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Systematic Failure Detection and Correction in Environmental Monitoring Systems

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Abstract: Sensor networks used in environmental monitoring applications are subject to harsh environmental conditions and hence are prone to experience failures in its measurements. Comparing to the common task of outlier detection in sensor data, we review herein the complex problem of detecting systematic failures such as drifts and offsets. Performing this detection in environmental monitoring networks becomes a stringent task especially when we need to distinguish data errors from real data deviations due to natural phenomenon. In this paper, we detail the scope of events and failures in sensor networks and, considering those differences, we introduce a new instantiation of a proven methodology for dependable runtime detection of outliers in environmental monitoring systems to address drifts and offsets. Lastly, we discuss the use of machine learning techniques to estimate the network sensors measurements based on the knowledge of processed past measurements alongside with the current neighbor sensors observations.

Keywords: Data quality, Failure detection, Sensor fusion, Machine learning, Sensor networks, Aquatic monitoring.

1. Introduction

When monitoring harsh environments, deployed sensors have to perform under unfavorable conditions, producing occasionally failures of several types. Measurements may be imprecise, incorrect, incomplete, incoherent or inappropriate to the problem at hand. Sensors may exhibit errors due to faults in sensors or other sources (e.g. communication), either being outliers, temporary disturbances or systematic deviations. These errors can ultimately contribute to the issuing of false warnings or wrong management decisions. We focus here on real environments subject to harsh conditions, namely aquatic environments. Many of the existing techniques for fault detection do not consider the presence of natural phenomena interfering with sensor measurements [1, 2]. These phenomena can ultimately lead to deviations in measurements that might be wrongly perceived as errors. In this paper we consider physical phenomena as events, which are natural occurrences and their impact on measurements should not lead to wrongly detect faulty behaviors.

In the past decade there have been many studies supporting the use of machine learning techniques and sensor fusion to identify or classify events, including failure situations [3, 4]. The most common situations are related to faulty data observations due to spurious errors, such as outliers or to communication faults or outliers derived from sensor faults. In fact, detection and mitigation techniques for drifts and offsets in the context of sensor networks have not been addressed thoroughly. Herein, we introduce a solution to detect and correct offsets and drifts, characterized by a systematic failure behavior observed during a determined time interval. These errors often occur when a sensor is functioning during a long period of time without intervention, requiring additional automated procedures to identify and correct faults in the measurements. In [5], we characterized a methodology that uses prediction methods and failure detection techniques in order to promote the identification of failure behaviors in sensor measurements.

Herein we propose an instantiation of the methodology presented in [6], comprising machine learning strategies for the prediction of the expected sensor measurements of each sensor node, but now accounting only for faults related to drifts and offsets.

This paper is organized as follows. In Section 2, we identify related work on mechanisms and techniques for detecting offsets and drifts, including the use of data fusion strategies. In Section 3 we briefly overview the base methodology and in Section 4 we describe the proposed instantiation and assumptions required for the application for drifts and offsets detection.

2. Related Work

Methods for detection and correction of drifting and offset failure behaviors in sensor devices are different for single device and multiple devices (network). In the first category, we discuss calibration and its variants as a process to prevent and correct such failures. In contrast, in a multi-sensor situation, it is possible to use data fusion techniques in order to detect and correct drifts and offsets.

The re-calibration process of sensors is usually performed off-field by removing the sensor of the monitoring environment and recalibrating it in controlled conditions, with potential data loss if no redundant way of collecting sensor data is available (and the added re-deployment costs).

Although sensor calibration may be sometimes a costly operation, given its frequency, it is necessary to assure the maintenance of good quality data. In order to minimize the number of interventions in the sensor, a possible alternative is the auto or self-calibration, which is a software-based procedure to enable sensors to monitor themselves and self-calibrate using a reference. This latter option, being adaptive, is potentially better to deal with varied and even unpredicted circumstances, and is also designated as measurand reconstruction or sensor compensation.

The auto-calibration process is referred to the methods aimed at diminishing the effect of the disturbing parameters in the features of sensors. The sensor becomes less sensible to past information, interfering environmental factors and noise. This is possible via numerical techniques that compensate the disturbances. These techniques are applied after the transformed signal being quantified, through digital signal processing. This method has been used with relative success, for instance exploiting statistical regression based on a priori knowledge [6] or using artificial neural networks [7, 8].

For the multi-sensor scenario, particularly in the context of sensor networks, these automatic calibration techniques have also been studied to correct drifts and offsets failures. However, these techniques only consider blind calibration, which means that there are no detection mechanisms for data faults. One of the first works is presented in [9], where the authors designed an algorithm to be used in high-density sensor networks in a post-deployment phase. This algorithm uses temporal correlations between pairs of neighbor sensors to correct their signal (measurements). An additional phase of the algorithm, particularly useful in the context of multi-sensor networks, is explained as an optimization step by dealing with groups or clusters of sensor nodes.

Balzano, *et al.* [10] deals with blind calibration in sensor networks softening the high-density requirement, assuming a linear model for the sensor calibration functions, meaning that sensor readings are calibrated up to an unknown gain and offset for each sensor. They too rely on sensor correlations to model their behavior. In fact, data fusion is a common subject in blind calibration studies (more examples in [11-13]).

For the single sensor networks scenario, there is a limited number of studies considering both detection and correction mechanisms of offset and drifts failures. Offsets analyses are more common than drifting ones, in particular in applications related to digital imagery. One exception is [15], where the authors present a machine learning approach to detect offset and drifts faults in WSNs. Their method consists in using Hidden Markov Models to capture both the dynamics of the environment and the dynamics of the faults. This work also presents an analysis on the extracted models to determine the types of faults (including offsets) affecting the sensor measurements.

Concerning specifically drifting failures, a research group presented several studies over the last years regarding a design and its various improvements of a drift-aware sensor network [15-24]. The original study presented the concept of a mechanism to detect and correct drifts in sensor networks. Afterwards, several data fusion techniques were introduced and demonstrated to be efficient. The group used statistical techniques, Kalman filters, Interacting Multiple Model algorithm, Recursive Bayesian algorithm, Spatial Kriging method, and ensembles of these techniques. Their work has been applied to high-density sensor networks measuring parameters such as temperature but also to image-related networks with geospatial information. Provided results in indoor sensor networks have proved the methods to be quite successful in detecting and correcting drifts and offsets in the range of (-10,10) added to the sensor measurements, presenting root mean square errors in the range of (5,8).

Lastly, focusing simply on the detection mechanism, [25] presents a fault detection method for WSNs based on a multi-scale Principal Component Analysis (MSPCA), applied in a laboratory network dataset, the same as the previous studies, to detect both offsets and drifts failures for temperature sensors. The provided results prove that the method is effective in detecting artificially injected systematic faults of different magnitudes and time duration.

Although these last studies have promising results in the field of detecting drifts and offsets in sensor measurements, their focus is mostly in laboratory or indoor conditions. Their methods do not consider the high variability of environmental monitoring, which we take in consideration in the methodology presented in [5].

3. Methodology Overview

A methodology for processing measurements from multiple sensors is proposed in [5]. This methodology addresses failure detection, data quality assessment and data correction applied to outliers. The methodology is mostly intended to be applied during runtime, for the detection of faulty measurements and the respective mitigation in a continuous way, during the sensor operation.

The purpose of the methodology is not only to detect failures in measurements but also to characterize the quality of each measurement and if this quality is below some threshold, be able to provide an estimation of a replacement measurement with better quality. Therefore, a solution for dependable data quality needs to encompass the decision-making capabilities of a classifier in order to detect faulty measurements, as well as the prediction mechanisms to model the sensors behaviors to estimate expected values for the measurements. However, this classification does not necessarily need to be based on machine learning approaches. Therefore, for the purpose of defining a generic methodology, both types of capabilities, that is, detection and estimation, are necessary.

The methodology encompasses the use of prediction methods to estimate the expected sensors measurements, which in practice exploit machine learning techniques. It also encompasses failure detection but the concrete techniques to implement failure detection may not be based on machine learning.

We defined it to be generally applicable to any WSN monitoring system in harsh environments. This is accomplished by defining essential functionalities. The described methods are proposed independently of the physical processes being monitored, but leaving room for the selection of methods whose results depend on the concrete behavior of the monitored processes.

A sensor network architecture composed of more than 1 sensor nodes is assumed where each node is equipped with one or more sensors measuring different, but correlated physical processes. Sensor nodes may be physically distant, but their measurements are also correlated. The network has a gateway or sink node that receives all sensor measurements, although we do not consider a specific network topology. The sink node is responsible for processing sensor measurements using the proposed methodology, making the dependable monitoring data available to other systems upstream.

Regarding temporal aspects, sensor nodes are assumed to be configured to periodically transmit a new measurement, but no assumption is made on the frequency of transmission nor on the synchronization between different sensor nodes. Message transmission delays are assumed to be negligible in comparison to the dynamics of the monitored physical processes. Furthermore, all measurements received at the sink node are considered to be assigned the timestamp obtained from its local clock, allowing temporal correlations between independent measurements to be considered by the processing methods. The local clock at the sink node is assumed to be correct.

Regarding the assumed fault models, there is a specific focus on sensor data with outliers, drifts and offsets, regardless the nature of these value faults. The handling of omissions (i.e., sporadic loss of a measurement) and the crash of sensor nodes are also considered, as well as recovery of lost information. For crash failures, however, this recovery is only partial.

The methodology requires several models to characterize the correct behavior of each sensor, composed of one or more supervised learning techniques. A preliminary step is to construct these models, which requires sensor data with absence of measurement errors from all the sensors to be used. The models will explore temporal correlations between consecutive past measurements of the target sensor, spatial and value correlations between past measurements of the target sensor and past measurements from a variable number of other sensors. Spatial correlations are used when the target sensor and other sensors are in different geographical locations. Value correlations exist for example between the target sensor and sensors placed at the same location.

Consequently, the methodology is designed as an ensemble of supervised learning methods, which require an offline initial training phase for each node's model construction.

The methodology is composed of 4 blocks that are executed for each new received measurement from each target sensor. The first block is the Prediction (P) block, where we employ prediction methods in order to get one or more estimates of the measurement expected to be obtained from the target sensor.

The second block is the Failure Detection (FD) block, which objective is to identify possible failure behaviors in the target sensor dataset, through procedures that help identify if a measurement is considered normal or abnormal, contemplating that these anomalies can be caused by a real environmental event and not a sensor fault.

The third block is the Quality Evaluation (QE) block. It determines the quality coefficient for the measurement and characterizes it whether it is faulty or not, setting the coefficient from 0 to 1.

The fourth and last block is the Measurement Reassessment (MR) block, where a replacement for a faulty measurement is estimated using as input the predictions in the Prediction block.

A flow diagram of the 4 blocks of the methodology is provided in Fig. 1.

The proposed methodology was evaluated and validated by instantiating it for the particular scenario of outliers detection and correction [5]. Firstly, we developed a solution according the methodology to detect outliers in an aquatic monitoring system in the Columbia River (Oregon, USA). Lastly, this instantiation was further compared with other state-of-the-art solutions in a benchmark case study for indoor monitoring, proving its validity by performing at least as good as the best solution in the comparison study.

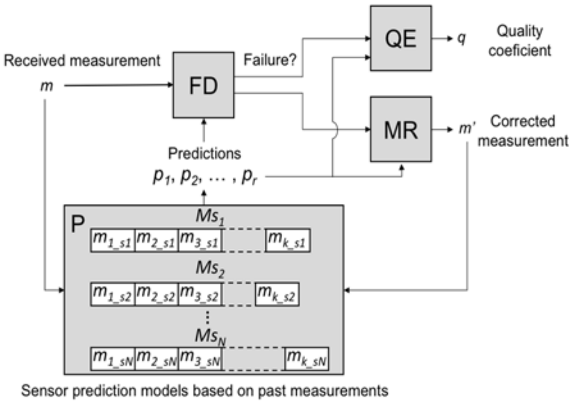


Fig. 1. Flow diagram of the methodology.

4. Systematic Failures Solution

4.1. Objectives

In monitoring networks, solutions for failure detection and mitigation need to aim not only to the more popular spurious failures as the outliers, but also the less frequent scenarios of offsets and drifts.

Another important concept considered in the methodology is the capability to distinguish the sensor faults from the environment-related events. These events can be perceived by the fault detection mechanisms as failures, which in this case are indeed false positives. To avoid this problem, we start by defining both events and failures as we comprehend them in our study.

We characterize events as the physical phenomena that impact the monitored environment to some extent. These can be of short duration or long lived like for instance heavy rain or incrustation of marine life in the sensors. All such events are difficult to predict, and may affect the sensors measurements. We consider that an event has a wide scope and it is not just a localized happening. For instance, an object collision with a sensor is a short-lived happening that may produce a sensor fault (possibly causing an outlier). The presence of animals in contact with or attached to a sensor's structure is an example of a long-lived fault (in this case possibly causing an offset error).

Furthermore, events may lead to deviations from expected values in measurements that may be wrongly perceived as faults. We want to distinguish between events and faults. Therefore, because according to our definition, events have a wide scope, we can exploit spatial redundancy to deploy multiple sensor nodes that will allow us to determine when unusual measurements are consistently observed and hence report an event. In a natural environment, as considered herein, the range of events is very wide and heterogenous. It is very hard to define all specific event signatures which could help to detect the events and differentiate them from faults. Therefore, the application of our methodology to offsets and drifts detection in these environments considers localized events as a fault.

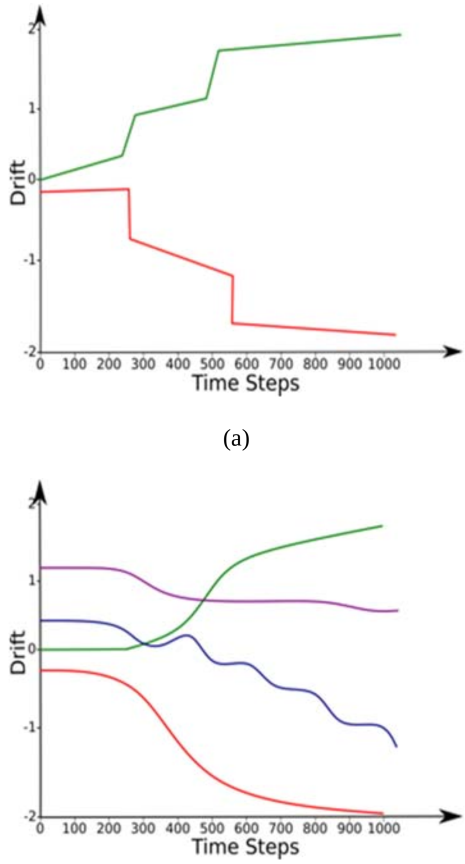
In the aforementioned methodology, we use redundancy and we compare several measurements in order to derive conclusions from these comparisons. If the sensor is performing as expected, which can be determined by analyzing the data produced by the sensor using data processing methods, then it is considered to be in a normal state. If the data processing method detects the existence of some anomalous measurements, then it is said to be in a failure state. Finally, it is possible that these anomalous measurements are also observed in the output of all other related sensors. In this case, all the sensors are in an event state. Otherwise, we need to reason in terms of the majority of observations. If the majority of the related nodes produce measurements showing anomalies, then the network is in an event state. Otherwise, the network is in a normal state and the minority of nodes that are not performing as expected are in a failure state.

The above definitions become particularly relevant when exploring the spatial correlations between neighbor sensors in order to correctly identify both the event and the failure behavior [26]. More importantly, these are the foundations for the implementation of the solution for systematic failures.

For the instantiation of the methodology to the detection and correction of systematic failures such as drifts and offsets, we follow the same techniques as the ones presented in [5] for the outlier setup strategy (ANNODE), namely artificial neural networks (ANNs) and statistical techniques respectively used in the Prediction and Failure Detection blocks of the methodology. However, since there are notorious differences between spurious and systematic errors, these have implications on the strategies for Prediction and Failure Detection blocks. Indeed, the procedures and techniques need to be customized specifically for failures that show a persistent behavior over a time interval.

4.2. Systematic Failures

Offset failures can be characterized by a period of time during which the measurements exhibit a given offset, constant or almost with no variance, with respect to the expected sensor readings. It is the behavior shown during a time interval that provides the systematic aspect, different from the spurious behavior of an outlier. On the drift failures, the drifting behaviors can be split into two categories related to their general pattern. A drift can be characterized by a smooth and slowly decay or growth, as in a linear or exponential function, represented in Fig. 2(a). The second category describes a drift also with a linear or exponential decay or growth but presenting discontinuities or sudden surges, abrupt changes or accentuated peaks, represented in Fig. 2(b).



(a)

(b)

Fig. 2. Categories of Drifting failures:
a) Sharp drifts; b) Smooth drifts.

4.3. Prediction Block

A solution for the detection and correction of offsets and drifts should follow three steps. First, in a sensor network there must be a selection of the network sensor nodes that are highly likely to be correlated. This correlation can be verified by considering either the physical distance or through expert knowledge of the specific environment dynamics.

The second step is the selection of the data fusion techniques for the Prediction (P) block, considering that such techniques must be adequate to resolve the estimation problem (predicting the target sensor next measurement). Finally, the third step includes the selection of the specific datasets for the training process (if required) of the chosen techniques.

We defined the type and structure of ANNs to use for the datasets of a case study [5], in which for monitoring measurements of a given target sensor, the inputs are comprised of the vectors with a history of measurements of the neighbor sensors and possibly of the target sensor itself. Regarding the layer structure, besides the input and output layers, the ANNs are composed also with two hidden layers. The ANNs output is trained to be a prediction of the target sensor next measurement (single value).

In terms of the predictions provided by the ANNs (P block), there is a clear difference between outlier and systematic detection. For systematic failures detection prediction models based on the target past measurements are not considered.

Consequently, we only consider ANNs trained based on the measurements of the neighbor sensors. Therefore, we discard past measurements from the target sensor because these have a strong influence in the predictions and could lead to wrong predictions.

One important difference between systematic and spurious errors is that in the former, they are observed over time while the latter are observed in a single measurement. Therefore, systematic errors cannot be detected as soon as they start, only after being observed for a certain time interval.

Another important aspect to consider for the specific situation of environment monitoring networks is that the sensors are widespread in space, which may diminish the prediction techniques accuracy. Moreover, without explicit sensor redundancy where we have at least two sensors in the same place (location), we are likely to have less accurate estimations for the target sensor measurement. Therefore, in order to obtain a more complete view of the monitoring system, we are required to have several correlated neighbor sensors.

4.4. Failure Detection Block

In the Failure Detection (FD) block, similarly to the outlier detection ANNODE solution [5], we consider a statistical technique as a comparison method, in order to calculate the differences between each measurement and the corresponding predictions provided by the Prediction block (P). This statistical technique uses a training dataset to learn the probability distributions fittings between the errors of the prediction models defined in P and the expected measurements. Using the training dataset, the square errors between the measurement and each prediction are obtained and we are able to obtain the final cumulative density function (CDF). This CDF allows us to calculate the probability of the error between current target sensor reading and prediction. Therefore, by defining a threshold for error probability, we can assess the significance of the observed differences between the measurement and the predictions.

In this solution for the detection of systematic errors, we have different detection conditions from those formulated in ANNODE. Firstly, each measurement of the target sensor is compared with the predictions. The number of significant differences, which can be between zero and total number of predictions, is then recorded. Afterwards, these differences are evaluated over a significant temporal window to perform the intended detection of systematic failure.

For this systematic detection, a temporal window must be defined so we can distinguish single point situations from systematic failures or even from an environment-related event. These single point situations can be spurious errors or just regular fluctuations in the differences between the measurement and the corresponding predictions, in which the difference can be significant for that instant but not in a systematic manner. This temporal window will allow us to characterize correctly a systematic failure, either being an offset or a drift.

The temporal window will have user-specified, pre-defined time units, which is typically defined by the application and related with the required failure detection latency. The rule of thumb is that the window must include enough measurements to characterize the temporal scales of relevance with enough resolution for the phenomena at stake, depending also on the frequency of sensor measurements. The number of measurements in the window must be at least 3, such that it is possible to conclude that a certain behavior is systematic, but it can be made larger as this will allow more precise conclusions.

5. Conclusions

We propose herein a new approach for drift and offset behaviors detection, specifically targeted for application in environmental sensor networks. The implementation is based on an instantiation of a past methodology [3], applicable to short- and long-term failures. The new methodology comprises relevant prediction models for the next measurement of the target sensor, using machine learning techniques based only on the neighbor's information. The next steps will be to demonstrate it with real world data, in a complex environment setting.

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