On the Design of Context-Aware Health Monitoring Without a Priori Knowledge; an AC-Motor Case-Study

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***Abstract*—Health monitoring without a priori knowledge can save a significant amount of design and implementation time. However, for smaller devices with limited available resources, this is not feasible using most conventional methods. For small footprint sensor and actuator devices, we propose a health monitoring architecture and algorithm, which uses context-awareness to assess the health status of an "Injective-function Black-Box" without having a priori knowledge about it. The proposed algorithm can identify normal modes of operation, change of states (operation modes), deviation from a state, and abnormal functional operation. We have tested the algorithm on an AC Motor where the system was able to identify its health and changes in the operation status accordingly.**

I. Introduction

In the context of Internet of Things (IoT) and system of systems, the number of small devices and sensors is exponentially growing [1], [2]. The natural diversity of these gadgets imposes an ever increasing engineering time and effort on the design process. To reduce these efforts and extra costs associated with it, more generic methods, which can be applied to a range of devices, are desired. Deep learning, data mining, and similar methods address this issue; however, they can be applied only to larger scale systems with massive resources. We tackle this issue under tight resource constraints, which is suitable for implementation on smaller gadgets with limited computation power.

Traditional methods of control theory are often used to steer motors for a desired action. For example, moving conveyor belts and robotic arms under normal conditions, that is when all parts operate within their respective specified operational specifications [3]. When parts in the system become faulty due to a wear-out or other effects, the system has to detect and diagnose this fault and change its operation accordingly. To save engineering efforts, it is desirable that this process is fully automated, in a reliable fashion, and without requiring extensive computational resources.

Therefore, here we propose a health monitoring system with a small footprint and without a priori knowledge about the design or specifications of the system under monitoring. The proposed system is suitable for monitoring all devices which

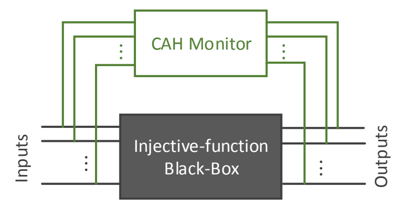

Fig. 1. Block Diagram of the proposed Context-Aware Health monitoring (CAH) system.

are considered an "injective function". That is, for the function f, we have $\forall\ a, b \in D, f(a) = f(b) \iff a = b$, where D is the domain on which f is defined. Our system uses contextual information, to find out normal modes of operation and perturbations therefrom. Since our Context-Aware Health monitoring (CAH) does not use a priori knowledge about the functionality and design of the device it monitors, it can be used for any black-box which constitutes an 'injective function'; the induction motor used as a case-study in this work included. Hence, to validate our method, we have tested it on the data for an AC induction motor, where normal modes of operation, change of state, deviation from normal mode (drift), and anomalies are detected.

The rest of this paper is organized as it follows; In Section II, we briefly review the requirements and specification of the use case, which justifies the needs and benefits of using CAH for this application. The architecture of the proposed system is presented in Section III. The set-up and result of our simulations are found in Section IV, and Section V concludes the paper.

II. Use-case Background: AC Motors

Induction motors are widely used in industry. The high costs of this equipment, its energy consumption, and the importance of avoiding downtimes highlight the necessity of continuous and reliable monitoring as well as regular maintenance [4]. Parameters, such as voltage, frequency, and mechanical torque, influence the various outputs of the motor such as its speed, and torque.

From a high-level point of view, a motor can operate normally, deviate from such a normal state, or fail. A normal operation is when the motor is rotating at a constant speed or changes its speed due to the process plan. However, the condition of the motor and its behavior is prone to decay, and the performance may deteriorate over time because of various causes. In some cases, this deterioration may be reflected in a small deviation from a normal operation mode. In this case, one or more signals are drifting (normally very slowly) away from the normal state. Finally, the motor may get unacceptably far from expected performance or break down, which is called a failure. Some of the causes for motor failures are presented in [5].

When the motor is not connected to a speed controller (in free-running operation), the synchronous speed is proportional to the frequency of power supply and the number of poles of the motor [6]. If the motor is not deteriorated, with the nominal value of power supply the nominal speed is expected. However, sometimes the motor should change its speed. Therefore, various techniques have been introduced to force the motor to rotate at desired values. A constant voltage-frequency ratio is considered as one of the simplest methods, which changes the frequency and voltage to adjust the speed [6]. Nonetheless, when the motor wears out (due to any causes including contamination, lack of lubricant, and corrosion), its speed deviates from the nominal behavior [7].

Health monitoring and fault diagnosis in induction motors have already been studied before, most of which aim at detecting faults in the machine. Nejjari et al. [8] proposed a neural network monitoring methodology to diagnose the electrical faults of induction motors. This system can distinguish between faulty and healthy states of the motor while running at a constant speed. Blodt et al. [9] present an on-line condition monitoring system which detects the mechanical faults of induction motor drives in various load conditions, using current analysis. A variety of health monitoring techniques such as thermal monitoring, vibration and noise monitoring, as well as current analysis, have been reviewed in [10]. The used methodologies can be categorized as methods based on models [11], thresholds [12], pattern recognition and neural networks [13], [14], as well as fuzzy logic [15]. However, to the best of our knowledge, no report on utilizing multiple signals to monitor the health and operation of a motor without a priori knowledge about the motor has been published so far. Such a technique makes the task of monitoring independent from the motor specification.

III. System Architecture

Figure 2 shows the proposed CAH monitoring system consisting of three blocks that are responsible for different tasks: pre-processing, controlling stability, and handling different states. Before describing each part in this section, we present the scope of the proposed system as it follows.

A. Scope

Since the proposed system has no information on the black box it monitors (i.e., the motor), the relations of the various signals are also unknown. However, we do assume that the black-box under study is an “injective function”. Therefore, any unique set of input data should correspond to a unique set of output data, and vice-versa. Thus, the working mode can be considered as normal only when a change of the output dataset is also reflected in a change of the input dataset and vice-versa. In other words, the black-box (in this case the motor) does not work well (is broken), when the output changes without being stimulated by an input, or if an input change does not lead to a changed output.

The second assumption is that the system is in a steady state. Therefore, unstable signals and states (in particular transient signals during state changes) need to be disregarded. Hence, data pre-processing steps are needed for some signals to convert the data to a format suitable for CAH.

B. Pre-Processing

The pre-processing block (shown in the red frame of Figure 2) covers both abstraction and low-pass filtering of a signal. For example, the abstraction receives the sinusoidal signal of voltage and provides its amplitude and frequency. Filtering removes some of the noise and unwanted signal values (e.g., oscillations during a transition). Pre-processing is the only case-dependent part of the system; although, the requirements on it are still generic.

C. Stability Controller

Even though filtered signals are better than the original ones, they may not be stable enough. Therefore, the Stability Controller block (shown in the green frame of Figure 2) is needed to decide whether a signal is stable or not. For this purpose, a sample history in the form of a sliding window (the size of which can be configured) saves the latest values. The Stability Controller compares an actual sensor value with the history and decides that a signal is stable if the disparity (in percentage) of the actual value to a defined number of values of the history is below a certain threshold. In other words, an actual value has to be sufficiently close to a defined number of the values saved in the history. A dataset is only stable when all the signals constituting the set are stable.

D. State Handler (SH)

The SH (shown in the blue frame of Figure 2) does the bulk of the work. This unit tries to recognize all states of normal operation, so that it can, subsequently, detect deviations therefrom.

1) Algorithm: One of the tasks of the SH is to verify whether the actual state is valid or not. For this purpose, the values inserted into this state are counted. A state is considered as valid only if enough values are already stored in it. While the SH saves valid states in the state vector, it discards invalid ones. This procedure ensures that extremely noisy data or

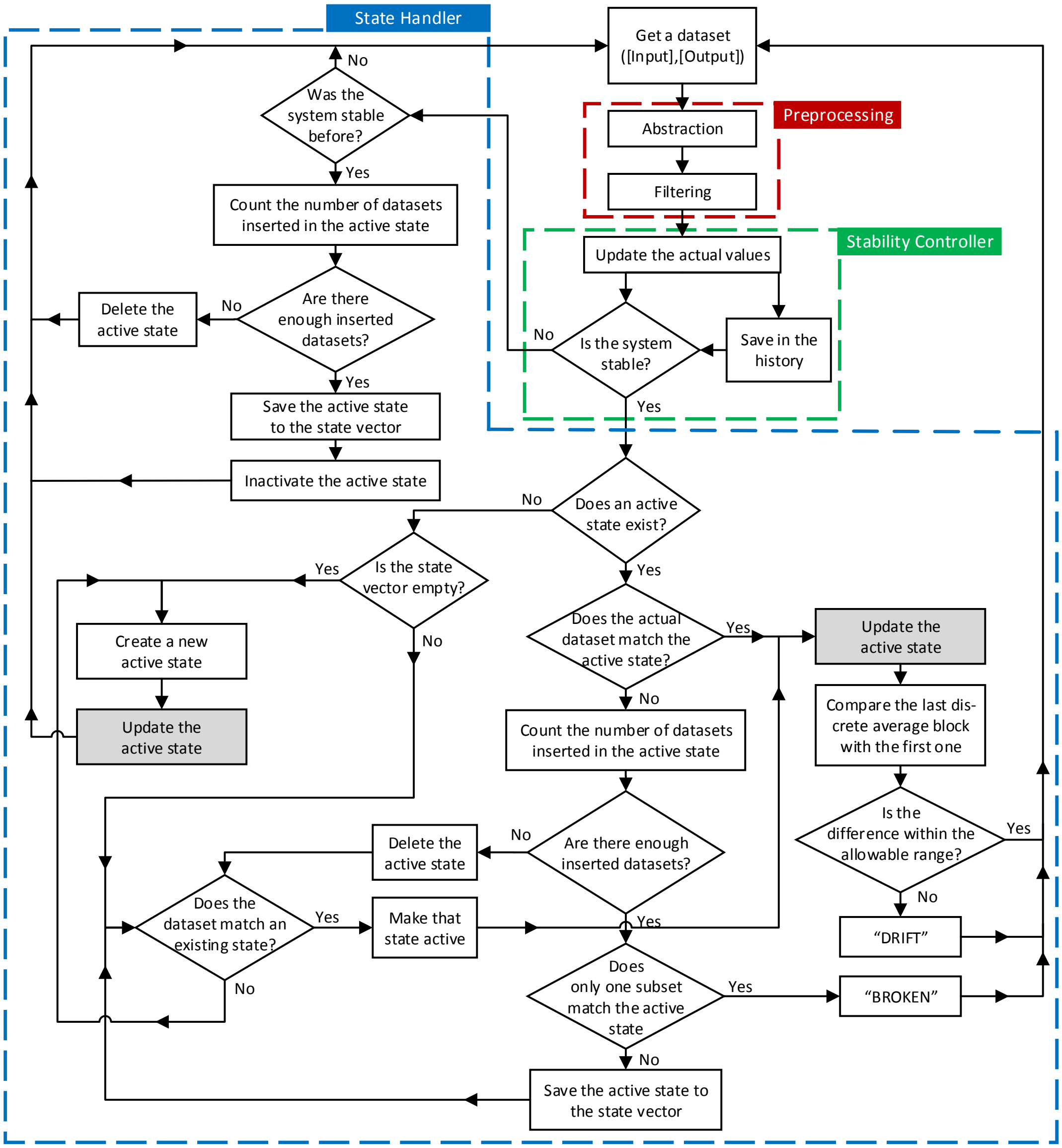

Fig. 2. Flow chart of the Context-Aware Health Monitoring system.

transition phases do not lead to creating a new state, which does not reflect the actual operation of the system.

The SH compares new values, marked by the Stability Controller as stable, with the actual state which is called active state. If deviations of both input and output datasets (measured in percentage), are not bigger than a certain threshold, the SH considers the active state still as active and updates it with the new values. Next, the discrete average of that state is updated and compared with its initial discrete average. If the two discrete averages have a difference larger than a defined acceptable threshold, a drift is observed. Discrete averages and its respective processes are described in more detail in the next subsection.

If the input or output datasets do not match the actual state, a change of state has happened, which can be normal or abnormal. Since the monitored system is treated as an injective function, the change of only one dataset (input or output exclusively) is due to an anomaly. Whereas, a change of both datasets indicates a normal state change. In the latter case, the question is whether the system changes to an already known state or a new state has to be created by the SH. Therefore, the SH goes through the entire state vector and compares all saved states with the new datasets. The SH sets an old state active if the new datasets match an old state. Otherwise, the SH creates a new active state and activates it.

2) Creating and Comparing Discrete Average Blocks (DABs): The CAH system is not meant to raise an alarm only when the system is broken, but it is meant to announce deviations from normal operations as well; that is, when some signals are drifting. In this context, drifting means a signal that changes continuously but very slowly (i.e., a change that is not reflected in continuous averaging). In other words, a series of values of a signal belong to the same state, but the signal is gradually deviating outside its normal expected range. The SH

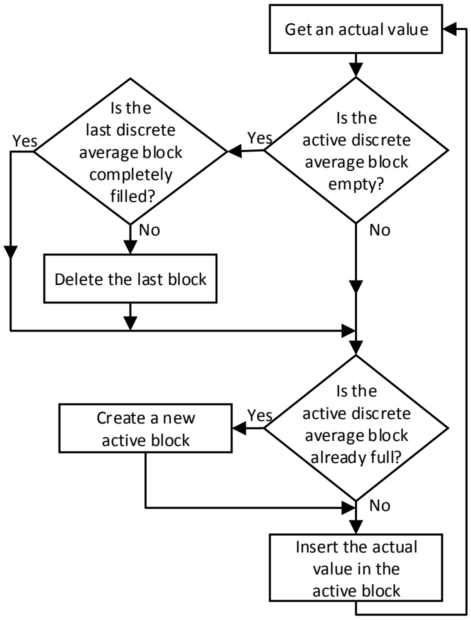

Fig. 3. Block Diagram of the state updating task of the proposed CAH system. Discrete averages are also created and kept in this procedure.

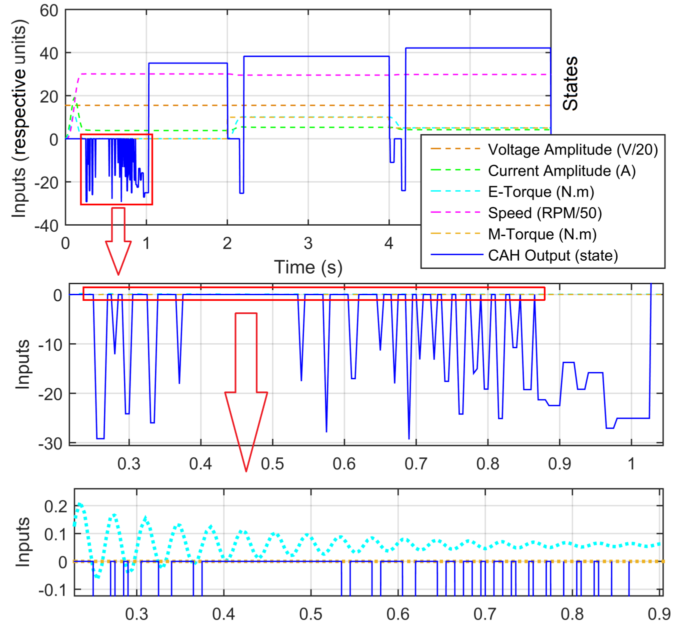

Fig. 4. Outputs of CAH system for an AC motor operating in normal mode when a load change is happening.

detects this behavior through periodically creating DABs of the signal values. To this end, the task of updating the active state (shaded in gray in Figure 2) consists of more operations than only inserting the actual datasets into a state. Figure 3 shows each step of this procedure. To avoid having semi-filled DABs, which are not reliable, the SH deletes the previous DAB, if it is incomplete and belongs to a previously active episode of that state. Afterward, the SH checks whether the active DAB is already full, in which case, the SH initiates a new active block and inserts the actual value into it. If the active DAB is not full[1], no new block is needed, and the SH inserts the actual datasets into the DAB.

A new value of a signal might be in the vicinity of the continuous average (CA) because the CA slowly changes following the drift of the signal. Thus, the comparison of the new values with the CA values does not indicate symptoms of deviation, since it is within the acceptable range of variation. In contrast to the CA, which slowly shifts due to slow changes, the difference between two DABs increases as a slow drift happens in a signal.

IV. Simulation and Results

To validate the proposed CAH system, we modeled it in C++ and simulated it on a set of data from an AC motor, operating normally, changing state, having a drift and failing.

A. Data

The data of the motor has been collected based on both simulations and real measurements. The data of normal and abnormal functional operations are based on measuring voltage, current, vibration, frequency, and torque (mechanical and electrical) signals from the sensors of a three-phase induction motor [16]. The normal state and change of states have been simulated as changes in load and operating speed. For the drift, the continuous increase of load was modeled using a gradual change in mechanical torque, to show the wear-out phenomenon. In the simulation, three-phase current and voltage, speed and load torque have been acquired and later used as inputs for the proposed health monitoring system. The motor is a squirrel-cage, three-phase, 380V, 50Hz, induction motor with 3KW power consumption and four poles [16]. The steady state model used for the motor is the model of asynchronous machine in MATLAB®.

B. Pre-processing

The voltage and current values had to be abstracted to extract information about their amplitudes. All output variables showed occasional unsteadiness, and therefore, they were filtered using a low-pass filter[2]. Other signals could be used without any modification. Last but not least, to avoid unnecessary extra processing, all datasets were down-sampled by a factor of 50, after which each two samples are $5ms$ apart. Here on, all the references to the numbers of samples are after down-sampling.

C. Simulations

1) Normal Operation with and without Changes: Figure 4 shows our test scenario for recognition of the normal operation of the system and respective state changes. In this scenario, the motor is started first, and then, runs monotonically; which

[1]Given that no state change has happened.

[2]We used an Equiripple filter, namely *fdesign.lowpass* function of MATLAB®, two times in a row, with following parameters: $Fp = 0.005, Fst = 0.1, Ap = 0.15, Ast = 0.999$. We note that a low-pass filter implementation is outside the scope of this work for which there are several light-weight methods of implementation on hardware or software.

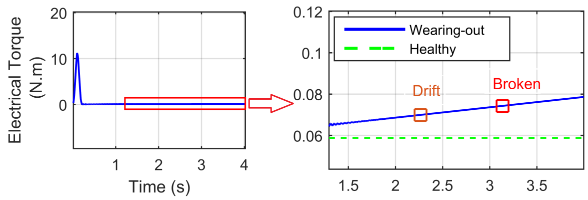

Fig. 5. CAH system outputs for a motor undergoing wear-out.

means, that no parameter changes. In the beginning, the output signals oscillate considerably. Around $0.2s$ (or the 42nd sample), for the first time, the stability-controller verifies the signals as stable. However, this changes within the next samples, and consequently the active state is discarded (shown as a negative state), and a new active state is created. This situation continues until the 196th sample ($\sim 1s$) where a new active state is created which remains stable and is updated by new samples. In this instance, the initial state collects 205 samples, until the load changes at around the 400th sample ($\sim 2s$). Since there are no big changes in any of the signals, the SH recognizes that the monitored system remains in the same state and tags the monitored system as healthy.

When the load changes, the system becomes shortly unstable. After a period of oscillating signals and instability, around the 431st sample ($\sim 2.2s$), the system settles into a new state. Once the system is stable again and recognized as such, the SH is updated again with new values. In this case, until the second load change at the 800th sample (or $\sim 4s$). The third and final state of this scenario is created at around 831st sample ($\sim 4.2s$) and remains unchanged until the end. We successfully ran a similar experiment to detect state changes due to speed changes.

2) State Drift (Wear-Out): The wear-out phenomenon describes a case where the system (here the motor) still works, but one or more signals are drifting away from the nominal value(s). In this example, shown in Figure 5, at the 188th sample ($\sim 0.9s$), a valid state is created, and after 265 samples, the CAH system recognizes a drifting signal and raises a flag. Since the drift continues, where the signal exceeds the boundary of being part of the existing state, the "drift" alarm is replaced by a "broken" alarm. This event occurs at the 628th sample ($\sim 3.1s$).

3) Anomaly: Caused by a bearing defect, the vibration signals, and the current change significantly. At the moment of failure, one of the output signals changed while the input signal (in this case the voltage) remained unchanged. Therefore, the SH raised a "broken" flag.

V. Conclusion

In this paper, we presented a small footprint health monitoring system which can track the health status of any "injective function black-box". Our system is able to achieve this without a priori knowledge about the specification or design details of the monitored system, by using only contextual information. For verifying the validity of the proposed approach, it was tested on an AC motor dataset, where it could successfully identify normal modes of operations, changes therein and deviations thereof (including drift and failure). This method reduces the engineering effort of designing health monitoring systems for various small gadgets, to a configuration setup of thresholds for an acceptable range of variation for the input and output values. In further steps, this process can be automated through a one-time application of optimization, self-awareness, or learning methods during setup or commissioning.

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