Detecting Anomalies in the Engine Coolant Sensor using One-Class Classifiers

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***Abstract*—In this paper we evaluate the presence of anomalies in the Engine Coolant Temperature (ECT) sensor operation by collecting telemetry data of a single car in two different operational modes. The proposed approach has evaluated ten different one-class classifiers in three different anomaly levels, defined from the sensor's malfunctioning. Based on the results from the experimental data, the evaluation has shown: the One-Class Support Vector Machine with third-degree polynomial kernel function as the best anomaly detection technique for the vehicle operation in movement trajectory and the k-nearest neighbor as the best technique for the vehicle stopped, but with the engine running.**

***Index Terms*—Anomaly detection, vehicle telemetry, one-class classification, engine coolant temperature sensor**

I. INTRODUCTION

The combination of Information and Communication Technologies (ICTs) applied to the development of innovative and sustainable solutions characterizes a new moment of interaction between product and consumer, also called the fourth industrial revolution or Industry 4.0. Among the new applied technology, the Internet of Things (IoT) stands out, considering the interconnection of different objects and the appearance of new functionalities from the various things connected.

Following the trends, vehicles tend to be connected in a way to establish new services for the driver. The connected car aims to exchange data from vehicles to anything (V2x), providing a new service or drive experience [1]. As a result of the connected vehicles, new functionalities can be established from the vehicular data analysis, such as the detection of abnormal behavior in specific components. Following the definition of [3], also used in [8], an anomaly is characterized as a consequence of an error, thus indicating the possible presence of a failure in the functioning of a sensor or a vehicle system. The abnormal data are values outside an expected range or data coming from behavior other than expected.

Considering the observations of vehicular data, outlier, and novelty detection, Theissler presented a series of papers regarding the discovery of anomalies in intra-vehicular signals modelling the problem as a classification task [9]–[12]. The first work proposes a learning system to detect anomalies in a DC motor.

As a continuation of the work, Theissler and Dear [12] proposed an approach to find the ideal set of parameters for the machine learning based in the Support Vector Data Description (SVDD) technique. In another contribution [11], they used a model to assist vehicle specialists in detecting anomalies. Their most recent contribution [9] presents an approach with detection of known and unknown anomalies for Engine Coolant Temperature (ECT) sensor and Short Term Fuel Trim (STFT). This approach does not require configuration of previous parameters. Furthermore, differently from previous works, a combination of classifiers was performed [9]. Besides contributions related to anomaly detection in vehicular sensors, a variety of papers have also addressed systems anomalies. In [13] an approach for real-time recognition of anomalies related to state-based driver behavior is proposed. Following the methodology of [9], Nair and Koustubh [6] explored models applied to the detection of anomalies in hybrid and electric vehicles.

A common problem faced by many drivers is the motor overheating. Specifically to the operation of the engine, the ECT sensor monitors the temperature of the coolant system and antifreeze mixture. The sensor returns the exact value of the engine temperature. Although most vehicle models having a diagnostic trouble code (DTC) to indicate the engine overheating, vehicles are not yet equipped with alerts of sensor malfunction and consequent problems regarding their measurements. Like any electronic component, the ECT sensor is subject to faults and behaviors that are not expected.

In this paper, we propose a vehicular anomaly detection system based on the analysis of data collected from a vehicular telemetry system. The proposed approach considers the evaluation of different anomaly detection techniques using the methodology proposed by [9] with an evaluation based on three different anomalies levels regarding different intensity levels of resistive faults in the Engine Coolant Temperature sensor.

This paper is organized as follows. In Section II we present the architecture of our proposed anomaly detection system.

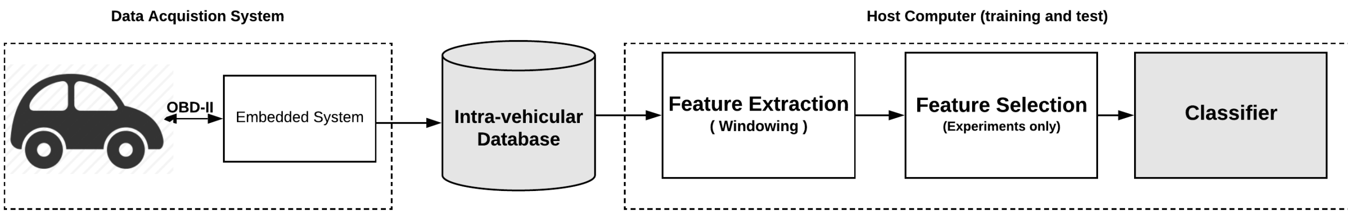

Fig. 1. System overview of the proposed anomaly detection system

Section III describes the experiments. In section IV we discuss the results of the proposed system. Finally, Section V brings the conclusions.

II. Proposed Anomaly Detection System

Fig. 1 shows the proposed architecture for the anomaly detection system. It is composed of four main modules described in the following subsections.

A. Data Acquisition

The data acquisition system is composed by an embedded system connected to the On-Board Diagnostic II (OBD-II) interface of a Toyota Etios (year 2014, Engine Displacement 1496 CC). The device used was the Carloop [2], an open-source development kit based on a microcontroller with cellular connectivity and OBD-II interface connector. Fig. 2 shows the hardware architecture of the embedded system. The system captures all vehicular data at a rate of one sample per second (1 Hz).

B. Feature Extraction

Since the vehicle generates one new data instance each second, the classification instance could be defined as an individual recording of the system. The approach of detecting individual anomalies, analyzing each attribute, is not reasonably practicable. Following the definitions of [3], the method proposed in our work is based on the detection of contextual anomalies.

More specifically, in order to detect the contextual anomalies, the feature extraction process used in this work is based on a sliding window with a configurable width (N). The features extracted from the windowing process are the windowing of each one of the 27 different parameters and the standard deviation of the Engine Coolant Temperature.

C. Feature Selection

Seven different vehicle parameters (Engine Load, Engine rotation, Long Term Fuel Trim, Tank Level, Manifold Absolute Pressure and Catalyst Temperature) were analyzed, based on the correlation index, to be part of the anomaly detection system as a feature, together with the ECT sensor value.

From the result of the system comparison performance and a correlation between attributes, the variable representing the number of revolutions per minute (RPM) of the motor is chosen, which together with the temperature value of the ECT

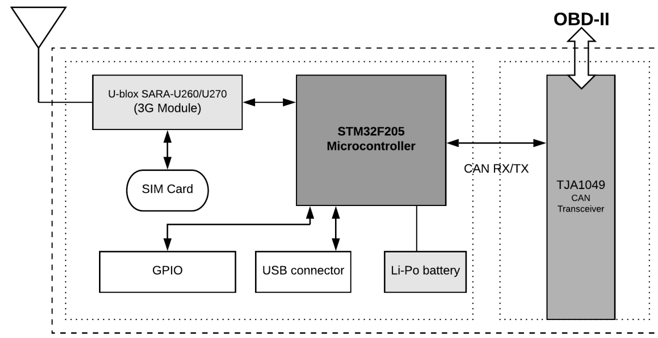

Fig. 2. Hardware architecture of the data acquisition system

sensor, are defined as system attributes. In addition to these variables, the values of the standard deviation and variance of the ECT sensor were also used, determining the feature array of the system. Both attributes are normalized to values in the range (0,1) before the feature extraction and selection process.

D. Classifier

The detection of vehicular anomalies proposed in this work is based on one-class classification. During the process of constructing the intra-vehicular database, none DTC has been activated. Therefore, all collected data only describes the normal operation of the ECT sensor.

Different approaches based on one class classifiers for anomaly detection were implemented in order to find the best one. The techniques used by [9] were used to compare the results. The different classifiers implemented, separated by their category, were:

- **Instance-based techniques**: k-nearest neighbour (k-NN).
- **Statistical methods**: Gaussian data description, Parzen window density estimator, Naive Parzen window estimator and Extreme Value analysis.
- **Neural networks**: Self-organizing Map (SOM).
- **Rule-based**: Minimum Spanning Tree (MST) and Mahalanobis distance.
- **Support vector machines**: Support Vector Data Description (SVDD) and One-class SVM (OC-SVM).

III. Experiments

This section describes the database, the parameter selection, and the system's performance evaluation.

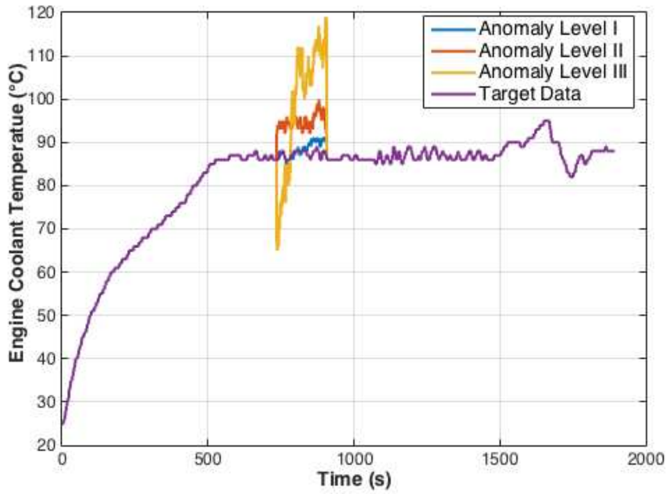

Fig. 3. Different anomaly levels applied to the ECT sensor signal

A. Injected anomalies in vehicular data

During the vehicle data acquisition process all the collected data were from normal functioning of the sensors. Those data were treated like target data. Due to the difficulty of collecting abnormal data, the anomalies were synthetically inserted in the normal data. The registration of scenarios with anomalies of faults would involve the analysis in several vehicles [8]. To evaluate the proposed system, anomalies are artificially injected to the ECT sensor signal based on three different anomaly levels, illustrated on Fig. 3.

The type of contextual anomaly evaluated in our proposal is the same as defined in [9], erroneous engine coolant temperature. In our analysis, the fault or sensor's malfunction is due to a resistive fault since the ECT sensor is based on a thermistor. The insertion of artificial anomalies considers the presence of a significant noise component into the ECT sensor signal. Although related, the process of detection of anomalies is distinct from the noise removal in signals [3]. Noise can be defined as an undesirable phenomenon in the signal of interest with an impressible instantaneous value.

Different types of noise are associated with the analysis of electronic circuits [5]. Considering resistive failures, the kind of noise related to a possible resistive fault is excessive noise (flicker noise). From the presence of flicker noise, we define the three different levels of noise in the ECT signal. They are determined by different signal-to-noise ratio (SNR), values of 18 (Level I), 8 (Level II) and 0 (Level III) dB respectively. These levels are defined in our proposal, considering the dynamic power range of the ECT signal.

B. Intra-vehicular Database

A specific firmware was developed to read the available OBD-II parameters and save as temporal signals. Following the nomenclature of [9], two different modes of vehicle operation are recorded:

- **Idle Mode**: corresponds to the state in which the vehicle is stopped, but with the engine on (running).
- **Motion mode**: corresponds to the vehicle in trajectory.

Only normal operation often called target data, are needed during the training phase of the different one-class classifiers. Defining $\|T\|$ as the size of the training database in seconds, $\|TT\|$ the size of target data test in seconds and $\|OT\|$ the size of the outlier data test in seconds, Table I describes the size of each vehicle mode database and the number of vehicle trips made. A trip corresponds to a driving cycle, in the case of the car in idle mode, corresponds to a period in which the vehicle stays turned on.

TABLE I
DESCRIPTION OF THE DATABASE USED IN THE EXPERIMENTS

Mode	$\|T\|$	$\|TT\|$	$\|OT\|$
Idle	16430 s	8400 s	1875 s
Motion	58231 s	19840 s	3375 s

C. Classifier Performance Evaluation

Considering the results of a confusion matrix: true positives, false positives, false negatives and true negatives, the following metrics are used to evaluate the system performance:

- **True Positive Rate (TPR)**: also known as sensitivity, or recall, measures how much a classifier recognizes positive examples.
- **Precision**: is the ratio of predicted negative samples which are actually negative.
- **F2-score**: the F2-score incorporates the results of true positive rate (TPR) and precision, emphasizing the detection rate.

These metrics were chosen to evaluate both the recognition of target samples, and the outlier samples. The F2-score was chosen to evaluate overall system performance. As defined in [4], the F-measure is the harmonic mean based on TPR and precision.

$$F_2 = \frac{5 \times prec \times sens}{4 \times prec + sens} \tag{1}$$

D. Base classifiers parameters tunning

Table III shows the best parameters found to each one-class classifier used in the experiments though variation and evaluation of the results. The parameters are specific to each technique and are valid for both modes of the vehicle operation.

IV. RESULTS AND DISCUSSION

The same train (target) and test (outlier) sets were used in order to compare the techniques. Furthermore, the results shown in Table II are average F2 score values from 30 executions of each classifier. The procedure for constructing the model is based on splitting each trip into two groups. The first contains only target data (normal operation), which are randomly divided into two parts: 70% to train the model and 30% as test data. Separately, a set of 300 samples from the second group of each trip was used as the input of the anomaly

TABLE II
ANOMALY DETECTION SYSTEM RESULTS FOR THE VEHICLE ON IDLE MODE

		Level I			Level II			Level III		
	Selected window size	TPR	Prec	F2	TPR	Prec	F2	TPR	Prec	F2
Gauss	10	0.920	0.225	0.568	0.935	0.375	0.720	0.935	0.375	0.720
k-NN	5	0.957	**0.972**	**0.960**	0.941	**0.983**	**0.949**	**1.000**	**1.000**	**1.000**
Mahalanobis	10	0.487	0.017	0.008	0.532	0.142	0.343	0.641	0.474	0.598
MST	6	0.687	0.109	0.333	0.738	0.318	0.583	0.869	0.672	0.820
Naive Parzen	6	0.717	0.325	0.577	0.821	0.617	0.770	0.927	0.859	0.912
SOM	7	0.698	0.217	0.483	0.682	0.172	0.428	0.692	0.196	0.459
Parzen	6	0.692	0.278	0.533	0.747	0.462	0.665	0.898	0.813	0.879
SVDD	4	0.718	0.383	0.611	0.814	0.649	0.774	0.832	0.724	0.807
Extreme Value	10	0.669	0.075	0.259	0.749	0.663	0.729	0.803	0.942	0.827
OC-SVM	3	**0.972**	0.488	0.811	**0.972**	0.485	0.809	0.977	0.587	0.862

TABLE III
BEST PARAMETER CONFIGURATION USED IN EACH TECHNIQUE

Classifier	Parameters description
Gauss	Regularization, $R = 0.001$
k-NN	$k = 1$, Threshold = $max(d)$
Mahalanobis	Threshold = $max(d)$
MST	Threshold = $max(d)$
Naive Parzen	h optmized
SOM	$5x5$ map size
Parzen	h optmized
SVDD	RBF kernel, $\sigma = 5$
Extreme Value	Threshold = σ
OC-SVM	Third-degree polynomial kernel

generator module. Combining the 30% of target data from each trip with the outlier data of each trip. Finally the resulting database was used to test the system.

The proposed anomaly detection system was implemented and evaluated in MATLAB® using the DD Tools toolbox [7] on a host computer.

A. Feature Extraction: setting the window size

The window size of each evaluated technique was based on the best f2 score found by varying it in the range of values between $N = 2$ and $N = 10$ using a subset of the test data. The analysis carried out was based on three different anomaly levels. The anomaly level chosen to define the window size was the anomaly level III, the worst scenario of sensor malfunction.

B. Results from idle mode tests

The first part of the experiments was related to the vehicle on idle mode, using the database described in Table II. An initial analysis on Table II shows k-NN as the best technique to detect outliers in idle mode. The k-NN parameters are defined to $k = 1$ and window size $N = 5$, based on preliminary analysis of the technique. The proper functioning of the k-NN in idle mode can be explained by the high precision on the three anomaly levels analyzed. Analyzing the sensitivity, the OC-SVM, with third-degree polynomial kernel function has accomplished the best TPR in anomaly levels I and II.

On the other hand, the Gauss data description, SVDD, and SOM one-class classifiers have not presented such good F2-score based on their outlier detection precision. Another observation is the dependence of the Extreme Value analysis result on the anomaly level.

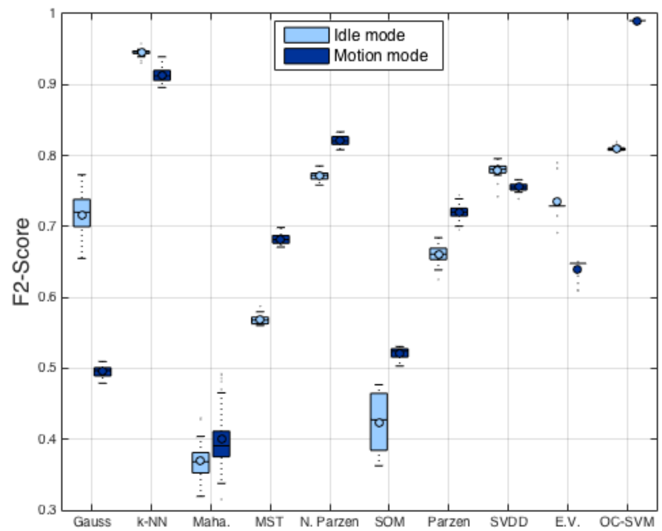

Fig. 4. Boxplot of F2-score for anomaly level II

C. Results from motion mode tests

Following the experiment's procedures of idle mode, Table IV presents the results for motion mode. According to the results, the OC-SVM with a window size of $N = 9$ has presented the best performance to the proposed system in all anomaly level scenarios. Different from idle mode, OC-SVM has also presented the best TPR in motion mode.

Another observation is that the three anomaly levels had practically the same result, for both TPR and precision. Comparing the selected window size (N) for both modes, most of the techniques in motion mode used a larger window size than idle mode. And finally, regarding the vehicle operation, the results have shown that ECT and RPM parameters can describe the ECT sensor.

Fig. 4 shows the boxplot for F2-score on both vehicle modes for anomaly level II. To ensure which is the best technique of each mode, the non-parametric statistical Friedman test was performed. Considering the two best techniques, k-NN and OC-SVM, for each mode, the Friedman test hypothesis test

TABLE IV
ANOMALY DETECTION SYSTEM RESULTS FOR THE VEHICLE ON MOTION MODE

		Level I			Level II			Level III		
	Selected window size	TPR	Prec	F2	TPR	Prec	F2	TPR	Prec	F2
Gauss	10	0.654	0.189	0.438	0.670	0.246	0.498	0.799	0.616	0.754
k-NN	6	0.939	0.873	0.925	0.927	0.847	0.909	0.934	0.868	0.920
Mahalanobis	6	0.685	0.005	0.024	0.717	0.129	0.375	0.823	0.550	0.748
MST	7	0.680	0.109	0.332	0.763	0.318	0.596	0.873	0.718	0.836
Naive Parzen	10	0.722	0.336	0.587	0.848	0.617	0.788	0.941	0.873	0.926
SOM	6	0.639	0.185	0.428	0.672	0.187	0.442	0.653	0.227	0.474
Parzen	10	0.669	0.301	0.537	0.771	0.448	0.673	0.884	0.842	0.875
SVDD	3	0.704	0.379	0.600	0.771	0.659	0.745	0.900	0.724	0.858
Extreme Value	10	0.831	0.071	0.264	0.872	0.319	0.648	0.921	0.816	0.897
OC-SVM	9	**0.998**	**0.957**	**0.989**	**0.998**	**0.957**	**0.989**	**0.998**	**0.943**	**0.986**

TABLE V
NEMENYI POST-HOC TEST RESULTS FOR IDLE AND MOTION MODES

Classifier	**Idle Mode Ranking**	**Motion Mode Ranking**
Gauss	48.200	15.300
k-NN	95.500	85.500
Mahalanobis	6.667	5.867
MST	25.500	45.533
Naive Parzen	67.433	75.500
SOM	14.333	25.333
Parzen	35.733	55.533
SVDD	73.300	65.433
Extreme Value	52.833	35.500
OC-SVM	85.500	95.500

with 99% confidence revealed that the results are not statistically different from each other. Therefore, being statistically equivalent.

To confirm the result, the Nemenyi post-hoc test was performed to find the best techniques based on rank sums. For both modes, the result, shown in Table V confirms the order of the best techniques according to the average F2-score, shown in Fig. 4.

V. CONCLUSION AND FUTURE WORKS

The most significant found result from this work has shown the need to evaluate anomalies in vehicular sensors in different malfunctioning or degeneration degrees. Based on the evaluation of different techniques, the results showed that some techniques only detect sensor malfunctioning in high degrees of sensor malfunctioning.

From experimental vehicular data collected by a telemetry system, in our experiments has revealed k-NN and OC-SVM as the best techniques for the respective vehicle operation modes. In addition to the described results, the proposed approach to injecting anomalies to resistive sensors, based on excessive noise simulating resistive failures, can be applied in other fields beyond the automotive.

As a continuation of the work, the usage of a single board computer or microcontroller can allow real-time anomaly detection from the intra-vehicular network. Besides, a system that detects the vehicle operation mode can be implemented to automatically select the best technique to detect anomalies. Further studies can also include the aging of the component to describe the presence of sensor anomalies more accurately.

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