Vehicle Online Monitoring System Based on Fuzzy Classifier

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***Abstract*— In the automotive sector, electronic, mechanical, and software components have evolved significantly, resulting in increased complexity in vehicle fault diagnosis. The use of fuzzy classification techniques has been adapted for the online diagnosis of complex systems. In particular, Learning Algorithm for Multivariate Data Analysis (LAMDA) fuzzy classifier provides additional information through the Global Adequacy Degree (GAD) allowing to perform early preventive actions and supporting the operator in the decision-making process. This paper presents a car fault diagnosis system based on the LAMDA fuzzy classifier. The algorithm identifies, while the vehicle is in motion (online monitoring), the state of the vehicle, i.e., normal driving behavior, aggressive driving (driving behavior reflecting an impatient or angry driver) or mechanical failure. The implementation of the monitoring system implementation is performed in a midrange Renault vehicle. The algorithm achieves a 92.52% correct functional state identification with a low computational cost.**

Keywords—Fuzzy classifier; on-board diagnostics; online monitoring.

I. INTRODUCTION

The monitoring process provides information about the system functional state (situation); this information is then used as a tool to perform troubleshooting tasks and scheduling, among others [1]. In the automotive sector, electronic automotive control has led to significant changes in technology, requiring costly scanning systems for fault diagnosis and detection in vehicles [2]. For pollutant emission detection in vehicles, On Board Diagnostics (OBD) systems were introduced in 1988 [3]. In 1996, OBD II was created in order to further restrict emissions [4]. The basic operation of these systems is to activate a malfunction warning light, Malfunction Indication Light (MIL) upon detecting a fault. Recently, third generation on board diagnostics (OBD III) identifies failures by satellite, in order to report emission problems to the regulator and to identify the position of the vehicle and the fault code in order to proceed to repair it [5]. The disadvantage of OBD systems is that critical faults are not detected early (i.e., they are only detected when they have already occurred).

In 2011, Hasan et al. [6] developed a system based on OBD system operation principle using a microcontroller which integrates the scanner to the vehicle, providing the driver a graphical interface for monitoring interesting signals in real time. The systems do not generate alarms to warn about the presence of failure.

In 2004, He and Feng [7] proposed a method based on fuzzy pattern recognition and the use of similarity measurements, for diagnosis and fault detection in combustion engines. The online diagnosis test to detect abnormal operation of fuel injection showed 80% correct fault detection.

In 2008, Schilling [8][9] implemented an insulation system and engine fault detection using Kalman filters [10]. Thus, when the filter residue exceeds a threshold, the presence of engine failure is detected. In this case, it is only possible identify two states, namely, normal or fault.

The study of the angular velocity signal has also been used for detecting engine faults. The algorithm proposed by Gani and Manzie [11] verifies certain thresholds to warn about the presence of failure; the disadvantage is that this algorithm has good performance at low speeds, but it is difficult to correct the influence of the engine torque inertia at high speeds.

On the other hand, fault diagnosis has been conducted in internal combustion engines valves based on vibrations, aiming to distinguish between normal or failure states through digital image processing. However, this method is not useful for differentiating between failure classes [12]. Fault detection from vibration allows detecting incipient faults in rotating mechanical systems using Probabilistic Neural Networks (PNN). Slowness in classifying new data is one of the disadvantages of the PNN [13].

In 2011, Wenqiang et al. [14] used Bayesian networks [15] and machine learning techniques [16] for detecting fault diagnosis in vehicles. They compared the diagnosis based on time-varying Bayesian networks with the traditional static method. With a percentage of 85.7% classification accuracy, the time-varying Bayesian network presents better performance than with the static method. The test was conducted under stationary conditions at a speed of 2,000 rpm, but the vehicle was not in motion.

Recently, the use of the Hilbert-Huang transform (HHT) and Support Vector Machines (SVM) have led to engine fault diagnosis using the engine's sound. It attains a percentage of 91.43% correct classification [17]. In this case, only one signal (microphone signal) was used; moreover, SVMs did not allow multiple classes, and the required calculation involved a high computational cost.

The above proposals are limited to identify engine failure and others extend to other parts of the vehicle, but only performing troubleshooting in a static vehicle. Moreover, proposals do not provide additional information about whether the system is in a normal state or have progression toward a fault condition.

To monitoring complex systems, fuzzy clustering techniques have been used, which have demonstrated good performance in industrial settings [18]. Fuzzy clustering algorithms allow, from a historical data, grouping similar data in the same class or functional state (e.g., normal, alarm, fault, etc.) and determining the degree of membership of a new data to all classes. Each class is associated to a functional state of the system. The LAMDA fuzzy clustering technique [19] has been widely used for process monitoring; especially due to its low computational cost [20] and because it allows the identification of new states which were not in the historical data, through the Non Informative Class (NIC) class.

In this work, a methodology for monitoring a vehicle online is proposed. The objective is to recognize the functional states (faults or not) online. The monitoring is based on a fuzzy classifier to estimate the GAD (Global Adequacy Degree) of a data vector (instantaneous values of the measured variables) to each class or functional state. Then, the data vector is associated with the class with the maximum GAD. The GAD may provide information that a system is in a normal state, but moving away from this class indicates the start of a fault, allowing early action to be taken.

The rest of this paper is organized as follows: Section II describes the monitoring systems and the method for acquiring and pre-treating data is explained. In the same section, the fuzzy clustering algorithm Learning Algorithm for Multivariate Data Analysis (LAMDA) is discussed and used to identify the functional states online in a vehicle. Then, the experimental setup is explained; and finally the results and discussions are analyzed and conclusions are described.

II. MONITORING SYSTEM

A monitoring system provided information in real time about the status of the process variables and location of faults [21]. Fuzzy clustering algorithms enabled monitoring, diagnosis and fault detection from *n-dimensional* analysis, independent of time [22]. Using LAMDA fuzzy clustering algorithm, the degrees of membership of a data vector to its classes is defined, providing important information for decision making in any system.

With the offline analysis of data and using the fuzzy clustering algorithm, a classifier was obtained with which it was possible to monitor vehicle operating status online. The diagram in Figure 1 corresponds to the proposed methodology used for the vehicle monitoring online.

The monitoring systems included a data acquisition phase where the critical variables of the vehicle (see Table 1) were analized. A pre-treatment of each signal was performed, and this made for each data vector in each sampling time. In an offline phase, the features of each class were identified with historical data of the vehicle and then, at an online phase, online recognition of the states of the vehicle was identified. This way was possible to early identify, the functional state in which the vehicle was located, before an incipient failure could generate a more serious fault. The following subsections explain each one of the phases.

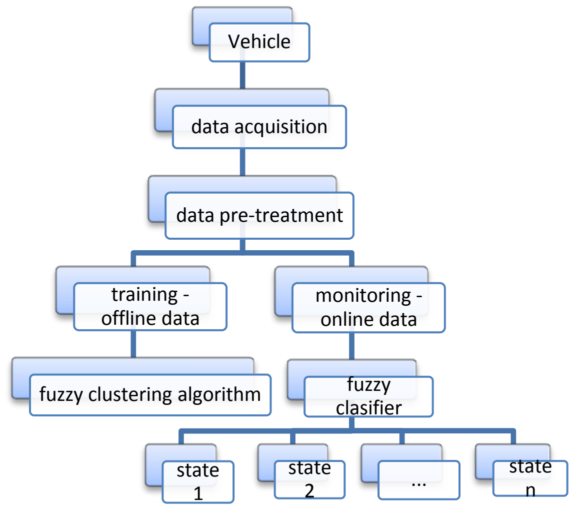

Figure 1. Methodology for the classifier.

A. Data acquisition and pre-treatment

Sensors required to measure the signals were installed on the vehicle. At each sampling time (one sample every 250ms), recorded values of the variables in the data vector $\boldsymbol{x}$ were analyzed.

Signals measured (shown in Table 1) were carried by the sensors to an onboard computer through the data acquisition card NI USB-6218. The monitoring and online classification of signals were performed by a Supervisory Control and Data Acquisition (SCADA), developed in Labview®, the interface of which is shown in Figure 2.

TABLE 1. SENSORS AND VARIABLES MEASURED

Measured variables	Sensor
Air flow	Mass air flow (Toyota - Denso Air flow meter 22250-45040)
Engine speed, measured in RPM (revolutions per minute)	Hall effect sensor
Butterfly valve position, indicates the percentage of accelerator opening	Throttle potenciometer
Voltage	Lambda or oxygen sensor
Vibrations from mechanical deformations	Piezoelectric accelerometer (AC150-2C Accelerometer)

Figure 2. User interface designed in Labview®.

Data acquisition card is configured to acquire sensor data every 250ms. The pre-treatment of data was performed using a low pass Chebyshev filter of order 6 [23], which eliminates the high frequency components. Then the average of each signal is calculated by means of a sliding window taking 300 samples of the same class for each average. Each sample (individual) corresponds to a data vector $\boldsymbol{x} = [x_1, x_2, \dots, x_d]$, with (d=5), with the information from the five variables (descriptors) systems.

B. Fuzzy clustering algorithm

In order to find classes or functional states in the training stage, it is possible to use fuzzy clustering algorithms such as Fuzzy C-means (FCM) [24], GK-means (GKM) [25], or Learning Algorithm for Multivariate Data Analysis (LAMDA) [26], among others.

The LAMDA fuzzy clustering technique has been widely used for process monitoring especially for its low computational cost [27][28][29] and because it allows identifying new states which were not in the historical data through the NIC.

LAMDA fuzzy clustering algorithm was employed with the aim of finding the degrees of membership (GAD) of a data vector to a class or functional state at each instant of time. This algorithm also takes into account the contribution of each descriptor (a variable measured in the vehicle) to other classes. For the contribution of a determined sample in the time n, the value of Marginal Adequacy Degree (MAD) is estimated in each variable for each class [30][31].

1) Training Phase (Offline)

From historical data, at each sample time, a data vector $\boldsymbol{x} = [x_1, x_2, \dots, x_d]$ (with d=total number of measured variables) is obtained. These vectors are used for training.

For each sample (data vector x) the Marginal Adequacy Degree is calculated. To calculate the MAD, possibility functions are used; in this case, the following probabilistic function was used (1) [32].

$$MAD_{j,l} = \rho_{j,l}^{\bar{x}_{i,l}} (1 - \rho_{j,l})^{(1-\bar{x}_{i,l})} \quad (1)$$

where $\bar{\boldsymbol{x}}_{\boldsymbol{i},\boldsymbol{l}}$ is the normalized value of the descriptor l of a particular data vector i, with $l = 1, \dots, d$ and $i = 1, \dots, n$. $\rho_{j,l}$ is the mean value for the j class and the descriptor l, with $j = 1, \dots, k$; this parameter was calculated using the historical samples belonging to each class (see (2)) [33].

$$\rho_{j,l} = \frac{1}{T_j} \sum_{i=1}^{i=T_j} \bar{x}_{i,l} \quad (2)$$

where T_j is the total number of historical individuals belonging to class j. As each of the historical data is analyzed, the value of $\rho_{j,l}$ is updated using an estimate of the moving average of the data for each descriptor in each class.

The membership from a data vector to a j class is estimated with the Global Adequacy Degree. The GAD_j for a j class is computed from the $MAD_{j,l}$ (see (3)). This interpolation is performed between the fuzzy operators *T-norm* (in this case *MIN*), which corresponds to a logical intersection operation, and *S-norm* (in this case *MAX*), which corresponds to a logical union operation. The Exigence Index α is a value between 0 and 1 that indicates the exigence with which an individual is attributed to a class; the closer this parameter to 1, the more demanding the classification.

$$GAD_j = (MAD_{j,1}, \dots, MAD_{j,d}) = \\ \alpha T(MAD_{j,1}, \dots, MAD_{j,d}) + (1-\alpha) S(MAD_{j,1}, \dots, MAD_{j,d}) \quad (3)$$

In the trained classifier, a data vector is associated to a class if the maximum GAD calculated corresponds to that class.

Each class represents a functional state (i.e., normal driving behaviour, aggressive driving or a type of mechanical or electrical failure).

2) Online monitoring

While the vehicle was in motion, current status (failure or not) could be identified using the trained classifier.

The online monitoring consisted of the GAD_j with $j = 1, \dots, k$ calculation at each sample time.

This way, at each sample time, the monitoring system estimates the membership to each class. The vehicle behavior online was classified in the class (functional state) with the maximum GAD value (for example, normal state) and the other GADs were useful to identify if there was a movement away from this class which indicated the start of a fault, allowing early action to be taken. If the vehicle had a failure, the data vector was classified into the class associated with this failure.

To prevent a misclassification, when a new state (not included in the training phase) is present, a Non Identification Class (NIC class) is included. For this class, the average value for all descriptors ($l = 1, \dots, d$) is $\rho_{NIC,l} = 0.5$, and the MADs and GAD_{NIC} values are estimated with the equations 1 and 3 respectively. The NIC automatically defines a threshold for classifying a data vector into the defined classes. Then, the behaviors that are not associated with any of the defined classes are classified into the NIC class.

III. EXPERIMENTAL SETUP

The failures to be identified in the proposed monitoring system were chosen as reported in Section I. The vehicle condition under normal and aggressive driving conditions was also taken into account, in such a way that aggressive driving was not confused with a failed state.

To build the database, the test protocol consisting of a distance of 1,700m was established. The time of a round trip was about 5min. For each state, 2 to 3 replicates were made. Each repetition consisted of a complete tour of the 1,700m. As a conditions of the terrain, the route was a paved runway with ridgesand slopes in some areas. Each failure was caused before starting the tour.

From historical data, 7,666 samples were obtained, where each functional state has approximately 1,100-1,300 data. By applying the pre-treatment, explained in Section II, samples were reduced to 5,866, of wich 70% (4,016 samples) were used for the training phase, each sample corresponded to a vector with the 5 variables described in Section II (see Table 1). The 4,016 data vectors $\boldsymbol{x} = [x_1, x_2, \dots, x_d]$ with d=5 were classified with a fuzzy clustering algorithm.

The classifier was obtained using the LAMDA fuzzy clustering algorithm with an exigency index α =0.5. Each class had an associated state. The classes considered in the case study are described in Table 2.

TABLE 2. DESCRIPTION OF CLASSES

Abbreviation of Classes	Class description
C1	Normal state vehicle – normal driving
C2	Normal state vehicle – aggressive driving
C3	Disconnect injector cylinder 1
C4	Disconnect spark plug cylinder 1
C5	Clogging of the air filter
C6	Lower rim
C7	NIC

Each class differs from the others according to a profile that characterizes it (see Figure 3), where each bar corresponds to the value of ρ (mean value of the descriptor in each class).

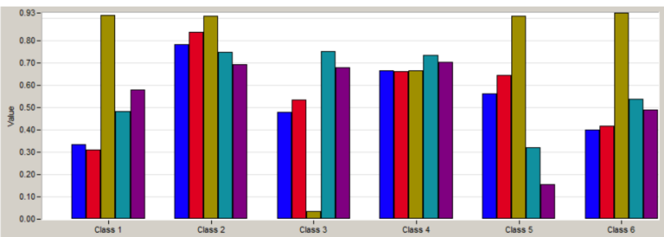

Figure 3. Profile classes

After the training phase, the vehicle was analyzed online using the same testing protocol implemented for the training phase, but only one full tour for each functional state was carried out. 1,760 samples were analyzed in the on-line phase. At each sample time (each 250ms), the data vector was analyzed by the monitoring system and the different functional states were induced and identified.

IV. RESULTS AND DISCUSSIONS

Figure 4 shows the classification obtained with the training data and the verification of the 6 classes corresponding to each functional state of the vehicle and the NIC class, as established in Table 2.

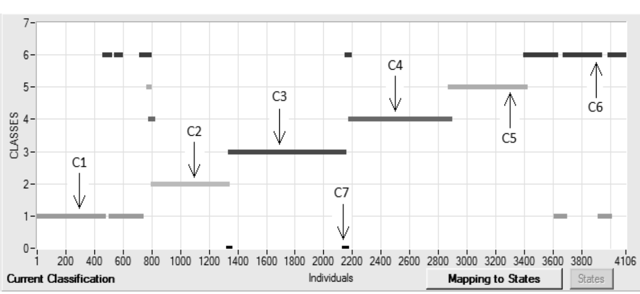

Figure 4. Classifier training data.

The X axis of Figure 4 indicates the number of individuals or samples used in classification and the Y axis shows the 7 classes identified. The graph shows some small groups of samples, different from those grouped in the NIC, which do not correspond to the class in which they were classified.

This occurs because data start to be acquired when the vehicle is idling, i.e., the engine is running but the vehicle is not moving; therefore, the first samples of classes 4, 5 and 6 are confused with other states. On the other hand, class 1 (Normal state vehicle-normal driving) and class 6 (lower rim) tend to merge because of the pressure the tyre loses when extracting the air to simulate the failure; it was not enough to ensure that system was fully differentiated in these two states of the vehicle.

The percentage of correctly classified individuals was 92.45% for the 4,016 data used in the training stage (see Figure 3).

Once the classifier was trained, the next step was monitoring performed when the vehicle was in motion to observe if the class that registers the SCADA system matches the functional state in which the vehicle was operating. At each sampling time, the recorded data vector was analyzed and the functional status that occurred in the vehicle was calculated. The graphical interface indicates the user, online, the current functional state of the system via a flashing light (see Figure 5), since this testing was performed under standard conditions and different faults were generated.

Figure 5. Functional state in which the vehicle is operating.

For the online phase, the percentage of correctly classified individuals was 92.52% for the 1,760 data (see Figure 6).

When comparing Figures 3 and 4, it can be seen that small test groups were not grouped in the class they really belonged to; this corresponds to situations similar to those already dealt with by the training data.

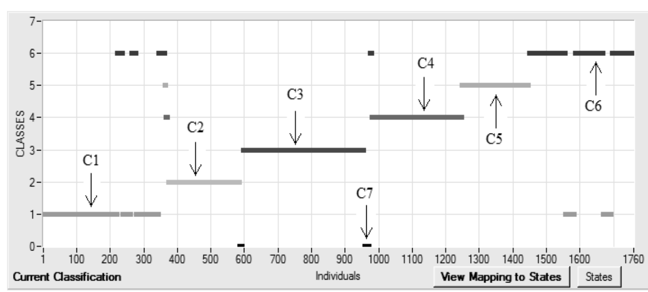

Figure 6. Online data classification.

In the online classification, the functional state of the system was correctly identified. Also, when entering new data, different from those recorded in the historical classification, the fuzzy classification algorithm groups them into the NIC class, generating in this way, a new class that had not been considered during training. This case identified a fault which occurred that was not included in the historical classification, causing the interface to indicate that the system was in the NIC class. The vehicle was then inspected at an Automotive Diagnostic Center and an electrical failure was diagnosed.

The LAMDA fuzzy clustering algorithm allows online identification of different states or classes through the GAD, which provides information about the possible change from a normal state to a failure state, allowing early action to be taken. This is possible by identifying the class to which an individual belongs (defined by the highest degree of membership) and the class that this individual could migrate to, by knowing the next lowest GAD and its associated class.

Table 4 shows the degree of membership associated with each of the two sample types, and it can be observed that while in a normal driving state, the sample has a degree of membership to an aggressive driving or a failed class.

TABLE 4. MEMBERSHIP DEGREES ASSOCIATED TO EACH CLASS

Sample	C1	C2	C3	C4	C5	C6
1070	0.5013	**0.5719**	0.4846	**0.5414**	0.5003	0.5089
1778	0.4702	0.4954	**0.5549**	0.5169	**0.4400**	0.4724

Sample 1,070, for example, has a degree of membership to class 2 (Aggressive driving) of 0.5719, while for class 4 (disconnect spark plug) the degree of membership is 0.5414 and in other classes the degree of membership is lower compared to the two previous classes. This way, it is established that the 1,070 samples belong to class 2 because their degree of membership to this class is higher than to the others. Therefore, if the system is in class 2, is more likely to go to class 4 than any of the other classes.

In the 1,778 sample, the highest degree of membership is to class 3 (Disconnect injector cylinder 1), while the degree of membership immediately below corresponds to class 4 (Disconnect spark plug) and the lowest of all the membership degrees corresponds to class 5 (Clogging of the air filter). This indicates that if the system is in class 3, it is more likely to change to class 4, and is less likely to change to class 5.

Moreover, this proposal has the advantage that the variables analyzed are easily accessible, since it is not necessary to open the ECU (Electronic Control Unit); this allows analysis of more system components apart from the engine. Additionally, the results were obtained with a low computational cost (to identify the situation in a sample, instant calculation requires no more than a few milliseconds). The data processing is performed on a laptop with Intel Core 2 Duo of 2 GHz and 4 GB of RAM, located at the front of the car. The analysis and classification of a data vector is executed in a much shorter time compared with the sampling interval (250ms).

The system correctly identifies new data that enters the algorithm and classifies correctly. Through the graphical interface shown in Figure 2, a flashing light warns the driver of the vehicle about the type of fault that the system has, so that a driver can check the type of fault identified and contact an Automotive Diagnostic Center.

The developed system is useful for Renault vehicle, if you want to replicate the experiment in a different system, the classifier must be trained again.

V. CONCLUSION AND FUTURE WORK

A useful system is proposed for online monitoring of a vehicle, using a LAMDA fuzzy clustering algorithm. A warning light advises the driver by a graphical interface about of the functional state of the vehicle, thanks to the online monitoring of the variables.

LAMDA fuzzy classifier provides information about how the system evolves, enabling identification of the current status of the vehicle and the possibility of migration to another state, fault or not, based on the degree of membership associated with each class.

LAMDA fuzzy clustering has a low computational cost and allows the identification of new classes that were not in the historical data, through the NIC class. Additionally, the algorithm achieves a correct functional state identification, in front of other techniques.

In the future, this algorithm will allow the inclusion of unforeseen situations, as it defines all kind of degrees of membership, including the NIC, and from this, it is possible to identify that there is not a high degree of membership to situations registered in the historical data. Possible future work would be to predict these states using prior knowledge of the degrees of membership obtained with the LAMDA algorithm.

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