



Contemporary Affirmation of Machine Learning Models for Sensor Validation and Recommendations for Future Research Directions

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Abstract- Wireless Sensor Networks (WSNs) are important and needed systems for the future as the notion "Internet of Things" has emerged lately. They're used for observation, tracking, or controlling of several uses in sector, health care, home, and military. Yet, the quality of info collected by sensor nodes is changed by anomalies that happen because of various grounds, including node failures, reading errors, unusual events, and malicious assaults. Thus, fault detection is a necessary procedure before it's used in making selections to make sure the quality of sensor information. A multitude of methods can be called multiple-changeable systems/agents. For example methods such as for example creating heating system, ventilation and air conditioner(HVAC) methods are changeable methods / agents . Multiple-changeable methods /agents such as for instance these commonly don't meet performance expectations imagined at design time. Such failings can be a result of a number of factors, for example difficulties due to improper installment, substandard maintenance, or products failure. These issues, or "faults," can comprise mechanical disappointments, management difficulties, design mistakes, and improper operator treatment.

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Contemporary Affirmation of Machine Learning Models for Sensor Validation and Recommendations for Future Research Directions

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Abstract- Wireless Sensor Networks (WSNs) are important and needed systems for the future as the notion "Internet of Things" has emerged lately. They're used for observation, tracking, or controlling of several uses in sector, health care, home, and military. Yet, the quality of info collected by sensor nodes is changed by anomalies that happen because of various grounds, including node failures, reading errors, unusual events, and malicious assaults. Thus, fault detection is a necessary procedure before it's used in making selections to make sure the quality of sensor information. A multitude of methods can be called multiple-changeable systems/agents. For example methods such as for example creating heating system, ventilation and air conditioner(HVAC) methods are changeable methods / agents . Multiple-changeable methods /agents such as for instance these commonly don't meet performance expectations imagined at design time. Such failings can be a result of a number of factors, for example difficulties due to improper installment, substandard maintenance, or products failure. These issues, or "faults," can comprise mechanical disappointments, management difficulties, design mistakes, and improper operator treatment. As a result of complexity of such multi-varying methods/agents, it truly is relatively typical for problems to proceed unnoticed for extended periods of time, and simply recognized when they become critical enough to cause whole gear failure, extreme energy consumption, and/or satisfactory performance degradation to activate user criticisms. In this paper we introduced the contemporary affirmation of the recent literature on sensor validations using machine-learning approaches. In this critique, we condition the requirements to style successful and effective fault detection designs and present the troubles of problem detection in WSNs.

Keywords: *wiireless sensor networks (WSNs); sensor validation, sensor data fault proneness detection; detection effectiveness; detection efficiency; energy consumption.*

I. INTRODUCTION

Several public-service practical divisions, such as for instance Transport, Temperature Information Program are employing sensors to gather asso-

ciated info. Within this respect the problem divisions use a group of sensors that gather preferred info. The info from these sensors can be used to look for the associated info. These details can be used to consider proper choices or steps. The info obtained in the sensors can be used some occasions to spend assets or even to consider delicate choices, which assists in operating the business within an effective and economical manner.

Over a period of moment because of several factors including climate, poor preservation, info obtained in the information noted by sensors will be fault-prone. This makes it vital that you retain these sensors in working order and ensure the parts are appropriate. The maintenance of these sensor models is pricey and it is performed manually. Routine re-preservation inspections and calibrations are expected to guarantee the correct working of these sensors. If there existed an automated process that may detect malfunctions in real time and alert the maintenance personnel it would be beneficial. Within this document we completed the contemporary acceptance of the current literature about machine-learning techniques made to calculate the fault-proneness of the sensors.

To discover a malfunctioning sensor utilizing ML approaches, the overall practice is to take notice of the sensor's productivity over a period of time of time for you to establish any substantial and / or systemic variations from the precise circumstances present that might reveal a sensor malfunction. It needs historic Alarm Information obtained in the site and it's particular nearby websites to master the patterns, to create Machine learning designs.

a) *Building Models of Sensor Data using Machine Learning*

Machine-Learning (ML) practices assemble versions depending on prior observations that may subsequently be used to predict new data. The model constructed is a result of a learning process that extracts beneficial details about the information technology procedure for the device utilizing the preceding findings. ML techniques take a set of information akin to the method (in cases like this the weather in a sensor) and

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develop a model of that method in many different strategies to anticipate that method. The ensuing type might be put on future data to try and estimate sensor prices. The ensuing forecasts are able to be in comparison to sensor prices claimed as well as in situations where you can find significant deviations; these sensors could be flagged as possibly malfunctioning.

We suggest to use many different ML procedures including classification processes (e.g., J48 Decision Trees, Naive Bayes and Bayesian Networks), regression processes (e.g., Linear Regression, Least Median Pieces) and Hidden Markov Models to attempt to call this information. In all cases we're trying to identify instances where sensors appear to have failed or are malfunctioning.

b) *Machine Learning*

Understanding can be defined in general as a procedure of getting understanding through encounter. We individuals begin the procedure of studying new points in the day we are born. This learning process proceeds throughout our existence where we try and collect more knowledge and attempt to improve what we have previously discovered through encounter and from tips collected from our setting.

ML calculations need a dataset, which make up the knowledge base, to construct a design of the domain. The dataset is a set of examples from the domain name. Each instance includes a set of characteristics which describe the properties of that example in the website. An aspect takes in a variety of ideals depending on its aspect kind, which may be discrete or constant. Distinct (or nominal) characteristics accept distinct values (e.g., car = Honda, weather = sunny) whereas continuous (or numeric) attributes take on numeric values (e.g., distance = 10.4 meters, temperature = 20°F).

Each instance includes a set of input signal characteristics and an output attribute. The input signal aspects are the information directed at the learning algorithm and the output attribute contains the opinions of the activity on that info. The value of the output signal attribute is presumed to depend on the ideals of the input signal characteristics. The aspect combined with the worth put to it determine a characteristic, which makes an example a function vector. The model built by an algorithm may be viewed as a function that maps the input signal aspects in the instance to some value of the output signal attribute.

When found with the nude eye huge amounts of data might appear random, but on a closer evaluation, we may uncover relations and routines inside. We additionally get a penetration in to the mechanism that creates the info. Witten & Joe [2005] determine data mining as a procedure for detecting patterns in info. It is additionally referred to as the procedure for extracting

associations from the given data. In general data mining is different from machine-learning in that the dilemma of the efficiency of learning a model is regarded along with the effectualness of the training. In data mining issues, we can have a look at the information creation procedure as the information and the domain name generated by the domain as the knowledge base. Thus, ML algorithms can be utilized to discover a model that describes the information generation procedure according to the dataset directed at it. The data given to the algorithm for assembling the product is called the training info, as the pc has been trained to discover from this data, and the design assembled is the outcome of the educational process. This product can now be utilized to call or classify previously hidden illustrations. New illustrations used to evaluate the model are called a test established. The accuracy of a product can be approximated from your distinction between the predicted and real worth of the mark aspect in the test set.

Calling weather problems also can be regarded as a good example of data mining. Using the sensor Data amassed from a spot for a certain period of time, we obtain a design to forecast variables such as temperature at a given moment based on the input signal to the product. As climate conditions are inclined to follow routines and are not entirely haphazard, current meteorological readings can be used by us together with these obtained a number of hrs earlier at a place and also readings obtained from nearby places to call an ailment for example the heat at that location. Hence, the information examples which are used to build the model may feature preceding and current hour's readings from a set of neighborhood places as input characteristics. The variant that is to be forecast at one of these simple places for the present hr is the objective characteristic. The type and variety of conditions which can be comprised in a instance is determined by the properties of the ML algorithm utilized and on the variable we are attempting to predict.

i. *Classification Algorithms*

Algorithms that categorize certain example in to a couple of discrete classes are called classification algorithms. These algorithmic rules perform on an exercise set-to produce a design or a couple of rules that categorize a specified input signal into one of a set of discrete output signal values. Although some of the categorization calculations demand every one of the input signal also to be distinct inputs can be taken by many categorization algorithms in any type, distinct or constant. The output is always in the kind of a distinct worth. Selection trees and Bayes internets are examples of classification calculations.

In order to employ classification calculations on our weather example we have to convert the output signal attribute in to categories. That is normally

completed by discretization, which will be the process of splitting a constant variable in to categories. Inputs aspects can be made as continuous if the algorithm relates to them or they are able to be converted into discrete values determined by the algorithm.

ii. *Regression Algorithms*

Algorithmic rules that develop a model according to equations or numerical procedures on the values obtained by the input traits to generate a continuous worth to represent the output are called of regression algorithms. The input to these algorithms may consider equally continuous and distinct ideals according to the algorithm, whereas the output signal is a continuous worth. We explain in more detail the regression calculations which were utilized in this dissertation below.

II. CONTEMPORARY AFFIRMATION OF THE RECENT LITERATURE

a) *Sensor validation using machine learning*

Matt Smith et al [1] have demonstrated that artificial neural networks can be good predictors of sensor data for some sensors. They also illustrated a fuzzy clustering affirmation process that has been defeated.

i. *Sensor Validation using Artificial neural networks*

Artificial neural networks (ANNs) are applications intended to mirror the arrangement and function of the human brain. Both are manufactured from layers of neurons. Genuine neurons, as seen on the left-hand side of fig. 1 on the subsequent page, obtain input signal from each neuron in the previous layer through their dendrites. Depending on the state of the inputs received, the neuron may subsequently fire its own output signal to the next layer through its axon. Likewise, the artificial neuron, receives input in the neurons in the previous layer, which it utilizes to compute a measured amount f , as in equation (1).

$$f = \sum_{i=0}^N w_i x_i \tag{1}$$

1. The closing worth of the end product is the worth of an activation function, g , with f as a disagreement. This is typically taken to be either a solely linear perform or the logistic perform, as seen in equation (2)

$$g = \frac{1}{1 + e^{-f}} \tag{2}$$

2. The range of the logistic operate is $[0,1]$. It truly is just like the system stage perform, but with a "softer" transition from 0 to AT LEAST ONE. It really is meant to mirror the firing of an actual neuron.

The system step function is a better approximation of this, because it truly is easier to work with computationally but the logistic function is used.

ANNs are ordered into layers. A network normally consists of three levels: concealed layer, input layer, and output layer. First, input is fed by the input signal layer to the concealed layer. The input signal layer does no computations; consequently, it is not actually consists of neurons. There is one node for each output. Next, the hidden layer receives from the input signal layer and output signal to the output signal layer. That is where many of the computations are done. The initial function of neurons in the hidden layer is ordinarily the logistic function. The variety of neurons in the hidden layer is chosen by an individual. Having more neurons affords better precision, but raises computational complexity. The concealed layer may include several levels of neurons within itself. Finally, the end product layer does a final round of calculations to generate the final end product of the network.

We wanted to utilize ANNs to predict information with a regression design. Our system was to use 85% of the information points we'd to train the network and fit the model. The remaining 15% percentage were used to examine the version created throughout training. We employed the main-mean-square malfunction between the network output and the real sensor data for these factors as our metric.

ii. *Sensor validation Fuzzy clustering*

Fuzzy clustering is a modification on classical set assumption. In conventional set theory, whether an element x of the universe of conversation X is a member of a given set A is specified by the characteristic function, χ_A , of A ,

$$\chi_A(x) = \begin{cases} 1 & \text{iff } x \in A \\ 0 & \text{iff } x \notin A \end{cases} \tag{3}$$

In additional words, an element moreover is a member of a set or it is not. Fuzzy set assumption, on the other hand, allows for a range of membership values given by the membership function

$$\mu_A(x) : X \rightarrow [0,1] \tag{4}$$

When μ is zero, x is not an constituent of A . When it is one, x is entirely a member of A . For values among zero and one, x can be said to be "sort of" a constituent of A .

The dissimilarity between conventional sets and fuzzy sets preserve is seen in fig. 2. The upper half is a predictable set A inside a universe of discourse. The universe is crisply divided into regions of A and NOT A . In the fuzzy expanse in the lower half of the figure, though, there is a gradient of membership in A seen by the desertion out of black.

b) *Machine Learning Approach to Pattern Detection and Prediction for Environmental Monitoring and Water Sustainability*

Erika Osborne et al [2] released an strategy that utilizes Gaussian processes and a general "fault bucket" to recapture a priori uncharacterized problems, along having an rough way of marginalizing the possible faultiness of all findings, which provided an increase to an effective, flexible algorithm for the detection and automated modification of errors. The probabilistic character of the technique is ideal for reporting uncertainty approximations to individual workers. The tactic also can be implemented to discover patterns, additional than faults, which are of excellent environmental significance. This design attempted to assault the problem of modification, design detection, and prediction in water observation signals.

This design depended on Gaussian processes (global Positioning System) due to their flexibility and extensively demonstrated effectivity at modeling non-linear distributions. This issue has been approached by preceding work along similar lines by creating statement models that establish the hoped-for possible fault types a priori [4], but this is usually an unreasonable premise in tremendously variable or poorly understood surroundings. In "fault bucket" strategy, the specification of precise fault designs just isn't necessitated. In this way, this model can simultaneously recognize flaws and robustly make forecasts in the existence of sensor problems. The result is an effective and fast technique for data-stream prediction that can manage a wide variety of problems without demanding important domain name-particular knowledge

c) *A Machine Learning Approach for Fault Detection in Multivariable Systems*

Ying Guo et al [5] offered a model that pertains to systems and techniques for discovering problems in multiple-variable systems/brokers. The strategy is especially appropriate for detecting faults in heat, venting and airconditioning (HVAC) methods and will be described in regards to that model but non-limiting embodiment. The fault detection approach is dependant on record machine learning engineering. This is reached by learning the steady nature of regular HVAC functioning, and then using the mathematical relationships between organizations of measures determine problems in all subsystems which is why sensor advice is accessible, regardless of the specifics of the install and to identify anomalous deviations in the norm. The approach designs the dynamical sub-systems (representatives) and series data in HVAC method. These versions (agents) are assembled via a studying procedure from some instruction info of normal running HVAC systems. The educated models (brokers) can subsequently be employed for automatic fault detection. Our algorithm may catch the truth that time

flows ahead by utilizing directed graphical models (representatives), it is flexible to environment modifications and is dependable in HVAC techniques. The strategy was tested predicated on actual information from commercial HVAC techniques. We can efficiently detect several common faults. The experimental answers are all really positive.

Using the adaptive learning approach requiring just obligatory sensors' data, this method provides a few advantages over rule based techniques. Particularly, the amount of expert, setup and customization knowledge demanded to implement such techniques on distinct HVAC systems is greatly lowered. The outcomes obtained by using the procedures establish that this algorithm has the property of versatility and robustness. Better fault detection results when the creating situation and environment properties adjustments, while conventional approaches are usually not adaptable to these changes automatically can be achieved by current purpose.

A variety of fault detection and diagnostic(FDD) techniques for multiple-changeable methods/brokers are understood, and their use offers several advantages [6][7]. Acting and by detecting on problems in multi-varying systems/agents substantial energy savings can be realized. Moreover, if minor errors are detected before getting significant problems, the beneficial service life of equipment can be prolonged, care costs may be decreased, and mending may be planned when suitable (averting outages and over-time work) [8][9].

Farther, and again using a HVAC program through instance, discovering problems permits for better control of temperature, humidity, and venting of occupied spaces. This, in turn, may enhance worker productivity, invitee/customer comfort, and/or merchandise quality control. Many current fault detection techniques for multi-changeable systems /brokers are rule-established [10][11][12][13]. The fault detection system originates an answer to a breach of these principles creates a threat profile, integrates and interprets incoming info in accordance with a predetermined set of principles, and autonomously. Rule-based methods are, however, restricted insofar they've been very particularly produced for/customized to some unique method and are very tough to update, change, or conform as to an alternative method. Also, rule-based systems usually fail miserably if conditions beyond the limits of the understanding comprised in them are encountered.

Even though less-common, another category of fault detection methods employed for multiple-varying systems/brokers are model-based systems [14][15][16]. Design-established techniques use analytic statistical models to identify problems. As with guideline-based techniques, nonetheless, model-based techniques have numerous limitations. By way of example, product-based techniques are computationally intensive and

normally complicated, and a sizeable amount of proficient function is necessitated to produce a design for an unique system. Also, to be able to create an useable model many inputs must explain the system being modeled and the beliefs of some of the required inputs might not be readily accessible.

Along with the above limits, many multiple-changeable techniques/agents are installed in different structures/environments. This normally indicates that rules or analytic models created for a unique method can't be easily applied to an alternate system. As a result, the challenging process of setting and determining guidelines or creating analytical statistical models should be tailored to each individual constructing/environment. Moreover, the project of setting the thresholds employed by such techniques to raise alerts is involved, and prone to producing fake alarms. Additionally, building states such as structure of the internal structures layout and actually outside variables (such as for instance shading and the growth of vegetation) often change after the program setup/initialization of a fault detection system, which may need guidelines/designs that have been initially suitable to be re-visited and updated.

d) *Application of Machine Learning in Fault Diagnostics of Mechanical Systems*

A diagnostic system based on Bayesian Networks (probabilistic graphical models) is offered. Unlike standard diagnostic strategies, in this procedure rather than concentrating on program residuals at one or a couple working points, analysis is done by assessing system behavior patterns over a window of functioning. It is shown how this approach can ease the dependency of diagnostic methods on precise system modeling while maintaining the desired features of fault detection and diagnosis (FDD) resources (problem isolation, robustness, adaptability, and scalability) at an acceptable degree. For instance, the process is used to problem investigation in HVAC techniques, a region with significant modeling and sensor network restrictions. The application of Bayesian networks in problem diagnostics has been examined in some areas [18], [19], [20]. They may be centered more on trigger-effect-association tactics. What's distinct here is the manner Bayesian systems are applied for diagnostic functions.

e) *A Machine Learning Approach for Identifying and Classifying Faults in Wireless Sensor Networks*

Kenji Tei et 's[21] developed a record strategy to discover and determine errors in a WSN. As it is vital to execute accurate retrieval activities in particular, this function focused on compartmentalization and the recognition of system and data problem kinds. Our strategy uses Hidden Markov Models (HMMs) to capture the problem-free dynamics of an surroundings and dynamics of defective data. It then performs a structural evaluation of these HMMs to determine the

variety of program errors and data affecting sensor measurements. The strategy was validated using real information got from over one month of samples from motes used in an genuine living lab.

HMMs have been extensively researched in fault detection systems [22], [23], [24], [25], [26]. In [24], the writers utilize a Markov sequence to classify normal against irregular activities by contemplating varied measurements. In [25], a HMM is learned to determine errors against internet-based and web servers programs. In [26], writers examine the precision of a Markov chain- centered strategy and determine that Markov chains execute well in fault detection. HMMs present a better medical appliance than fundamental Markov versions.

In [27], the writers present a method depending on pattern-recognition that's additionally combined with a finite-condition HMM. The strategy provides an excellent technique for modeling temporary context in observation errors in elaborate dynamic systems. In [28], the writers utilize a HMMs method for intrusion detection, utilizing distributed observation across multiple nodes. The writers of [29] current an innovative powerful, machine learning based technique for automatically detecting errors in HVAC systems. As well as powerful Bayesian Networks and HMMs, data combination can be employed to join fault detection outcomes from multiple problem versions so that they can attain a more accurate fault detection outcome. The strategy in [29] grows HMMs to understand probabilistic relationships between organizations of points throughout both standard and defective operation. HMMs are effectively.

f) *Automatic Detection of RWIS Sensor Malfunctions using Machine Learning*

Aditya Polumetla et 's [30] offered a product that can predict climate at a given RWIS place using the current advice with that place and encircling places (notice Figure 1.1). We use M L algorithms including regression, classification and HMM systems to build the designs to predict weather conditions at a selected trial of RWIS web sites in the state-of Minnesota. We utilize these compare them with the values noted by the RWIS sensors to identify possible failures and foreseen values. Of the climate conditions reported by RWIS models we focus on calling visiblensness, rainfall sort and heat. We hypothesize that the versions we assemble can correctly detect deviations in the estimated sensor readings which will allow us to identify sensor malfunctions.

III. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

Despite these existing investigation efforts, the diagnosis, isolation, and settlement of the instrument faults in a powerful program stays a difficult dilemma. In the use of the car engine, as an example, the needs for

reduced emissions and greater fuel-efficiency has powered the growth of complex power-train systems including the turbocharger and the dual-camera varying valve-teach. The launch of added parts into the traditional engine enables the exploitation of innovative burning methods, which additionally raises the significance of additional sensing elements for example the ethanol sensor in ex-fuel vehicles for the advancement of committed managements. In the meantime, using additional sensors additionally features program sophistication, and hence increases difficulties in diagnosis.

Because of the cost limitations in most applications, the use of a components redundancy approach is restricted. Furthermore, despite accumulated program information, the additional parts and feeling factors expose uncertainty in to the program.

So, considerable attempts are demanded to increase the existing model-based diagnostic system or understanding-based professional program. With advances in simulator and measuring technologies, the data-driven approach has presented guaranteeing possibilities in various domains including modeling, optimization, controls, and identification. Nonetheless, as a result of dearth of a thorough comprehension of the prospective program, such an approach can encounter difficulties in compensation and the identification of faults. Moreover, the prerequisites of real time program monitoring, for example the On Board Investigation (OBD) requirements in auto applications, boosts additional problems due to the restrictions of online memory and computation abilities. So, tactics that could integrate the existing first-theory knowledge into the data driven approaches are vital to take care of the recognition, isolation, and damages of instrument faults in a powerful system with increasing complexity.

The goal of the proposed study would be to explore procedures that may execute quantitative appraisal of sensor performance in damages and a sensor network of the outcomes of its destruction on system manage and identification. Without using copy sensing equipment, the technique plans to utilize the inserted analytic redundancies for isolation and the detection of faulty sensors, even in the existence of failures in the tracked program. With a quantitative evaluation of the operation of each sensor within the network, the measuring of a flawed sensor may be reconstructed and its effects on the controller as well as other measured variants may be compensated, hence improving the reliability of the target program.

In order to accomplish a quantitative and independent assessment of the performance within a sensor network and its tracked method, future research may be directed in regards to overcome the subsequent difficulties:

- Identify the fundamental analytical redundancies in the target system making use of sensor measurements and handle signals observed throughout regular procedures rather than making use of unique input signal.
- Isolate the entangled dynamics of the sensor(s) and the observe system,
- Eliminate the authority of a fault in one sensor on additional sensors.
- Isolate of the effects of a responsibility in the sensor network and one in the monitored system on the calm measurements.

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