ECSEL Joint Undertaking

Electronic Components and Systems for European Leadership

MANTIS

Cyber Physical System based Proactive Collaborative Maintenance

D1.2 Consolidated State-of-the-Art of Sensor-based Proactive Maintenance Appendix 8:

Algorithms for anomaly detection, failure prognosis and remaining useful life

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Abstract

This appendix provides an overview of algorithms for anomaly detection, failure prognosis and the prediction of remaining useful life. Anomaly detection is the identification of those items, events or observations, which do not conform to an expected pattern or other items in a dataset. In the context of MANTIS, the focus will be on detecting anomalies in time series of sensors monitoring physical systems and the networked environment they operate in. Subsequently, maintenance-decision support regarding the anomalous system can be offered. In essence, it is relevant to operators to determine the cause, i.e. fault diagnostics, and the remaining useful life (RUL) of the anomalous system, i.e. fault prognosis, in order to optimally plan maintenance.

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1 Anomaly detection techniques

Anomaly detection covers the identification of items, events or observations, which do not conform to an expected pattern or other items in a dataset. In the context of MANTIS, the focus will be on detecting anomalies in time series of sensors monitoring physical systems and the networked environment they operate in.

In the current literature, discriminative approaches are available that use various metrics to measure the similarity between such sequences (e.g., match count based sequence similarity [1], normalized length of common longest subsequence [2]). In order to cluster the time series, popular algorithms exist - such as Expectation Maximization (EM) [3], (phased) k-Means [4], dynamic clustering [5], k-medoids [6], single linkage clustering [7], clustering in the principal component space [8], one-class SVM [9] and self-organizing maps [10]. It is noted that many real-world domains have a rich relational structure (e.g., different components of a machine interact with each other, or machines operate in a networked environment).

For many recent applications - such as the ones envisaged in this project - off-the-shelf anomaly detection algorithms are not suitable because of the wide variation in problem formulations. Instead of ignoring this relational structure and flattening it to independent and identically distributed (i.i.d.) attribute vectors like traditional machine learning approaches do, it has been shown in [11] that exploiting relational information present in the domain has led to substantially better results for clustering and the detection of anomalies [12, 13].

The online detection of outliers in streaming data makes the problem even more challenging, because existing algorithms typically require multiple passes over the data, which makes them too resource-demanding. Some steps in this direction were made by the exact-STORM and approx-STORM algorithms [14], or algorithms that are based on the concept of sliding windows [15]. Their success was found to be highly dependent on the size of the window, because outliers may be considered as inliers in another window. In the work of Elahi et al. in [16], an alternative approach is proposed where the data stream is divided into chunks of data and analyzed for temporal outliers. A lot of research on data streams is still ongoing. In [17], a recent survey is presented that gives an overview of the state-of-the-art methods for outlier detection for temporal data. Some commercial products (such as SkyLine) offer sliding window-based solutions for anomaly detection in the context of computer and server logs.

2 Failure prognosis and remaining useful life

Providing maintenance-decision support regarding the anomalous system is vital for decision support. In essence, it is relevant to operators to determine the cause, i.e. fault diagnostics, and the remaining useful life (RUL) of the anomalous system, i.e. fault prognosis, in order to optimally plan maintenance [18].

Fault diagnosis implies that the root cause is determined from the observed anomaly. Damage features originating from an earlier data-reduction or data-model, are linked to a particular failure mode, i.e. diagnostic classification. A common application of such an approach is a vibration-based condition monitoring of gears and bearings in rotating machinery. One of the solutions used in such an application [19] is to use an adaptive neural-fuzzy inference system (ANFIS) as a diagnostic classifier to link measured features to different failure modes of ball bearings. In [20] a similar problem is solved using support vector machines and the method's performance is compared to other diagnostic classifiers in literature. The key is that these techniques use supervised learning, using existing datasets during different failure modes to perform the classification for newly detected anomalies. These techniques will benefit from a fleet-based strategy operating on a network of collaborative systems. In here, training data can originate from a large database of similar systems, i.e. a fault can be diagnosed in system X using previous fault information in system Y. The key challenge remains to guarantee proper performance of these techniques within a large range of operational variability.

After classification of the fault, RUL can be determined either by a physics-driven model or based on data mining. In [21] a crack in a ball bearing is detected and RUL is determined by modelling the crack growth using the Paris' law of fatigue crack growth, which implied the use of time-varying models. A more general, yet less physics-driven approach is to assess fault progression within the system and estimate the RUL by extrapolating this fault progression. A review of different fault prognosis techniques, either statistical, model-based or through machine learning is given in [18]. In [22] the estimation of the RUL of individual aircraft engines is demonstrated by learning from a fleet of 30 identical machines.

Alternatively, RUL can also be determined without any occurring anomaly, through monitoring the consumed lifetime of the system and determining the life-consumption rate during different operational conditions. This approach was demonstrated for a system of large-span bridges subjected to harsh environmental conditions in the Hong-Kong area [23,24]. Extrapolating these life-consumption rates will allow estimating RUL for a variety of environmental scenarios. For systems subjected to a larger variety of operational conditions, such as wind turbines, this approach can be tuned to assess consumed fatigue-life based on SCADA and environmental data [25, 26]. However, it lacks an analysis towards the fatigue life consumption for different systems interacting in a larger network of heterogeneous and collaborative systems.

In telecommunication networks, the "Availability" is one of the most important key performance indicators. This is also true for the manufacturing; it is part of the "Overall Equipment Effectiveness" (OEE) metric. The availability of a system is determined by the availability of its components, and it can be calculated from the Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR) metrics which are two important KPI's in maintenance.

Mean Time Between Failures = (Total up time) / (number of breakdowns)

Mean Time To Repair = (Total down time) / (number of breakdowns)

For something that cannot be repaired, the correct term is "Mean Time To Failure" (MTTF). This distinction is important if the repair time is a significant fraction of MTTF. The "availability" of a device is, mathematically, MTBF / (MTBF + MTTR) for scheduled working time [27].

For networking devices, MTBF and MTTR are catalogue-data provided by the equipment vendor. Based on the vendor provided MTBF and MTTR data the availability of the network can be calculated, and failure probabilities can be calculated. However, these statistics provide no information about the next failure location or time, just the probability of a fault.

To actually predict a failure, the straightforward way in networking is to parse the log files collected by the Network Management System (NMS). There are several examples in literature: [28] uses Bayesian networks to predict failures in the NMS while [29] uses System log pre-processing to improve failure prediction. A survey of the online failure prediction methods is provided in [30].

There are other, more sophisticated methods besides the log analysis to predict network failures, like using signal measurements [31] or even Big Data Analysis [32].

3 Conclusion

Regarding anomaly detection, current literature details discriminative approaches that use various metrics to measure the similarity between such sequences. For many recent applications, off-the-shelf anomaly detection algorithms are not suitable because of the wide variation in problem formulations. The online detection of outliers in streaming data makes the problem even more challenging; however, this survey reviews the current approaches.

The key challenge for fault diagnosis remains to guarantee proper performance of these techniques within a large range of operational variability. After classification of the fault, RUL can be determined either by a physics-driven model or based on data mining. Alternatively, RUL can also be determined without any occurring anomaly, through monitoring the consumed lifetime of the system and analyzing the results. The State of the Art here is also reviewed in this document.

Experience from the telecommunications domains shows that metrics such as the Mean Time Between Failures (MTBF), Mean Time To Failure (MTTF) and Mean Time To Repair (MTTR). These can be measured, and these can be used during the various failure-occurrence predictions. There are many data processing approaches used in this domain as well; the most recent ones belong to the Big Data analytics field.

4 Related standards

- iec 61649: Weibull analysis

- IEC 61703: Mathematical expressions for reliability, availability, maintainability and maintenance support terms

- ISO 13379-2 Condition monitoring and diagnostics of machines -- Data interpretation and diagnostics techniques -- Part 2: Data-driven applications

- IEC 61710: power law model - goodness of fit tests and estimation methods

- IEC 61164: reliability growth - statistical test and estimation methods

- ISO 13379-1 Condition monitoring and diagnostics of machines -- Data interpretation and diagnostics techniques -- Part 1: General guidelines

- ISO 13380 Condition monitoring and diagnostics of machines -- General guidelines on using performance parameters

- ISO 13381-1 Condition monitoring and diagnostics of machines -- Prognostics -- Part 1: General guidelines

- ISO 17359:2011 Condition monitoring and diagnostics of machines -- General guidelines

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