Fault Diagnosis of a Vehicle Based on a History Data Hybrid Approach

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Abstract

The main goals of a fault diagnosis system in a vehicle are to prevent dangerous situations for occupants. This domain is a complex system that turns the monitoring task a very challenging one. On one hand, there is an inherent uncertainty caused by noisy sensor measurements and unmodeled dynamics and in the other hand the existence of false alarms that appears in a natural way due to the high correlation between several variables. The present work is a variant of a proposal made by the author. This paper presents a new approach based on history data process that can manage the variable correlation and can carry out a complete fault diagnosis system. In the first phase, the approach learns behavior from normal operation of the system using an autoassociative neural network (AANN). On a second phase a fuzzy system (FS) is carried out in order to diminish the presence of false alarms that could be originated by the noise presence and then a competitive neural network (CNN) is used to give the final diagnosis. Results are shown for a ten variables vehicle monitoring.

Keywords: Vehicle Dynamics, Fault Detection, Fault Diagnosis, Autoassociative Neural Network, Competitive Neural Network, Fuzzy System, History Data.

1. Introduction

Engineering systems fault diagnosis is related to detection of faults in complex machinery by detecting specific patterns of behavior in observed data. A modern vehicle is an example of such complex engineering system where there are a large number of sensors, controllers and computer modules embedded in the vehicle that collect abundant signals. Vehicle fault diagnosis relies on the processing of such signals, which have dynamic ranges in magnitude, oscillation, frequency, slope, derivative, etc. Therefore, it is extremely difficult to develop a complete diagnostic using a model based method that can fully answer all questions related to automotive engineering faults. A vehicle fault detection and diagnosis using an autoassociative neural network (AANN) and a Fuzzy System (FS) is proposed. This system is a process history based method; only normal operating conditions data is needed for training the system. The organization of the paper is as follows. Section 2 reviews the state of the art. Section 3 gives the preliminaries and the background knowledge on AANN and FS. Section 4 gives the approach general description. Section 5 shows how this framework works in a simulation example. Finally, conclusion ends this paper in section 6.

2. State of the art

Research related to automated or semi-automated highway vehicles has seen a tremendous amount of progress during last years. Vehicle fault diagnosis relies on the processing of signals that most of the times include non-linear and noisy characteristics. In the past, different combinations of techniques have been done to deal with this problem, but in general we can find works that use model based approaches in order to carry out a complete fault diagnosis system. [1] describes a system for the detection of critical situations occurred when driving a car. A bank of observers combined with estimators is designed. Residuals are compared using the sequential test of Wald. [2] proposed a fault tolerant sensor system based on modeling the vehicle dynamics. A Kalman filter and two-track model are designed to create analytical signals replacing the faulty sensor. By reconfiguring the yaw rate, the longitudinal acceleration or the lateral acceleration can be estimated with small discrepancies. A fault tolerant sensor system is the goal of this research. [3] presents a model based approaching doing parameter estimation and using parity equation for symptom generation then it applies fuzzy logic to detect small faults. [4] uses a multi-model-based methodology for estimation of some variables.
these estimations, residuals are generated and manipulated with a fuzzy system. Specific patterns are used to detect and identify the location and type of sensors faults. Even though there are important results in the aforementioned projects, no one considers the correlation between variables in order to find the root cause of the faults. In an early project, a diagnosis system based on a vehicle model and soft computing techniques was proposed. [5] and [6] are based on the same philosophy of detection as they are earlier works of the author of the present manuscript. [5] shows an approach divided in two phases. First, the vehicle model is used to obtain a set of residuals. Second, a vector is formed with the residuals and then, using fuzzy logic, a comparison against their normal operating limits is made to look for those residuals standing out of limits. Finally, a competitive neural network classifies the output, indicating the faulty component in the vehicle. [7] uses an approach that combines a Takagi-Sugenno fuzzy model to describe the non-linear two degrees of freedom vehicle motion and a bank of observers, using sliding mode design techniques to estimate the system state vector. [8] gives an approach that combines the linear-quadratic control method and the control Lyapunov function technique. [9] presents a methodology based on the use of an ANFIS in order to do a fault diagnosis of a vehicle driveline system and shows how this model free methodologies can be applied expecting a high accuracy on the final diagnosis. In [10-12] authors propose approaches that are classified as model based methodologies, needing in this way a good and complete knowledge of the system being modeled in order to have a good accuracy when giving the final diagnosis.

Now a new vehicle fault detection and diagnosis proposal on the history data using an AANN, FS and a CNN is proposed.

3. Preliminars

3.1. Autoassociative neural network

[13] proposed an AANN, used as a Non-Linear Principal Components Analysis (NLPCA) method to identify and remove correlations among problem variables as an aid to dimensionality reduction, visualization, and exploratory data analysis. NLPCA operates by training a feed-forward neural network to perform the identity mapping, where the network inputs are reproduced at the output layer. The network contains an internal bottleneck layer (containing fewer nodes than input or output layers), which forces the network to develop a compact representation of the input data, and two additional hidden layers. Figure 1 shows the architecture of this AANN with five layers.

![Figure 1. Architecture of an AANN.](image)

This AANN has one input layer and one output layer each with N neurons and three hidden layers with $H_1$, $H_2$ and $H_3$ neurons respectively. When an observation $x$ is presented at the input of the network, the output neuron equation of the $l^{th}$ layer is function of the neurons at the $(l-1)^{th}$ layer, given by equation 1, and shown in Figure 2.
\[ y_j = f \left( \sum_{i=1}^{n(l-1)} w_{ij}^{(l)} y_i^{(l-1)} \right) \quad l = 1, \ldots, 4 \quad (1) \]

Where \( y_j^{(0)} = x_n \), \( n = 1, \ldots, N \) represents the components of the observations vector at the input of the network; \( y_n^{(4)} \); \( n = 1, \ldots, N \), represents the components of the estimation \( x \) given at the output of the network; \( n(l-1) \) gives the number of neurons at the \((l-1)\)th layer. Function \( f(.) \) is the neuron activation function, which is sigmoidal. The observations must be normalized as they lay inside of a unitary hypercube.

Figure 2. Connection of the \( i^{th} \) neuron of the \((l-1)\) layer with the \( j^{th} \) neuron of the \( l \) layer

If the network has to learn a specific task, it is necessary to adjust the weights of the connections between neurons in order to minimize the difference between the expected and given output by the AANN. This minimization is carried out when computing the derivative error. The method commonly used is the back-propagation exploiting the gradient descendent method.

3.2. Fuzzy logic

Fuzzy logic consists of the theory of fuzzy sets and possibility theory, and it was introduced by Zadeh in 1965 in order to represent and manipulate data that was not precise but rather fuzzy. Fuzzy logic (FL) is a soft computing technique necessary for analyzing complex systems, especially where the data structure is characterized by several linguistic parameters. Fuzziness is a property of language. The human brain interprets imprecise and incomplete sensory information provided by perceptive organs. Fuzzy set theory provides a systematic calculus to deal with such information linguistically, and it performs numerical computation by using linguistic labels stipulated by membership functions.

The mathematical foundations of fuzzy logic rest in fuzzy set theory, which can be thought as a generalization of classical set theory. In contrast to a classical set, a fuzzy set, is a set without a crisp boundary. That is, the transition from belong to a set to not belong to a set is gradual, and this smooth transition is characterized by membership functions, that give fuzzy set flexibility in modeling commonly used linguistic expressions.

3.2.1. Definition and terminology

Let \( X \) be a space of objects and \( x \) be a generic element of \( X \). A classical set \( A \subseteq X \), is defined as a collection of elements or objects \( x \in X \), such that each \( x \) can either belong or not belong to the set \( A \).

By defining a characteristic function for each element \( x \) in \( X \), it could be represented a classical set \( A \) by a set of ordered pairs \((x,0)\) or \((x,1)\), which indicates \( x \notin A \) or \( x \in A \), respectively.

Definition: Fuzzy sets and membership functions

If \( X \) is a collection of objects denoted generically by \( x \), then a fuzzy set \( A \) in \( X \) is defined as a set of ordered pairs:

\[ A = \left\{ (x, \mu_A(x)) \mid x \in X \right\} \quad (2) \]
Where \( \mu_A(x) \) in equation 2 is called the membership function (MF) for the fuzzy set \( A \). The MF maps each element of \( X \) to a membership grade or membership value between 0 and 1. Then a fuzzy set is completely characterized by its MF. Usually \( X \) is referred to as the universe of discourse. Since most fuzzy sets have a universe of discourse \( X \) consisting of the real line \( R \), it would be impractical to list all the pairs defining an MF. Thus, an MF should be expressed as a mathematical formula. Some typical examples of MF among others are: Triangular, Trapezoidal, Gaussian and Sigmoidal MF.

Linguistic variable is a variable whose values are words or sentences in a natural or synthetic language. For example, the arguments for the linguistic variable *temperature* may be LOW, MEDIUM, and HIGH.

Fuzzy If – Then rule in which the antecedent and consequents are propositions containing linguistic variables. They encode knowledge about a system in statements of the form:

**If (a set of conditions are satisfied) Then (a set of consequences can be inferred)**

Thus, a fuzzy If – Then rule assumes the form shown in expression 3:

\[
\text{If } x \text{ is } A \text{ Then } y \text{ is } B \quad (3)
\]

Where \( A \) and \( B \) are linguistic values defined by fuzzy sets on universe of discourse \( X \) and \( Y \), respectively. Often \( x \) is \( A \) is called the antecedent or premise, while \( y \) is \( B \) is called the consequence or conclusion.

The starting point and the heart of a fuzzy system is a knowledge base consisting of the so called fuzzy If – Then rules as those shown above. Next step is to combine these rules into a single system.

## 4. Framework description

According to [14] this proposal is a process history based method because the need of a data set when the system runs under normal operating conditions. The general fault detection and diagnosis framework is shown in Figure 3.

**Figure 3. General fault detection and diagnosis framework**
The difference between [5] and this work is the way the residuals are obtained. During the first phase of diagnosis, the former paper obtains the residuals when comparing the results of a vehicle model and the sensors measurements. In the present paper, the residuals are generated by the use of the AANN. First of all a standardization procedure is performed in order to manage all variables over a same scale. Then, a subset of 80% of the total data set is randomly generated. Using this subset the AANN model is learned. A five layers AANN is a network whose outputs are trained to emulate the inputs over an appropriate dynamic range. This characteristic is very useful to monitor variables of complex systems that have some degree of correlation with each other. Hence, each output receives some information from almost every input. During training, to make each output equal to the corresponding input, the interrelationships between all the input variables and each individual output are embedded in the connection weights of the network. As a result, any specific output, even the corresponding output shows only a small fraction of the input change over a reasonably large range. This allows the AANN to detect a failure by simply comparing each input with the corresponding output, obtaining in this way the residuals. After this, the limits for these residuals under normal operating conditions are computed. After that, a second phase based on fuzzy logic, looks for those residuals out of normal operation limits. Then, a competitive neural network classifies each output of the fuzzy system to know the actual operation mode of a system. For the second phase, firstly a data set of the residuals coming from the normal operation of the system is required. Then the minimum, maximum and statistical mean values for each of these residuals are obtained to design the rules of the fuzzy system. They will be used to verify if a residual is out of its normal operation limits or there is noise presence. In this work, we use the Gaussian membership function for the fuzzy system. The set of fuzzy rules are stated in this form:

\[
\text{If value is inside limits then } R_n \text{ is zero} \\
\text{If value is outside limits then } R_n \text{ is one}
\]

Where \( R_n \) is the residual obtained from the comparison between the \( n^{th} \) output of the AANN and the measurement of the \( n^{th} \) sensor, in other words the \( n^{th} \) input of the AANN. The first phase delivers the residuals in a vector of real numbers \( R_{test} \) of dimension \( I \times n \):

\[
R_{test} = [R_1, \ldots, R_n] 
\]  

(4)

The \( R_{test} \) vector in expression 4, is analyzed by the fuzzy system to obtain the residuals out of limits. If this is the case, the fuzzy system assigns this residual a value of one, otherwise, is indicated with a zero. In order to detect false alarms, an index must be defined to monitor the number of consecutive points, given by the fuzzy system, that lay out of their given limits. In this way we can distinguish between noise presence or the existence of a real fault. Thus, this index \( I_n \) will count the consecutive number of times or points the residual \( R_n \) has out of limits, in such way that when \( I_n \) reaches \( h \), that is a constant number set by the user, a binary \( R_{test}^b \) vector will be formed as that shown in equation 5. Here, it is shown for instance, the \( R_{test}^b \) formed when the fourth residual \( R_4 \) of an \( R_{test} \) vector formed by six residuals, has reached \( h \) consecutive points out of its limits.

\[
R_{test}^b = [0, 0, 0, 1, 0, 0] 
\]  

(5)

This vector is the input of a competitive neural network classifier. For instance the vector shown in expression 5 could indicate a fault in the right rear wheel sensor. As this process is carried out over each of the \( R_n \) residuals forming \( R_{test} \) vector, it is possible to know in which time or sample number a fault started.

4.1. Algorithm of the proposal

The algorithm of the learning process for both phases can be summarized from step (1) to (8) as follows:
1. Take a normal operating conditions data set.
2. Randomly take a subset (80%) of the total amount of data.
3. Normalize the data subset. Train the AANN and learn the model.
4. Generate the normal operating conditions residuals
5. Obtain the minimum, maximum and mean values for each residual of the set of normal operation data from step (4).
6. Build the fuzzy system for each residual of the system being monitored according with the values obtained in step (5) with the if-then rules of the form:

   If value is inside limits then \( R_n \) is zero
   If value is outside limits then \( R_n \) is one

7. Define an index \( I_n \) for each residual in order to distinguish between noise presence and a fault presence. If \( I_n \geq h \) Then a fault is present on \( R_n \) Else measurement noise is present on \( R_n \). \( h \) is the threshold of consecutive points out of the limit allowed before setting an alarm of a possible fault presence, and it is set by the user.
8. Learn a competitive neural network with the different fault signatures in order to classify the output of the fuzzy system.

When monitoring a process, the diagnostic system performs as follows:

9. Build a residual test vector of the form

   \[
   R_{test} = [R_1 \ldots R_n]
   \]

10. Take the \( R_{test} \) vector as the input of the fuzzy system. The output of it is a \( R_{test}^b \) binary vector that will have a 0 if the residual is inside its normal operation limits and will have a 1 if it is out of them.
11. Verify the index of each residual \( I_n \). If the points laying out of limits are consecutive Then increment the index \( I_n \) and Go to step (12) Else reset \( I_n \) to zero.
12. If \( I_n \geq h \) Then stop the monitoring process and Go to step (13) Else return to step (9).
13. Set the \( R_{test}^b \) vector obtained in step (10) as the input of the competitive neural network previously trained. Give which fault is present and its location.

5. Case study

This proposal was tested with measurement data coming from VE-DYNA (i.e. a vehicle simulator). Ten variables were monitored in this system. Table 1 shows the description of variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \delta_f )</td>
<td>Front wheel steer angle</td>
<td>Input</td>
</tr>
<tr>
<td>CMar</td>
<td>Motor couple applied at rear wheels</td>
<td>Input</td>
</tr>
<tr>
<td>( a_x )</td>
<td>Acceleration in x-axis</td>
<td>Output</td>
</tr>
<tr>
<td>( a_y )</td>
<td>Acceleration in y-axis</td>
<td>Output</td>
</tr>
<tr>
<td>LFW</td>
<td>Left Front Wheel angular velocity</td>
<td>Output</td>
</tr>
<tr>
<td>RFW</td>
<td>Right Front Wheel angular velocity</td>
<td>Output</td>
</tr>
<tr>
<td>LRW</td>
<td>Left Rear Wheel angular velocity</td>
<td>Output</td>
</tr>
<tr>
<td>RRW</td>
<td>Right Rear Wheel angular velocity</td>
<td>Output</td>
</tr>
<tr>
<td>( V_x )</td>
<td>Longitudinal velocity gravity’s center</td>
<td>Output</td>
</tr>
<tr>
<td>Yaw</td>
<td>Yaw velocity</td>
<td>Output</td>
</tr>
</tbody>
</table>

The diagnosis system was tailored according to the steps described on subsection 4.1. The experiments were performed by simulating a vehicle maneuver in a highway of double change of lane. Figure 4 shows this maneuver.
A database, called chicane, was generated from VE-DYNA with 501 points, and conformed the normal operating conditions of system. Randomly 400 points (80% of data) were obtained of the database and formed a matrix whose dimension is 400 x 10. This matrix serves as the 400 examples for each of the 10 variables in the learning process of the AANN. The remaining data of normal operating conditions were exploited for validation. Figure 5 shows the normal operating conditions space created by the output of the AANN.

Figure 5. Output of the AANN for the Normal operating conditions space defined by the AANN.

Several simulations were carried out, where faults with different magnitudes on different number of samples were introduced at any time.

**Faulty LFW.** A fault of a change of 11% over the normal operating conditions in the left front wheel angular velocity (LFW) was introduced from sample number 45 to 57. Figure 6 shows how the 3 non-linear principal components (NLPC) of the faulty data lie out of the space depicted by the 3 NLPC under normal operating conditions, indicating that a fault is present on the system. Note how it is easy to see the 13 samples that are in faulty mode, such that the FS just corroborates the fault presence.

Figure 6. Nonlinear Principal Components
Figure 6. Output of the AANN for chicane database when a fault of an increase 11% in 13 samples of LFW was induced.

After looking the output of the AANN the FS gives the residual vector identifying the variable that has a fault present on it. Figure 7 shows the identification of a fault present by the FS.

Figure 7. Fuzzy system fault identification.
For the present example, the FS gives the following residual vector

\[ R_{\text{test}} = [0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0] \] (6)

Which at a time is the input to the previously trained competitive neural network that gives the final diagnosis. In this case, according to the equation 6 and the classification made by the competitive neural network the final diagnosis indicates that there is a fault present on \( LFW \) variable as expected.

Table 2 shows the results obtained after 50 different simulations scenarios for each row of it. Each simulation scenario considers different measurement noise magnitudes present in all the residuals simultaneously for each of the different quantities of consecutive points \( h \). According with this table, the approach presents its better performance when \( h = 10 \) because with this index, the methodology could distinguish between noise presence and fault present along all the simulations carried out.

### Table 2. Performance of detection for different magnitudes of measurement noise present in all the residuals simultaneously for different \( h \) values.

<table>
<thead>
<tr>
<th>Noise Magnitude</th>
<th>( h = 10 )</th>
<th>( h = 7 )</th>
<th>( h = 5 )</th>
<th>( h = 3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0001</td>
<td>100 %</td>
<td>100 %</td>
<td>95 %</td>
<td>80 %</td>
</tr>
<tr>
<td>0.001</td>
<td>100 %</td>
<td>100 %</td>
<td>85 %</td>
<td>45 %</td>
</tr>
<tr>
<td>0.01</td>
<td>100 %</td>
<td>90 %</td>
<td>65 %</td>
<td>25 %</td>
</tr>
<tr>
<td>0.1</td>
<td>100 %</td>
<td>75 %</td>
<td>25 %</td>
<td>5 %</td>
</tr>
</tbody>
</table>

### 6. Conclusion

This paper has presented an online fault detection framework for a vehicle, based on the history data process. The diagnosis is carried out in two phases. The first phase uses a combination of an autoassociative neural network to obtain the residuals between the normal operation behavior and the information coming from sensors. The second phase is compose by a fuzzy system that could distinguish between noise or fault presence and a competitive neural network that classifies the output of the system in order to give the final diagnosis. As the system diagnoses each residual individually, this approach detects which variable is in faulty mode and its time of occurrence.

### 7. References


