

A Heuristic Approach for Offboard-Diagnostics in Advanced Automotive Systems

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ABSTRACT

As the complexity of current automobiles increases, new and innovative diagnostic methods for car maintenance and diagnostic inspection are greatly needed. This paper introduces a new diagnostic approach, which learns from previous repair cases with the help of neural networks in order to assist future diagnostic inspections. Practical experiments have shown that this approach is able to provide promising results even with the data that is already available today.

INTRODUCTION

A great challenge in the development of new vehicles consists of improving their reliability and maintainability despite the increasing complexity [1]. As a result, innovative diagnostic methods and systems are needed. Many causes of system failures in highly networked and distributed systems such as today's automobile electronics can only be identified reliably with consistent and system-overlapping diagnostic concepts. As a result of this, the functional dependencies between individual systems and the networking of control units create multiple interdependencies between these systems [2]. The consequences of errors in such distributed systems are difficult to survey.

Consequently, diagnostic inspections carried out in car repair shops are not able to identify malfunctions in over sixty per cent of the known cases [4]. Therefore, inspection time for repairing as well as replacing functional parts increases. The result is rising costs. Additionally,

diagnosis is aggravated by the fact that one symptom can have numerous causes, and one cause often results in several symptoms [3].

STARTING POINT

Most of today's electronic control units (ECUs¹) are self-diagnosable thanks to diagnostic routines within the ECU software. This allows the status estimation of the sensors and actuators involved. Model-based diagnostic methods are often used for that purpose [6]. If a malfunction is recognized by the system, a diagnostic trouble code (DTC²) is determined and can be accessed via a diagnostic interface [5].

In contrast to the on-board diagnostics, off-board systems are attached to a vehicle in car repair shops which access the vehicle's systems via a diagnostic interface. These systems provide the possibility to collect the stored diagnostic trouble codes of all available vehicle ECUs.

Efficient diagnostic systems shall not only provide all information from the analyzed ECUs to the customer service employee but also actively support him in fault diagnostics. The guided diagnostic process (GDP) in the customer service of Volkswagen is an example of such systems. The GDP uses inspection plans which are based on decision trees created by experts. These in-

¹ An electronic control unit can also be considered a system.

² DTC – Diagnostic Trouble Code

spection plans are translated into different languages and distributed to users worldwide. An inspection plan needs to be developed for every single diagnostic trouble code that can occur in a vehicle. Since vehicles can have numerous equipment options it is quite demanding to cover all versions. This fact has to be taken into account when inspection plans are created since malfunctions can have different reasons due to various car models. Therefore, inspection and repair instructions can vary significantly. An additional problem of manually created inspection plans is the difficulty in recognizing and covering all potential malfunction sources in advance.

In practice, the points mentioned above lead inevitably to tradeoffs since taking all possible error sources as well as all vehicle variants into account is only manageable with tremendous effort. Particularly the increasing complexity and the trend towards distributed functionality leads to reduced and more unspecific inspection plans (e.g. "error tracing using circuit diagrams").

An important step towards improving diagnostic quality is to provide capabilities for evaluating events in the repair shops, such as the introduction of a database for repair case data. That way, all relevant data for a repair case, e.g. diagnostic trouble codes, could be recorded. With today's available information, evaluations are already carried out in order to improve the inspection plans. However, this evaluation process as well as the subsequent improvement of the inspection plans are carried out manually and cannot be automated with acceptable effort. Hence, only a low number of inspection plans can be improved by the described procedure. At this point, the experience-based diagnostic system described in this paper is a promising approach.

PRINCIPLE

There are several thousands of car repair shops for many automobile manufacturers worldwide with more than one hundred thousand employees. The exchange of experience between the individual car repair shops is quite a challenge.

An example illustrates the principle. When a complex repair problem appears, customer service employee 'A' needs a certain amount of time for fault diagnostics as well as for replacing several suspicious parts. That means that customer service employee 'B' at another car repair shop with the same problem needs to invest the same effort in order to locate the error. Consequently, customer service employee 'B' does not benefit from the experience of customer service employee 'A' and vice versa. If previous experiences were to be made available to employee B, a potentially large effort reduction could be achieved.

Therefore, the objective should be to learn from past repair cases and to apply the extracted knowledge to future instances. However, similar to the GDP, the resulting amount of data and knowledge is enormous.

Thus, the learning process as well as the application can only be profitably efficient when the complete process is automated.

PROBLEM ANALYSIS

For a learning system, the type and the quality of the existing data is of decisive importance. The system should learn from previous repair cases in car repair shops. Therefore, the focus should be set on defining a general diagnostic and repairing process first. Figure 1 illustrates this process in simplified form as an iterative process.

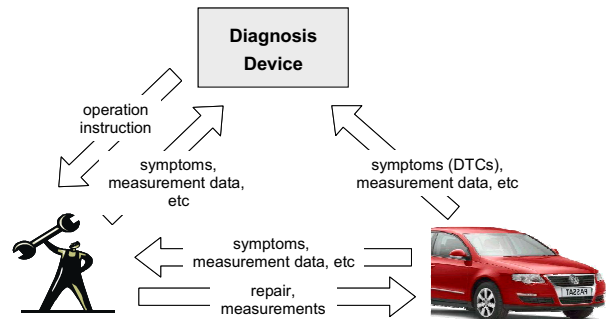


Figure 1: Simplified repair process according to [8].

In the first step, the diagnostic system acquires symptoms which are either taken from the vehicle or entered manually by the user. As shown in Figure 2, such symptoms can be noises, vibrations, measurements, defective functions, diagnostic trouble codes as well as subjectively perceived symptoms that were coded in a suitable way. In the second step, the diagnostic system outputs instructions to the user. These instructions can either be repair actions or possible causes of the fault that the system suggests for inspection.

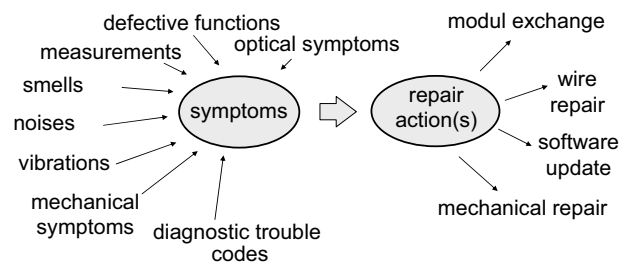


Figure 2: Repair process as a mapping from symptoms to repair actions.

If the suggested instruction did not lead to the identification of the cause of the fault or to the elimination of it, the user will give feedback to the system which will provide further instructions analogously to Step 2. User feedback demanded by the system can be measurements, observations and additional symptoms. This process ends either with a repair that is assumed to be successful by the user or with an undetectable defect in the most inauspicious case.

The description “No Trouble Found” (NTF) indicates that the cause of the fault was not found by a direct or indirect indication of the diagnostic system. In this case, the diagnostic system was not helpful. The process is superimposed by an iterative process. If the defect was only solved putatively, it is assumed that the customer will return (at least in case of warranty) to the car repair shop in order to request another repair.

According to the repair process described above, the information content of a single repair case Rep according to (1) can be abstracted as a mapping from the repair context R and the symptoms S_R to a set of repair actions A_R (compare Figure 2). The symptoms S_R of the power set $\wp(S)$ of all known symptoms S and the repair actions A_R are from the power set $\wp(A)$ of all repair actions A . Therefore, a concrete repair case represents a mapping function according to (2).

$$Rep : R \times \wp(S) \rightarrow \wp(A) \quad (1)$$

$$Rep(r, S_R) = A_R \in \wp(A), \text{ where } r \in R, S_R \in \wp(S) \quad (2)$$

All symptoms $s \in S$ observed during a repair process are summarized in a set of symptoms $s \in \wp(S)$. These symptoms not only include the technically and well-defined symptoms, e.g. DTCs, but also the subjectively perceived symptoms that were coded in an appropriate way. Operations carried out by customer service employees, e.g. exchanged parts or work items, are summarized in the repair actions. Among other things, the repair context R includes general repair-specific attributes like the current date, car repair shop and repair progress which influence the result of the repair process function Rep . In this way, a repair can be regarded as a closed process. The system Σ which the process Rep is applied to is given by the specific vehicle being observed. However, vehicles to be repaired are not absolutely identically constructed ones, but rather all vehicles are different due to possible variants even if they belong to the same class. Figure 3 illustrates these system variants in accordance with [9].

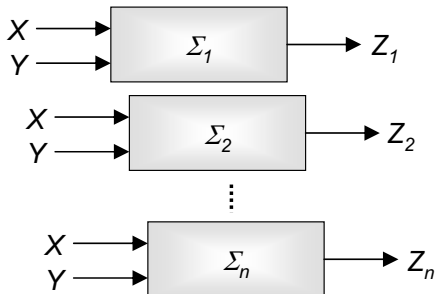


Figure 3: Different system variants.

All observable input values are depicted by the vector X . The vector Y contains unobservable input values, while $Z_i, 1 \leq i \leq n$ represents the vector of output values. In the

following, the variance of a system³ Σ_i is summarized as the system context C_i . If all observable values $C_{o,i}$ of C_i are now considered as additional components of X , and all unobservable values $C_{no,i}$ are regarded as additional components of Y , the systems $\Sigma_i, 1 \leq i \leq n$ can be assumed to be one resultant system Σ . Hence, the diversity of variants can also be regarded as part of the learning task. As a consequence, the mapping of (1) to (3) as well as the mapping of (2) to (4) must be extended.

$$Rep : R \times \wp(C) \times \wp(S) \rightarrow \wp(A) \quad (3)$$

$$Rep(r, C_R, S_R) = A_R \in \wp(A), \quad (4)$$

where $r \in R, C_R \in \wp(C), S_R \in \wp(S)$

The resulting learning task consists of deriving a model from the existing data which reflects the observed input and output values in the best possible way. Only observable values X and C_o can be used for modeling which yields to a model Π mapping the observable context C_o and a subset of the symptoms to a set of repair actions according to (5). For further considerations, C_{no} will be neglected and, additionally, C will be used instead of C_o .

$$\Pi : C_o \times \wp(S) \rightarrow \wp(A) \quad (5)$$

The examination of different technologies at the Institute of Control Engineering, Technische Universität Braunschweig, has shown that artificial neural networks (ANN) are particularly suitable for that purpose. An introduction to ANNs can be found in [7]. An important benefit of ANNs for this particular task is the recognition of patterns within the existing training data. Furthermore, they have the generalization ability enabling them to provide a meaningful result even over symptom sets which are not part of the trained patterns.

IMPLEMENTATION

The purpose of the realization is a distributed iterative diagnostic approach which permits an automatic feedback taking former earlier experiences into consideration. The principal data flow is shown in the diagram of Figure 4. All processes in the car repair shop are summarized in the repair process. A selection of the resulting data, primarily repair case data according to (3) and (4) respectively, has to be transferred to the data warehouse.

Subsequently, the learning system creates models by using the vast amount of data available in the data warehouse. The resulting models have to be transferred as diagnostic knowledge into a database called a Diagnostic Knowledge Base. This knowledge base will be distrib-

³ The variance of a system can also be regarded as vehicle specific qualities.