

Diagnostics based on the Statistical Correlation of Sensors

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ABSTRACT

The paper describes a new strategy for real-time sensor diagnostics that is based on the statistical correlation of various sensor signal pairs. During normal fault-free operation there is a certain correlation between the sensor signals which is lost in the event of a fault. The proposed algorithm quantifies the correlation between sensor signal pairs using real-time scalar metrics based on the Mahalanobis-distance concept. During normal operation all metrics follow a similar pattern, however in the event of a fault; metrics involving the faulty sensor would increase in proportion to the magnitude of the fault. Thus, by monitoring this pattern and using a suitable fault-signature table it is possible to isolate the faulty sensor in real-time. Preliminary simulation results suggest that the strategy can mitigate the false-alarms experienced by most model-based diagnostic algorithms due to an intrinsic ability to distinguish nonlinear vehicle behavior from actual sensor faults.

INTRODUCTION

Demands for safer vehicles are both customer driven and regulatory based and the challenge herein is to deliver safety features with high reliability and minimal cost [1]. Antilock brakes (ABS) [2] and traction control systems (TCS) were the starting point of active safety systems available in vehicles. Today, state-of-the-art systems such as Brake Assist, Electronic Stability Control (ESC) [3] and Rollover protection [4] are being offered in order to assist the driver in accident avoidance. As we look forward to the invention of more safety-critical systems, the emphasis will be placed on the addition of active safety elements that not only provide added functionality but to also support the passive safety systems like seat-belts and air-bags for improved performance [5]. The opportunity for the sum to be greater than the individual parts is clear, but the processes used to enable these technologies will be critical to provide a high quality, robust product to the consumer which meets the commercial and technical requirements of the OEM's and suppliers.

Sensor diagnostic algorithms form an integral part of safety-critical vehicle system design. This is because the integrity of sensory data is critical to generating the correct control decision at the right time. System safety

regulations, which dictate the response time for the diagnostic algorithms, require that a fault be detected, isolated and mitigated in a few milliseconds making the design and development of these algorithms challenging. Moreover, with the future technologies leaning towards a more modular approach to safety, sensors may have to provide information to more than one safety-system making their reliability all the more critical.

Since production automobiles cannot afford the costs of hardware redundancy (sensor duplication or triplication followed by a voting scheme); analytical and knowledge-based diagnostic techniques have been the center of focus for researchers over the past few years. Also, robustness concerns have plagued the implementation of diagnostic methods since their introduction. False alarms and incorrect identification of faults due to noise, disturbances, plant parameter uncertainties and unmodeled system dynamics have lead researchers to seek various innovative approaches in dealing with the design of robust fault detection algorithms. Many of the past applications involving diagnostics have been rule based. That is, simple production rules are used to provide a mapping between the possible causes and the inputs of the system and the possible faults. For example, Milne [6] surveys various knowledge based diagnostic strategies. These techniques depend on the designer's knowledge and understanding of the system such as operating range of sensor values, the expected rate of change in sensor outputs etc. Needless to say these techniques may not be always sufficient until the creation of an expert system [7] which can model the decision process of a human, revise and expand its knowledge base as new information is acquired and take into account probabilistic uncertainty. On the hand, self-checking sensors, in production today may not be robust enough to satisfy the safety requirements of critical systems. This led to the investigation of diagnostic techniques based on physical models of the system in more recent times. Physical modeling is most useful when the behavior of the system and its components are well understood. The resulting system description is usually detailed and provides good insight into the operation of the system. One can develop input-output and component fault detection algorithms from these models as long as the physical meaning of the parameters used in the model is maintained. The main drawback of physical models is that their detailed nature

may result in fault detection and isolation algorithms that require extensive computing resources for implementation and thus are sometimes unsuitable for real-time or on-board automotive applications. On the other hand using simplified, linearized physical models for diagnosis may increase the level of false alarms [8].

A significantly different approach to the diagnosis of faults in automotive systems is the use of pattern recognition and signature analysis methods. This field has been well studied and a rather comprehensive review of various techniques is presented by Braun [9]. The key is to develop an algorithm that can exploit the various signal processing techniques available. This paper describes a new strategy for real-time sensor diagnosis that is based on the statistical correlation of various sensor signal pairs. During normal, fault-free vehicle operation there is a strong correlation between the sensor signals and this correlation reduces during nonlinear or unstable operation and in the event of a sensor fault. The algorithm tries to capture the level of correlation between sensor signal pairs using a quantifiable real-time scalar that is based on the concept of the Mahalanobis-distance metric [10]. These scalar metrics are usually a small number (less than a defined threshold) during normal vehicle operation indicating a strong correlation between the sensor signals. Nonlinear or unstable operation manifests in an increase in these metrics beyond the defined threshold suggesting a loss of correlation between sensor signals. If however, faults occur in any sensor; then changes are observed in only the metrics that use the faulty sensor for their calculation. Thus by using a suitable fault-signature table one can effectively detect and isolate the faulty sensor in real-time. The strategy is appealing from an implementation standpoint as it does not require huge comparison tables or high-fidelity high-order vehicle models. Instead, the on-board implementation is carried out by simple, small order matrix multiplications making it a viable real-time option. The sections that follow motivate viewing the operation of a vehicle as a Mahalanobis-Taguchi System and we leverage the results in [10] to develop the proposed diagnostic strategy.

BACKGROUND: THE MAHALANOBIS-TAGUCHI SYSTEM

In 1930, Mahalanobis introduced a statistical tool called the Mahalanobis Distance, which is used to distinguish the pattern of a certain group from other groups, much like the process by which a doctor determines whether a patient has a difficult to diagnose disease. Taguchi [10] introduced Mahalanobis distance to define a reference group and to quantify the separation of individual subsets from the reference group. For example, we could use the Mahalanobis distance technique to measure a person's degree of health at the time of a health examination ranging from healthy to severely ill by using all available multidimensional test data. For the healthy group of the population, the calculated Mahalanobis distance averages the pattern distance of the healthy group.

Outside the group, we expect the pattern to gradually change, creating a larger distance from the defined zero point. Thus the Mahalanobis-Taguchi System (MTS) provides a systematic method to evaluate and optimize a Diagnostic/Pattern recognition system which is otherwise not easy since it is based on multi-variable continuous and attribute data with correlations among those variables. MTS has since been successfully applied to a variety of applications like medical diagnostics, fire alarms, automotive accident avoidance, business forecasting, image processing, and defect detection.

THE BASIC CONCEPT

Figures 1 and 2 provide a simple 2-dimensional example to understand the basic concept behind the MTS. The two variables in the example diagnostic system are a person's weight and height. Fig. 1 provides an example distribution for the weight and height of a group of people. Take for example, a person Sid, who weighs 300 lb and is 5 ft. tall. If we consider the variables individually, then the observations would conclude that Sid is a heavy person, but not necessarily abnormal. Similarly, he would appear short, but not necessarily abnormal.

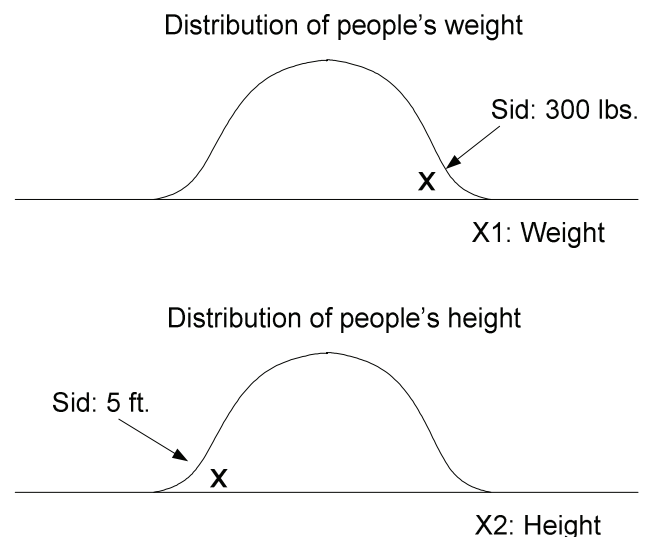


Figure 1 – Example Distribution for the Weight and Height of a Group of People

However, if we consider both variables together, then common sense would suggest that Sid is not so normal. This is due to the fact that a person's height and weight are strongly correlated. Figure 1 suggests that if we were to construct a 2-dimensional reference space of people with normal height and weight, then Sid would probably fall outside that subset and the distinguishing characteristic would be the Mahalanobis distance associated with his height and weight. Dynamic vehicle operation can be analyzed using the same principle as above. The operation of a vehicle is captured through a series of correlated sensor signals like hand wheel angle, lateral acceleration, yaw rate, roll rate etc. If we monitor each sensor signal individually, we might not be able to capture anomalies especially if their outputs are still within the valid operating range. However, by

observing all the sensor signals together and quantifying their correlations as a whole we may be able to pick up patterns that suggest anomalies in their behavior.

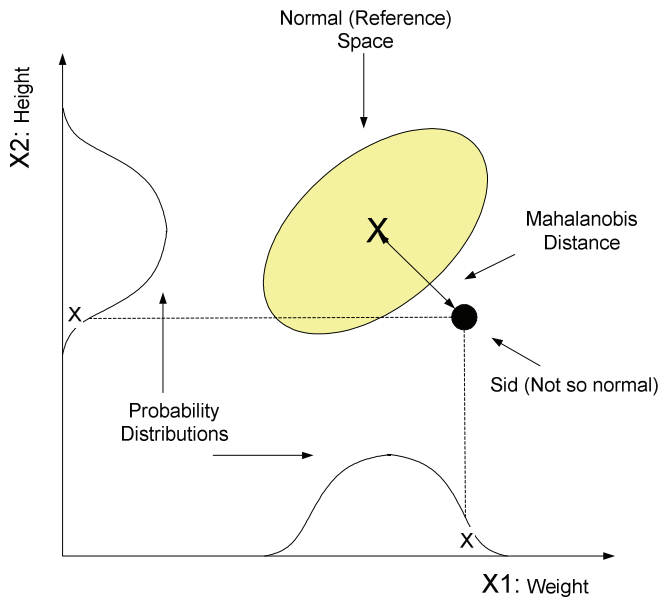


Figure 2 – A Simple 2-Dimensional Example of the MTS

The above example provided a simple explanation of the MTS which can be evaluated by a visual inspection for correctness. However, when systems are described by multi-dimensional empirical data, it becomes harder (if not impossible) to recognize a visual pattern. In such cases the analytical Mahalanobis distance metric becomes a good, powerful tool for diagnosis/pattern recognition. In the sections that follow we analyze the vehicle operation as a MTS using the outputs of several correlated sensors. Next, we quantify the correlation between the various sensor signal pairs using the Mahalanobis distance metric and leverage that tool to identify patterns corresponding to sensor faults.

DYNAMIC VEHICLE OPERATION AS A MTS

Just as a person's health is captured by a series of correlated variables like body temperature, blood pressure etc., the operation of a vehicle in motion can be captured through certain key correlated sensor measurements. Thus, the dynamic operation of a vehicle can be viewed as a Mahalanobis Taguchi System.

Most of the safety-critical control systems in production today are geared towards controlling the yaw motion of the vehicle. Some even attempt to keep vehicle sideslip to a minimum. More advanced system like active rollover prevention also takes into account the roll and pitch motion of the vehicle. These systems provide the necessary control based on the real-time information they gather from key sensor measurements. In general, vehicular systems with sensors to measure lateral acceleration, yaw rate, roll rate are becoming standard. For the purpose of illustration, in this paper we focus on the dynamic lateral, yaw and roll motions of a vehicle.

Accordingly, we develop quantifiable metrics based on sensor measurements that capture these motions of the vehicle. The same idea can be extended to accommodate additional sensor measurements if required. To understand the underlying principle we start by looking at a 3-degree-of-freedom vehicle handling model [8] which is as follows

$$F_{yf} + F_{yr} = M(\overbrace{v_x \dot{\psi} + \dot{v}_y}^{a_y}) + M_s h_s \ddot{\phi} \quad (1)$$

$$F_{yf} a - F_{yr} b = I_{zzo} \ddot{\psi} + I_{xzso} \ddot{\phi} \quad (2)$$

$$(M_s h_s g - k_s) \phi - c_s \dot{\phi} = M_s h_s (v_x \dot{\psi} + \dot{v}_y) + I_{xxso} \ddot{\phi} + I_{xzso} \ddot{\psi}. \quad (3)$$

Here, F_{yf} and F_{yr} denote the lateral forces at the front and rear axles respectively and the vehicle parameters are defined in Table 1.

Table 1 – Vehicle Parameter Definitions

M_s	Vehicle sprung mass
M	Total vehicle mass
h_s	Height of center of gravity
a	Distance of CG to front axle
b	Distance of CG to rear axle
I_{xxso}	Sprung mass moment of inertia about roll axis
I_{xzso}	Sprung mass product of inertia about roll axis
I_{zzo}	Total vehicle moment of inertia about z-axis
k_s	Overall suspension stiffness
c_s	Overall suspension damping

In addition, the dynamics of the vehicle are captured by sensors that measure v_x the vehicle speed, $\dot{\psi}$ the yaw rate, $\dot{\phi}$ the roll rate, a_y the lateral acceleration, and δ the steering angle which is embedded in equations (1)-(3). The lateral velocity v_y of the vehicle can be measured using an optical sensor. It should be noted that in most on-board applications we cannot measure v_y owing to the high cost of the optical sensor. In this study we assume the presence of a lateral velocity sensor measurement for only the offline data collection part. It will be primarily used for data sifting and to identify the normal region of operation which is essential to development of the MTS. The actual real-time implementation of the proposed diagnostic strategy will not require the real-time measurement of the lateral