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A GEOMETRIC APPROACH TO FAULT IDENTIFICATION IN STOCHASTIC DYNAMICAL SYSTEMS

Summary. A novel geometric approach to fault identification (isolation) in stochastic dynamical systems is introduced. This approach is based on the notion of fault mode as the set of all faults of a particular nature, its geometric representation in a feature space equipped with a proper metric, and its regression-type approximation via hyper-surfaces. Unlike alternative schemes, the proposed geometric approach is capable of: (a) Identifying faults of various magnitudes and of all possible (sensor, actuator, system) types; (b) operating effectively in stochastic environments; (c) operating effectively with systems of various complexities without resorting on detailed state-space representations; and, (d) using a minimal number of measured signals, including the single signal case. The effectiveness of the approach is demonstrated with its application to the problem of fault identification in a stochastic structural system.

ZASTOSOWANIE REPREZENTACJI GEOMETRYCZNEJ DO IDENTYFIKACJI ZAKŁÓCEŃ W LOSOWYCH SYSTEMACH DYNAMICZNYCH

Streszczenie. W artykule pokazano oryginalny sposób identyfikacji zakłóceń (defektów) w stochastycznych modelach systemów dynamicznych. Sposób opiera się na klasyfikacji zakłóceń i odwzorowaniu klas w przestrzeni metrycznej, umożliwiającej określanie podobieństw elementów przestrzeni.

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GEOMETRISCHE IDENTIFIKATION DER STÖRUNGEN IN STOCHASTISCHEN MODELLEN VON DYNAMISCHEN SYSTEMEN

Zusammenfassung. Im Aufsatz wurde originale Weise der Identifikation der Störungen (Defekte) in den stochastischen Modellen von dynamischen Systemen dargestellt. Die Weise stüzt sich auf der Klassifikation der Störungen und der Abbildung der Klassen in dem Metersraum, der zur Bestimung der Ähnlichkeiten von Elementen erlaubt.

1. INTRODUCTION

The problem of fault detection and identification in stochastic dynamical systems is of particular importance in engineering practice. This is due to the fact that complex systems, that are widely employed in modern industry, are subject to various types of uncertainty and/or random excitation while often consisting of tenths or hundreds of inter-dependent working parts which are individually subject to malfunctions or faults. Such faults may present unacceptable economic loss or hazards to personnel, and, in certain cases, even threaten human lives.

To avoid such circumstances it is necessary to design fault detection and identification schemes capable of early fault detection, as well as identification of the fault nature and magnitude (size). This allows for the assessment of the impending dangers and the immediate initiation of proper corrective actions. The effectiveness of the approach is demonstrated with its application to the problem of fault identification in a stochastic structural system.

Although the first part of the problem, that is fault detection, has received considerable attention in recent years (Patton et al., 1989), significantly less attention has been paid to the second part, that is the identification of the fault nature and magnitude. The various available methods for fault identification, namely the Multiple Model method (Willsky, 1976; Basseville et al., 1986), the Beard-Jones-type methods (Beard, 1971; Jones, 1973), the parameter-estimation-type methods (Isermann, 1984; Rault et al., 1984), and the Nearest Neighbor method (Gersch et al., 1983), are, due to their own construction, known to often lead to fault misclassification problems, while being also unable to estimate the fault magnitude. The nature of this weakness is closely associated with the fact that, in most of them (with a few exceptions which are restricted to actuator and/or sensor faults and are not applicable to the broad and particularly important class of system faults), the notion of fault magnitude is essentially ignored, and the methods' training is based on representative faults of specifically selected magnitudes. As a consequence, when faults of the same nature but of magnitudes different from those used in the training occur ("unmodeled" faults), the methods generally fail to properly recognize and classify them. An illustration of such a case is presented in Sadeghi and Fassois (1991) within the context of fault detection and isolation in an automobile active suspension system.

Additional problems with the existing fault identification methods include the fact that more than one signal measurements is generally required, that detailed (usually state-space) system representations are necessary, and that most of the methods are well-suited for deterministic systems while being suboptimal in stochastic environments (Willsky, 1976; Kerr, 1989; Patton et al., 1989).

In the present paper a novel geometric approach to fault identification is introduced. This approach is: (a) Capable of correctly identifying faults of various magnitudes and of all possible (actuator, sensor, and system) types; (b) effective in stochastic environments; (c) capable of operating with simplified representations of systems of various complexities, without requiring detailed state-space models; and, (d) capable of operating with a minimal number of measured signals, including the single signal case.

This fault identification approach is presented in Section 2, and its effectiveness is examined in Section 3 via numerical experiments with a structural system subject to faults of various causes and magnitudes. The conclusions of the study are summarized in Section 4.

2. THE GEOMETRIC FAULT IDENTIFICATION APPROACH

The geometric fault identification approach is based upon the introduction, and appropriate geometric representation, of the concept of fault mode. This term is used to denote the collection of all faults of the same nature (physical cause mechanism), but of various magnitudes, which typically are of an infinite number. Unlike alternative approaches considering only particular faults of fixed magnitudes, the geometric fault identification approach thus considers the continuum of all faults associated with each cause. The dynamical system being monitored is then assumed to operate either in its normal operating mode, where no fault has occurred, or in one of the various possible (but finitely many) fault modes.

For the mathematical and geometric representation of the fault modes the prior selection of a proper feature space is necessary. This feature space consists of system characteristics (features) which are selected based upon their sensitivity to the various potential faults and fault modes. Their main selection criterion is, in other words, the exhibition of substantial sensitivity to both the type and magnitude of the various potential faults. The feature space dimensionality may be properly selected based upon engineering considerations which involve a trade-off between fault identification accuracy and computational complexity. The feature space is additionally equipped with a proper metric (Rudin, 1976), which converts it into a metric space and introduces the notion of distance between different points. In certain cases a pseudo-distance function (Sadeghi, 1994) may be also used. The selection of a proper metric or pseudo-distance function is, in any case, important, as it affects fault identification accuracy. In addition, both the feature space and the metric function selection are important for the proper functioning of the approach within a stochastic environment (Sadeghi, 1994).

Once the feature space has been selected, the fault modes need to be properly represented within it. Such representations are, typically, in the form of fault mode hyper-surfaces, with each one defined as the locus of all possible faults of a particular mode within the feature space. These geometrical fault mode representations may be obtained either analytically or experimentally (Sadeghi, 1994). The first method is based on analytical calculations using the system model, and is most appropriate for relatively simple and linear systems. The second one is based on numerical experiments with a simulation model of the system, and is most appropriate for complicated, large-scale, and non-linear systems.

The gest of the geometric fault identification approach is then based upon the comparison of the current "state" of the system with the various fault modes. The former is obtained by estimating the system model using measurable inputs and/or outputs, and is represented as a single point in the feature space. Theoretically, assuming that a fault has indeed occurred in the system and that the modeling of the fault mode hyper-surfaces and the system are perfect, the current system point should lie on one of them. Nevertheless, due to a number of reasons, including unavoidable estimation uncertainty within a stochastic environment, this will almost never be the case, and for the proper identification of the system fault the proposed approach proceeds with the computation of the distances from the current system point to each one of the fault mode hyper-surfaces. These distances are obtained by solving a constrained optimization problem using a Lagrange multiplier formulation. The current system "state" is then associated with the fault mode whose hyper-surface is closest to the system point in the feature space.

From an operational point of view the proposed fault identification approach thus consists of three stages: The first stage, which is performed once and may be regarded as an off-line pre-classification (or learning) stage, involves the selection of the feature space and the fault modes, as well as fault hyper-surface construction. The second stage involves the on-line estimation of the current system model and feature extraction, whereas the third stage involves the computation of the distances between the current system point and each fault mode hyper-surface, and thus the determination of the actually occurred fault mode. The last two stages are performed in an on-line fashion once a fault is detected.

3. APPLICATION EXAMPLE: FAULT IDENTIFICATION IN A STOCHASTIC-STRUCTURAL SYSTEM

The geometric approach to fault identification is now used for the identification of system faults in the simple 4 degree-of-freedom structural system of Figure 1. The numerical values of the parameters are $m_1 = m_2 = m_3 = m_4 = 1$[kg], $c_1 = c_2 = c_3 = c_4 = 10$ [Nt*sec/m], and $k_1 = k_2 = k_3 = k_4 = 100$ [Nt/m]. The system is monitored through measurements of the input force excitation acting on mass m1 and the resulting displacement of the mass m2; the latter being corrupted by stochastic measurement noise.

Four types of faults (fault modes 1-4) are considered, with each one representing stiffness changes in each one of the springs (k_1-k_4, respectively). The objective of the experiment is to properly identify the fault mode (that is the defective spring) based on the obtained measurements.

The force excitation is wide-band random, and the corresponding response is obtained by using a fourth-order Runge-Kutta method, and is, subsequently, noise corrupted at a 10% noise-to-signal ratio. All signals are re-sampled at 25 (Hz), and 1,500-sample-long records are obtained. The mathematical system representation selected is of the AutoRegressive Moving Average with eXogenous excitation (ARMAX) type (Lee and Fassois, 1992) with orders (8,7,3), that is:

$$\sum_{i=0}^{8} a_i y_{t-i} = \sum_{i=0}^{7} b_i F_{t-i} + \sum_{i=0}^{3} c_i w_{t-i}$$

In the above $a_0 = c_0 = 1$, F_t and y_t represent the measured force and noise-corrupted displacement signals, respectively, and w_t an unmeasurable (noise) stochastic innovations process with zero mean and variance σ_w^2.

The feature space is selected to include all of the autoregressive parameters $\{a_i : i=1,\dots,8\}$, as well as their covariance matrix elements (Sadeghi, 1994). This is necessary in order to account for the stochastic nature of the problem. The fault mode hyper-surfaces are, for purposes of simplicity, approximated by hyper-planes obtained through numerical experiments using the system model and linear regression techniques. For this purpose the elasticity coefficient of each spring is separately varied within the interval from 125 up to 750 [Nt/m] with a discrete step size of 25 [Nt/m]. The metric used in the fault identification method is the Kullback distance function (Kullback, 1959).

Three different faults, corresponding to spring constants of 140, 340, and 565 [Nt/m], are then considered in each fault mode; a total of 12 cases. Fault identification is, in each case, based upon 1,500 sample-long force and noise-corrupted displacement data records. The fault identification results are presented in Table 1, and are considered good, and representative of the capability of the geometric approach to correctly identify the system fault mode. Only two of the tested cases are erroneously identified, and in both of them the faults examined correspond to the smallest considered spring constant [140 Nt/m]; a value that is relatively close to the normal spring constant. These two cases represent no coincidence, but a rather expected result related to the fact that the failure mode hyper-surfaces get close to each other in the normal operating point neighborhood, and intersect exactly through that. Although fault detection may present no particular difficulty, the correct identification of fault modes in such cases is always difficult, especially in the presence of stochastic noise.

4. CONCLUSION

A novel geometric approach to fault identification in stochastic dynamical systems was introduced. The approach is based on the notion of fault mode and its geometric representation within a proper feature space, and allows, for the first time, for the identification of faults of various magnitudes and of all possible (system, actuator, sensor) types, within stochastic environments, with a minimal number of measured signals, and in connection with systems of various complexities by making use of considerably simplified mathematical representations.

In the application example considered the feature space included the structural system's autoregressive parameters and their covariance matrix elements, and made use of the Kullback distance function. The results confirmed the capabilities and effectiveness of the approach in realistically solving this important engineering problem. They also revealed the difficulties associated with fault identification in the neighborhood of the system's normal operating point.

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Table 1

Fault identification results for the 4 degree-of-freedom structural system (fourteen cases, four fault modes). The asterisk indicates identification error

	Kullback distance			
Fault	Distance from Hyper-plane K_1	Distance from Hyper-plane K_2	Distance from Hyper-plane K_3	Distance from Hyper-plane K_4
K_1=140	6.1632e+00	3.8626e+03	6.5936e+01	3.1451e+03
K_1=340	3.7794e-01	4.2399e+04	1.2805e+04	2.5220e+04
K_1=565	6.0827e-02	3.7893e+05	2.8982e+04	3.5648e+05
K_2=140	1.0737e+03	4.8116e+00*	3.2307e+00	3.5216e+01
K_2=340	8.8330e+05	2.9604e+02	6.6902e+02	2.9888e+05
K_2=565	3.1743e+05	2.4403e+01	4.6067e+02	5.9433e+05
K_3=140	8.0465e+01	1.4503e+01	2.2613e+00*	8.6755e-02
K_3=340	4.1388e+04	1.0943e+01	1.8021e+00	8.4225e+00
K_3=565	1.1617e+04	1.0252e+03	1.4724e+01	7.9283e+03
K_4=140	9.4799e+00	1.2128e+00	1.3017e+00	4.0747e-02
K_4=340	9.3134e+01	1.4312e+03	1.1343e+01	8.1000e-03
K_4=565	1.1770e+03	2.3636e+01	7.3017e-01	4.9200e-02

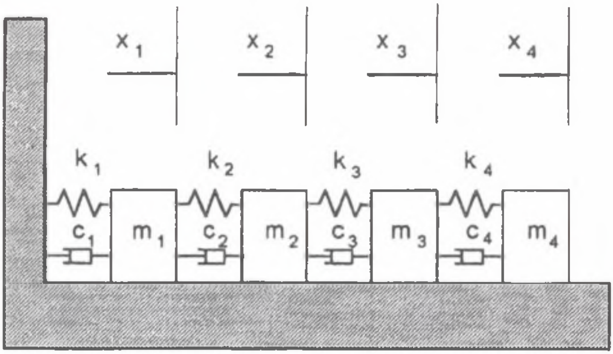

Fig. 1. The 4 degree-of-freedom structural system.
Rys. 1. System strukturalny o 4 stopniach swobody.

Streszczenie

Wykrywanie i identyfikacja defektów (zakłóceń) w modelowaniu systemów dynamicznych o strukturze stochastycznej stanowi istotny problem w praktyce inżynierskiej. W niniejszym artykule przedstawiono koncepcję zastosowania reprezentacji geometrycznej do potrzeb identyfikacji (wyodrębniania) takich defektów. Koncepcja ta opiera się na założeniu, że możliwe jest wyodrębnienie rodzaju (mody) defektu i przedstawienie go poprzez zbiór wszystkich możliwych defektów tego typu. Zbiór taki może być przedstawiony w odpowiedniej przestrzeni cech, przy czym zdefiniowanie w takiej przestrzeni odpowiedniej metryki umożliwia porównywanie zbiorów reprezentujących różne mody z wykorzystaniem opisu rozgraniczeń takich zbiorów za pomocą odpowiednich hiperpowierzchni. W takim ujęciu przedstawiona w artykule koncepcja nawiązuje do prac nad możliwościami wykorzystania w zadaniach inżynierskich metod z obszaru „rozpoznawania cech (ang. pattern recognition)". W porównaniu z alternatywnymi metodami reprezentacja geometryczna umożliwia identyfikowanie defektów o różnym natężeniu i dużej różnorodności możliwych typów, pozwala także na skuteczne wykorzystanie do ich opisu i analizy środkow i sposobów analizy statystycznej. Zdaniem autorów, proponowana metoda pozwala na skuteczne odwzorowanie zagadnień o różnym stopniu złożoności bez konieczności rozdzielania ich poprzez wykorzystanie odwzorowania w różnych przestrzeniach stanu, a także daje możliwość uzyskania wyniku przy ograniczonym zbiorze danych (także w przypadku, gdy dysponujemy pojedynczym sygnałem). W artykule pokazano skuteczność proponowanego rozwiązania na przykładzie jego zastosowania do identyfikacji zakłocenia w wybranym stochastycznym systemie strukturalnym.