instead of an ABF. That is, an uncertainty module was created to enrich existing sensor data streams with statements about the associated measurement uncertainty.

5. FLOW OF METROLOGICAL DATA AND METADATA IN SENSOR NETWORKS

To summarise the different elements described in the previous sections, let us consider the flow of metrological data and metadata in sensor networks, see Figure 3.

For the individual sensors we assume the availability of information about their metrological properties. At least this information should be available in terms of a manufacturer's data sheet from which information about measurement capabilities, units of measurement and tolerances can be extracted manually. Ideally, the information is provided in digital, machine-readable way. For instance, the sensor may communicate metadata using an IoT standard, such as OPC-UA, RAMI 4.0 or provide a DCC. This metadata could contain fundamental information about the sensor: serial number, units of measurement, measurement uncertainty, calibration information. For an automated handling of this information, the metadata itself has to be machine actionable. That is, units of measurement have to be given using a suitable data model (e.g., D-SI, UCUM, QUDT). A representation of this information in accordance with the FAIR principles would furthermore require the use of some kind of persistent identifiers (PID) to ensure machine-interpretable interoperability with other data models.

The metadata at the sensor level could also contain information on the quality of sensing. That is, the sensor could be self-aware or be complemented with other sensor data. For instance, a radar sensor in an autonomous vehicle may be complemented with a rain and fog detector to enrich the radar sensor data with metadata about the weather conditions. Other potentially useful metadata could be whether the sensor is battery powered, general energy restrictions or measurement strategies (e.g., raw data or averaged data). Depending on the sensor network use case, this information can be crucial for the metrological assessment of the measuring system's quality and reliability.

The sensor metadata has to be made available throughout the data lifecycle in the sensor network to enable its use in the data processing and decision making. The first steps, data curation and data aggregation in the processing of sensor data are often already the place where the sensor metadata is lost. However, information about the propagation of quality of sensing (e.g., measurement uncertainty) must be carried out to ensure proper assessment of the overall sensor network quality. The individual sensor quality is not sufficient for this assessment. The data lifecycle metadata can be enriched in the data processing by information about the applied algorithms, their

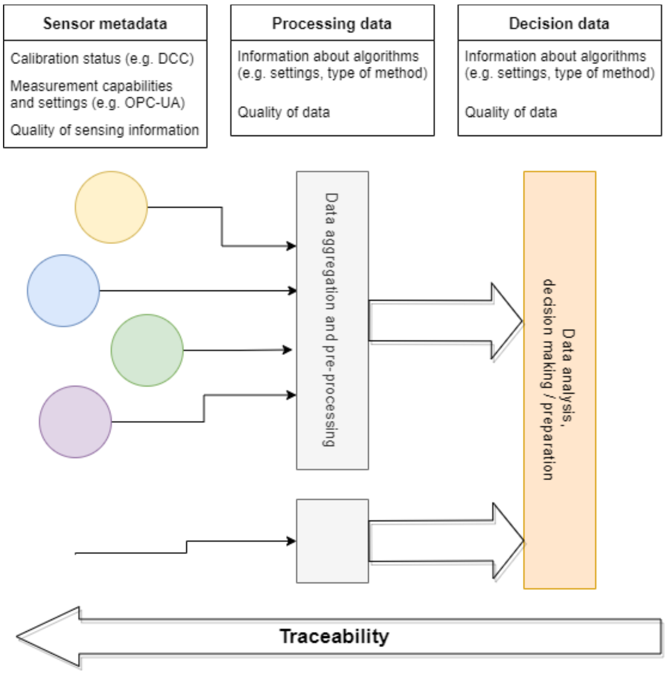

Figure 3 Flow of data and metadata from individual sensors (left) to the final decision making (right). With proper data treatment in place, traceability to SI is possible from right to left.

parameters/settings and other information related to the reliability of the processing result. Moreover, the quality of sensing has to be translated and propagated into a quality of data following the data processing steps. With this in place, a proper, reliable, and data-driven decision making is possible that is not only based on the raw sensor data but takes all relevant metadata and information into account. Moreover, it enables a traceability from the quality of the decision making to the quality of sensing as well as traceability of sensor network results to the SI units of measurement.

6. CONCLUSIONS

Sensor network metrology combines several aspects from metrology, signal processing, semantics, IoT and web technologies. The treatment and metrological assessment of sensor networks, thus, needs to take these fields into account. Although sensor networks can be found in many applications, a rigorous sensor network metrology has not been established yet. Existing guidelines in metrology are typically focused on individual measuring instruments and quantities. The same holds true, by the way, for the organisation of metrology institutes and calibration laboratories. First metrology research efforts developed some basic elements required in sensor network metrology: dynamic calibration of digital sensors, cost-efficient calibration of MEMS sensors, digital representation of metrological metadata, evaluation and propagation of uncertainties, semantic modelling of sensor network information. Future research needs to further develop these individual aspects and extend their integration into a consistent framework and toolset. Moreover, a systems metrology approach needs to be developed to assess sensor networks in a systemic way.

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