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Anomaly detection method applied to vehicle monitoring

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Abstract: Anomaly detection is a topic studied in the literature for a large number of applications. As more and more data is collected continuously, numerous algorithms have been developed for anomaly detection in time series. In this paper, we first propose a method for time series anomaly detection that can be used in different fields. This method is then applied in a real case study for the detection of anomalous behavior of hybrid trucks. Finally, the results obtained are analyzed to propose lines of improvement.

Keywords: Anomaly detection, time series, method, vehicle monitoring.

1. INTRODUCTION

With the development of Industry 4.0, more and more data is produced and analyzed regarding vehicle operation and maintenance. It is not a surprise that stakeholders invest large sums to extract meaningful insights from this data. In 2018, aftersales business (maintenance, repair, wear, etc.) accounted for a revenue of 0.9 billion dollars for the world's original equipment manufacturers, representing a quarter of their total profit (Deloitte., 2020). Analyzing time series recovered from vehicles' daily operation not only helps this industry reduce maintenance costs by developing preventive strategies but can also extend fleet life by identifying best practices or anomalous behaviors affecting user experience and vehicle performance.

To this matter, anomaly detection in time series is not a new subject but it has been largely developed in the past decades for a wide range of applications. In addition to vehicle monitoring, other cases of study cover healthcare (Namoano *et al.*, 2019), information technologies (Cook *et al.*, 2019) and text mining (Gomes *et al.*, 2014). The literature contains a vast number of algorithms for anomaly detection. Long Short-Term Memory (LSTM), Hidden Markov Models (HMM), Convolutional Neural Networks (CNN), Autoregressive Integrated Moving Average (ARIMA) and Principal Components Analysis (PCA) are just some examples (Cook *et al.*, 2019). Given the age of the subject, it is remarkable that so little of the literature covers anomaly detection from a methodological point of view. Apart from all the developed algorithms and their variants, few structured methods have been found regarding anomaly detection in time series.

Thus, the first objective of this article is to provide a method to address anomaly detection of time series. This method aims to structure the anomaly detection strategy beyond the detection algorithms that have been studied in past works.

The second objective is to apply this method to a real industrial case. This will help in the process of evaluation and improvement of the proposed method. For the moment, this method has been applied to the detection of anomalies in the operation of hybrid trucks. The first results have been obtained and their analysis has made it possible to define the areas of improvement of the method.

In Section 2, a literature review will be presented covering the state of art of anomaly detection and its applications. Our method will be presented in Section 3 and its application to vehicle monitoring will be studied in Section 4. Finally, Section 5 will cover the analysis of the results, limitations of our work and next steps.

2. LITERATURE REVIEW

Detection of anomalies or identification of outliers are two ways of addressing the problem of novelty detection. This large field has applications in fields such as information technologies (Cook *et al.*, 2019), healthcare (Namoano *et al.*, 2019), industrial monitoring (Lu *et al.*, 2020), text mining (Gomes *et al.*, 2014) and traffic management (Hoang *et al.*, 2018). Five approaches for anomaly detection are studied in (Pimentel *et al.*, 2014): probabilistic, distance-based, reconstruction-based, domain-based and informatic techniques. For this paper, the literature review will focus on techniques regarding industrial monitoring with a domain-based approach using time series analysis for anomaly detection.

2.1 Anomaly detection methods in time series

Many tools and methods dedicated to anomaly detection in time series are available in the literature. Techniques vary from one application to another, mainly depending on the type of data to process and the nature of anomalies to be detected. One can find time series or data streams, temporal or

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spatiotemporal, univariate or multivariate, punctual anomalies or subsequence outliers, supervised or unsupervised (Gupta *et al.*, 2014) (Atluri *et al.*, 2018). In the context of this article, some examples of algorithms for univariate and multivariate time series are presented below.

Anomaly detection methods for univariate time series cover non-regressive approaches such as Recurrent Neural Networks (RNN) (Goh *et al.*, 2017), Gated Recurrent Unit (GRU) (Fanta *et al.*, 2020) or Long Short Term Memory (LSTM) networks (Dong *et al.*, 2021) and regression-based approaches like Autoregressive Moving Average (ARMA) (Alizadeh *et al.*, 2021).

Methods for multivariate time series anomaly detection include dimensionality reduction by Principal Component Analysis (PCA) (Hoang *et al.*, 2018), clustering methods such as Local Outlier Factor (LOF) (Na *et al.*, 2018) or Support Vector Machine (SVM) (Chen *et al.*, 2020b) and other methods including Hidden Markov Models (HMM) (Li *et al.*, 2017) and combinations of the above (Cook *et al.*, 2019).

Other less conventional approaches for both univariate and multivariate time series are Symbolic Time Series Analysis (STSA) and Symbolic Aggregated approXimation (SAX), which have been introduced in (Ray, 2004) and (Lin *et al.*, 2003) as novel ways of identifying anomalies for complex dynamical systems and large temporal data bases. Their approach transforms the temporal series into a sequence of finite symbols or alphabet, reducing its complexity. To this end, Piecewise Aggregate Approximation (PAA) is employed in many cases. After discretization, the sequences can be treated with traditional anomaly detection techniques and text mining derivations to detect deviations from the regular behavior.

Later publications have adapted the original SAX methodology to better fit into specific applications. Enhanced SAX is presented in (Zhang *et al.*, 2019) to detect anomalies in vibration signals. Trending SAX is presented in (Fuad, 2021) for improving performance in time series classification. (Tamura *et al.*, 2017) introduces a moving average convergence/divergence histogram-based SAX (MHSAX) and applies k-medoids to cluster experimental data sets. Examples of Symbolic Time Series Analysis are found in electronics, robotics, electric engines, and seismic applications.

Anomaly detection is an important matter in time series analysis. A vast number of algorithms have been developed for this purpose, including univariate and multivariate time series applications, supervised or unsupervised learning and symbolic approaches. Most are used in practical application cases with satisfactory results. However, no clear methodology has been found to structure the anomaly detection process.

2.2 Applications in vehicle monitoring

Vehicle monitoring using symbolic analysis is studied for univariate time series in (Li *et al.*, 2015) to identify the state of charge of batteries and in (Li *et al.*, 2021) for fault diagnosis based on feature extraction of railway vibrations.

Regarding multivariate vehicle monitoring applications, (Alizadeh *et al.*, 2021) performs an Autoregressive Integrated Moving Average (ARIMA) to identify abnormal states of vehicles with a multichannel operating time series data. In simple terms, ARIMA models predict the behavior of a given channel (e.g., Fuel Rate) by exploiting the autocorrelations with other channels (e.g., Vehicle Speed and Transmission Oil Temperature). Differences between predictions and observations are used to characterize the abnormal time series.

The importance of pretreatment in time series analysis is remarkable in both (Chen *et al.*, 2020a) and (Spiegel *et al.*, 2011). While the former uses a Kalman Smoother method to eliminate undesirable noise, the latter employs a Savitzky-Golay filter to smooth acceleration signals and more easily find local maximums and minimums.

2.3 Conclusions from the literature review

Literature methods for anomaly detection using multidimensional time series such as Classical and Hidden Markov Models, LSTM, PCA and Neural Networks have been effectively implemented in industrial applications, but they quickly become too complex for human interpretation and their application to large time series data greatly increases computational costs.

Classical SAX and its new variants use symbolic analysis to solve this problem but, to our knowledge, little literature has been produced regarding multivariable applications from a symbolic approach, and none were related to vehicle monitoring. The later may be due to the limitations of the fixed window width used by SAX.

In this paper, an anomaly detection method is presented, aiming to give a structured canvas of the whole anomaly detection process. A particular emphasis will be given to interpretability issues shown in literature by using symbolic time series analysis with a different featuring approach. The proposed method for anomaly detection is then applied to a real industrial vehicle monitoring case study to evaluate its performance.

3. ANOMALY DETECTION METHOD

Following the approach of (Gupta *et al.*, 2014), our method relies on the detection of window-based outliers in a database of multivariate time series. The basis of this approach is to divide time series into a sequence of windows, and for each window, an anomaly score is computed. Significant improvements have been introduced to achieve performance gains in the detection of new anomalies and increase human interpretability of the results to aid latter diagnosis.

In Figure 1 we present the general methodology to identify and classify anomalies form the input data as: new anomalies, already known anomalies and other candidates. Known anomalies are those whose existence is known but have not been located in time. New anomalies are those that had not been previously identified and that present different characteristics from the rest of the anomalies previously detected. Other anomalies refer to those which have not been validated as anomalies but might be of interest if further analysis is performed.

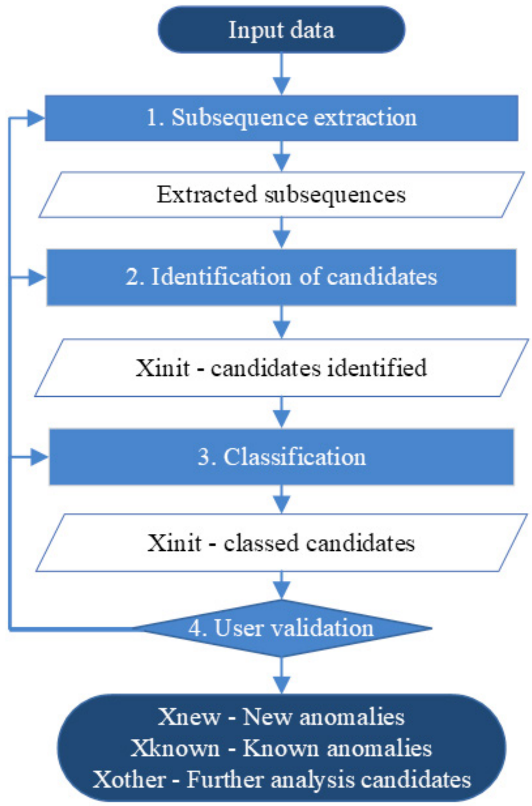

Fig. 1. Anomaly detection method

The methodology presented in Figure 1 has the next steps:

Subsequence extraction: This step aims to extract from the input data the simplest unit of analysis containing the necessary information according to the given application. This unit of analysis is directly related with the type of anomaly to identify. A time-stamp unit of analysis will be suitable for point anomalies (Na *et al.*, 2018), and a window-based approach for detecting subsequent outliers (Zhang *et al.*, 2019). Window-based methods traditionally use a fixed width as seen in PAA. However, in this paper it is proposed to divide the input data into windows with variable widths. The width could be determined by characteristics of a given time series or by the combination and interaction between several time series.

Although not mentioned above, it is important to remember that prior to subsequence extraction, the input data must be preprocessed. This operation includes normalization, filtering or treatment of missing data depending on the nature of the input data and subsequent operations (Spiegel *et al.*, 2011).

The output of the subsequence extraction stage is a finite number of subsequences containing the relevant information of the original data. Those subsequences will become the object of analysis in the next steps.

Identification of candidates: An Anomaly Score (AS) is calculated for each subsequence, and an anomaly threshold is then determined. A subsequence is considered a candidate when its AS exceeds the threshold. The computation of AS varies from one application to another, and one or multiple channels can be used to calculate it. The output of this stage are *Xinit* identified candidates, each with an associated AS.

For the first iteration of the proposed methodology, quantity is preferred over quality. Therefore, a vast number of potential candidates are detected, assuming that many of them will not be validated. As iterations of the feedback loop are performed, the number of potential candidates will decrease.

Classification: All candidates identified in step two are now classified in a limited number of categories of anomalies with similar behavior. To this purpose, algorithms such as k-means, k-medoids and nearest neighbor are typically used in literature (Spiegel *et al.*, 2011) as well as distance methods like Dynamical Time Wrapping (DTW) or Longest Common Subsequent (LCSS). In other cases, a simple quantitative method could be used to categorize anomalies by ranges of anomaly score. In certain applications, qualitative classification performed by domain experts can complement quantitative methods.

Xinit classed anomalies are the output of the classification stage and the input for user validation.

User validation: The fourth step of the methodology refers to the validation of the classified candidates. Several validation methods can be employed at this stage depending on the industrial application and the number of iterations. In early iterations, an exhaustive supervised validation may be necessary, and each candidate is examined in detail by experts before validating. In this way, meaningful insights are obtained from the validating process and used to improve previous stages of the process. In more advanced iterations, the level of detail may decrease. Focus is not put on individuals but on whole categories of classified candidates and using non-supervised learning tools helps accelerate the validation process and enable the processing of larger amounts of data.

At the end of stage four, *Xnew* and *Xknown* candidates are accepted as anomalies, whereas *Xother* candidates are not yet considered as anomalies until further analysis is performed. User validation will be used to improve stages one to three, as illustrated by the loops in Figure 1, allowing the refinement of the results.

4. CASE STUDY

4.1 Context

The above-described methodology has been put into practice with the collaboration of an industrial partner. The company in question belongs to the hybrid vehicle sector; it provided the data coming from its pioneer electrical Stop-Start Module (SSM) for heavy-duty vocational trucks (e.g., garbage trucks). This system can reduce the engine usage time by half and save 30% of fuel by stopping the vehicle engine while the truck is not moving. SSM is installed in already-in-operation vehicles, switching to electric mode when the truck is stopped for a long time (e.g., operators are charging and discharging merchandise). Of all the functionalities of the SSM, automatic restarting the thermic engine is said to be the most critical operation for the company. Therefore, in this study we focus on detecting anomalies in the engine start-up phase.

For the correct functioning of the SSM, the vehicle's status must be constantly monitored. A total of 258 channels including mechanical (engine speed), electric (fuse voltage), digital (engine restart bit) and thermal (temperature of control unit) are processed and recorded each 0.1s by the SSM. An average of 200,000 recorded timestamps per vehicle per day over the course of months provides the total data to be analyzed. In addition to the large amount of data, the SSM brings with it the challenge of being unique on the market, meaning no similar studies have been performed for this kind of system before.

Currently, the SSM uses a common error identification system capable of detecting errors due to failure in lecture of the sensors. The system does not consider the temporal dimension of the signals or the interaction between channels. These two aspects are key to the detection of more complex anomalies, for example, related to the behavior of the driver. Those abnormal behaviors are currently identified by exhaustive inspection of all the monitoring data by an expert. In this study, we will consider both time dimension and multichannel analysis to detect anomalies within the restarting operation of the SSM.

4.2 Application of the methodology

The data set provided by the industrial partner is composed of 175,753 timestamps recorded every 0.1 s. 27 signals have been selected by experts of the industrial partner for advanced anomaly detection. For all those signals, preprocessing is done by cleaning sensor reading errors, normalizing signals and smoothing out the noise with a Savitzky-Golay filter (Spiegel *et al.*, 2011). No previous inspection has been performed in the data, meaning no anomalies had been yet identified by the industrial partner, except a restart problem from a driver, for a duration of 5 s, illustrated in Figure 2, where acceleration pedal is being pressed but no speed is observed.

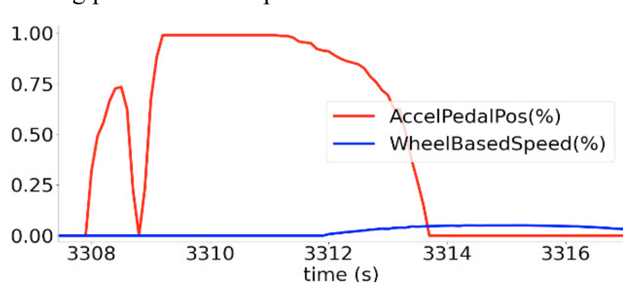

Fig. 2 Known anomalous behavior during restarting

For the first iteration, the relation between Acceleration Pedal Position (APP) and Wheel Based Speed (WBS) is analyzed using the proposed methodology. Both acceleration and speed are mechanically correlated, so the initial idea for anomaly detection aims to identify the gaps where this correlation is abnormal, particularly during restarting operation.

Subsequence extraction: To determine the appropriate unit of analysis, tests with different segmentation techniques for time series are performed and validated by the partner's experts. Fixed-window-width methods such as Piecewise Aggregate Approximation (PAA) were categorized by the experts as inadequate since anomalies in restarting operations have variable length and imposing a fixed window width could result in the non-detection of anomalies whose duration exceeds the window width.

Another approach is tried: extracting critical points from the input signals. Local extrema of the signals (Spiegel *et al.*, 2011) or methodologies such as Perceptually Important Points (PIP) (Jiménez *et al.*, 2016) are employed to this end . In this approach, the unit of analysis is set as the portions of signal in between those critical points. The high number of local extrema in the APP signal results in too short windows, and Perceptually Important Points resulted in high computational times and segments that were not physically interpretable.

Given the non-satisfactory results with PIP and local extrema to extract the subsequences from the signal, a more human interpretable unit of analysis is developed. Critical points are then identified as the timestamps where APP signal changes from zero to non-zero as shown in Figure 3.

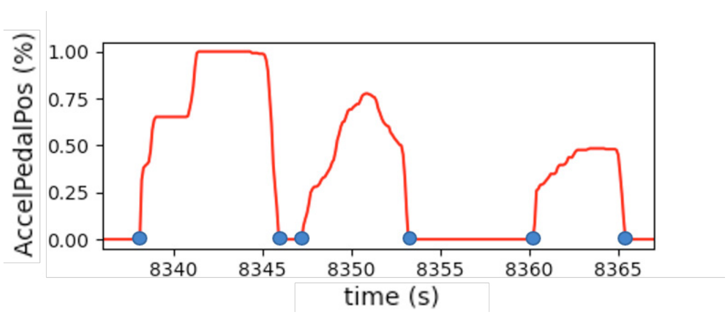

Fig. 3. Segmented Acceleration Pedal Position

The resulting portions of signal between critical points are divided in two categories: *silences*, defined as the timestamps between critical points where APP stays at zero and w*ords*, defined as portions of signal between critical points where APP is different from zero. In a first analysis, the focus will be on the *words* rather than *silences* because anomalies are more likely to appear in those intervals where the acceleration pedal is been pressed.

The concept of *word* is derived from Symbolic Time Series Analysis and one of its advantages is that it simplifies the temporal component through aggregation. Attributes such as *word* starting time, length, mean, standard deviation or area, characterize each *word*. The whole time series is then seen as a table of *words* with attributes that can be analyzed with anomaly detection techniques like Local Outlier Factor (Na *et al.*, 2018) or simple statistical methods.

Identification of candidates: As mentioned in section 3, candidates are identified using an Anomaly Score (AS) calculated for each unit of analysis. In the case study, an AS is computed for each *word*. Due to the mechanical relationship between acceleration and speed, correlation between both is used as the anomaly score to identify the candidates. AS is defined by the following ratio:

$$AS = \frac{\sum_{ts}^{te} APP_t}{\sum_{ts}^{te} WBS_t}$$

AS represents the quotient between the area under the acceleration (APP) and the area under the speed (WBS) for a given *word*, where *ts* and *te* refer to the starting and ending times of the *word*. Figure 3 represents the defined ratio.

The AS threshold is determined to detect at least 10% of the total *words*. Considering that, at present, the anomalies identified by the driver do not represent even 0.1% of the total vehicle running time, the chosen threshold will maintain the idea of quantity over quality in the first iteration of the loop.

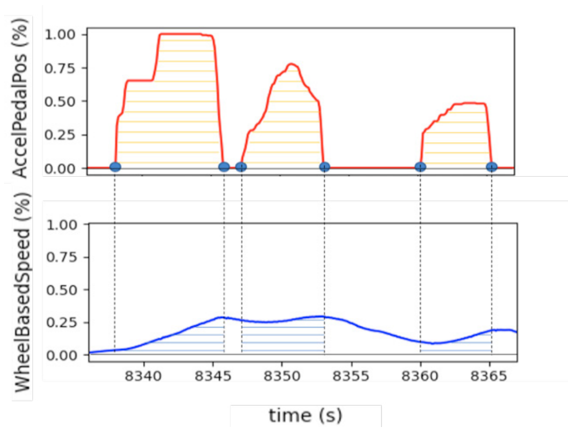

Fig. 4. Graphical interpretation of the anomaly score.

As an example of anomaly, an extremely high value of this AS shows that APP is increasing while WBS is not following in a regular way. Therefore, this *word* is detected as an anomaly.

Classification: Firstly, a quantitative classification is performed regarding anomalies based on AS. *Empty accelerations* are called the *words* whose AS tends towards infinite. *Slow accelerations* called the rest of the *words* whose AS is greater than the previously defined threshold.

Qualitative classification is performed based on experts' knowledge. Experts classify the *words* by visual inspection, adding other signals to the analysis. Expert's classification feedback will improve the loop in the next iterations, other signals will be added to the analysis and there are plans to implement an automatic classification based on pattern recognition. The output of this stage are *Xinit* classed candidates into 6 different categories.

User validation: For the first iteration of the loop a portion of, at least, 20% of candidates in each class are validated by visual inspection one by one by industry experts. This detailed validation determines whether a category of anomaly is already known to the company (*Xknown*), if it is a new type of anomaly (*Xnew*) or if, on the contrary, it is not recognized as an anomaly (*Xother*). Once a class of anomalies is labeled as *Xknown*, *Xnew* or *Xother*, all anomalies belonging to that class automatically get the same label.

4.3 Results

Table 1 summarizes the results obtained in the first loop of the proposed methodology applied to the monitoring data of a working day of a garbage truck. This data set is composed of 175,753 timestamps recorded every 0.1 s. To our partner's knowledge, before any other analysis has been done this set of data includes just one anomaly identified by a driver during a restarting operation in a gap of 50 timestamps (5 s).

Initial subsequence extraction decomposes the original time series into 991 *words*, of which 228 are labeled as potential candidates in stage 2. Representing more than 20% of the total *words*, this figure may seem excessive, but it is preferred to increase the number of candidates in the first iteration to be able to learn more in the validation process with the industrial partner. In fact, in terms of duration, those *Xinit* identified candidates represent 1.6% of the total.

Stage	Label	Count of *words*	Duration (s)	% of total time
1	Total *words*	991	17575.3	100%
2	*Xinit*	228	279.6	1.59%
3	Class 1	12	4.3	0.02%
	Class 2	1	1	0.01%
	Class 3	30	53.7	0.31%
	Class 4	26	53.7	0.31%
	Class 5	3	8.5	0.05%
	Class 6	156	158.4	0.90%
4	*Xnew*	13	5.3	0.03%
	Xknown	59	115.9	0.66%
	Xother	156	158.4	0.90%

Table 1 Summary of the output in first iteration of the method

Classification and subsequent user validation lead to 13 new anomalies, representing 0.03% of operation time. Those anomalies have never been analyzed by our partner but can have a direct impact on the driving experience.

The anomaly detected by the driver is part of the 59 *words* detected as known anomalies. The anomalous behavior of the SSM in these cases is known to the partner, but they are only able to detect them by manual analysis. The interest in automatic detection of this type of anomaly is that it can help in the subsequent diagnosis phase.

Finally, there are 156 candidates, representing almost 1% of the operating time. Although they are not directly considered as anomalous behaviors, their detection and classification can be interesting for other types of SSM behavior analysis.

5. CONCLUSION

In this paper, we presented a method that addresses the lack of a structured methodology for anomaly detection in time series detected in the literature. This methodology has been implemented in an industrial monitoring case thanks to the collaboration with a partner. As a result, in a first iteration of the methodology, it has been possible to detect in an automated way the anomalies that were previously detected manually, as well as to detect new anomalies that had not been initially studied by the partner. The interpretability of the results has facilitated the industrial validation of the method by the experts, and subsequent iterations of the method are expected to refine the results using the insights obtained in the first iteration.

Classification and validation stages are still a work in progress and other challenges remain, including the incorporation of more variables into the analysis and the scaling up of this methodology for its application to larger databases. To this matter, reevaluating the role of industry experts for the classification and validation stages will be necessary to keep the balance between interpretability and scalability.

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