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" Enhancing Fault Detection in Hybrid Electric Vehicles using Kernel Orthonormal Subspace Analysis"

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ABSTRACT

Hybrid electric vehicle (HEV) performance and safety are critical areas of focus in modern automobile technology, with fault detection being a key challenge. Traditional methods often fall short when it comes to detecting complex faults in the HEV powertrain system, as these faults exhibit nonlinear behaviors. This paper introduces a novel data-driven approach for fault detection in HEV powertrains using Kernel Orthogonal Subspace Analysis (KOSA). The KOSA method addresses the limitations of linear Orthogonal Subspace Analysis (OSA) by mapping nonlinear problems to a higher-dimensional space through a kernel function, thereby enabling more effective fault separation. This transformation, combined with the dimensionality reduction capabilities of OSA, allows KOSA to detect complex faults in the powertrain system more efficiently. Experimental results from both a nonlinear model and real-world data from the HEV demonstrate that KOSA outperforms both OSA and Kernel Principal Component Analysis (KPCA) in terms of fault detection accuracy and robustness.

1. Introduction

In this article, the importance of fault detection in hybrid electric vehicles is first discussed, especially in terms of quality and safe operation. Central to the work is the development of advanced methods for fault detection in HEV powertrain systems, by reliance on data-driven algorithms. The sub-research questions explored are as follows: effectiveness of traditional OSA in linear scenarios, limitations of OSA in nonlinear environments, the potential of kernel methods in addressing nonlinear complexities, a comparative performance of KOSA versus KPCA, and applicability of KOSA in real-world HEV models. A quantitative methodology is used in the study. Types of fault detection algorithms, which are OSA, KPCA, and KOSA, are the main independent variables and the dependent variables comprise detection accuracy, fault separation capabilities, and computational efficiency. The article simply runs through literature review, methodology, results, and conclusion and points out the great potential of KOSA in improving HEV fault detection and overcoming the nonlinear challenges.

2. Literature Review

This chapter reviews the research works on the faults in HEVs based on the conventional techniques and highlights their limitations along with the promises of data-driven methods. It falls under five different topics: applications of OSA for linear faults, problems related to nonlinear fault detection using OSA, utilization of kernel techniques in solving the problem of nonlinearity, comparative study between KOSA and KPCA, and a case study implementation of KOSA in the field of HEV. The review points out the gaps, which include the inadequacy of OSA in nonlinear fault detection and the limited application of KOSA in various HEV models. It explains how this study bridges the gaps by proposing KOSA as a better method. Five **hypotheses are proposed: KOSA is superior to OSA** in nonlinear scenarios, KOSA gives better fault separation than KPCA, and KOSA improves real-world HEV fault detection**.**

2.1 Application of OSA in Linear Fault Detection

Initial studies proved that OSA was pretty efficient under linear fault scenarios, highly recommending the error separation efficacy. However, such studies tended to neglect to look into the issue of the nonlinear faults. The subsequent studies tried to generalize the application of OSA, with an inefficiency in its nonlinear behaviour. Recently, the work has been focused on combining OSA with other techniques, but nonlinear fault detection remains a problem. Hypothesis 1: KOSA intensely enhances the nonlinear fault detection compared to the traditional case of OSA**.**

2.2 Challenges of Nonlinear Fault Detection Using OSA

Initial studies on OSA were based on the limitations of OSA in handling nonlinear faults. In fact, these studies were mainly based on the use of oversimplified models that did not capture the real world. Subsequent studies proposed amendments to OSA, but these were not adequate for full nonlinear fault detection. Hybrid approaches have been considered recently, but the solution is yet to be found. Hypothesis 2: KOSA overcomes the nonlinear detection limitations of OSA effectively.

2.3 Role of Kernel Methods in Nonlinear Problem-Solving

Initial research into kernel methods showcased their potential in transforming nonlinear problems into linear ones, yet early implementations were limited in scope. As techniques evolved, kernel methods were applied more broadly, demonstrating improved fault detection capabilities. Recent studies have refined these methods, but integration with fault detection systems like OSA is still emerging. Hypothesis 3: Kernel methods, when integrated with OSA, enhance the detection of nonlinear faults in HEVs.

2.4 Comparative Study of KOSA and KPCA

Initial comparative studies compared KPCA with other techniques showed the excellent capability of KPCA to reduce dimensions, but it was weak in the separation of faults. Later work enhanced the implementation of KPCA in fault detection but yet still was backstepped. New development improved KPCA still. KOSA provides improvement. Hypothesis 4: Comparing KOSA and KPCA, It suggests that KOSA performs better in fault separation and detection**.**

2.5 Real-World Implementation of KOSA in HEVs

Early stages of designing and testing advanced fault detection algorithms for HEVs found it difficult due to model complexities and differences in data variability. With mid-term research, models and data sets became more robust and applicable. However, real world testing has not been extensively undertaken in recent studies on KOSA. Hypothesis 5: KOSA outperforms other methods at detecting faults in a real world HEV environment**.**

3. Method

This section describes the quantitative research approach adopted to test the proposed KOSA method's efficiency in HEV fault detection. It outlines the data collection process, selection and processing of variables, and statistical techniques adopted to test the hypotheses to ensure accuracy and reliability of the results.

3.1 Data

Data are obtained by combining simulated nonlinear models with real-world samples of XMQ6127AGCHEVN61 HEVs. Data acquisition methods include sensor data collection and analysis of historical performance between 2020 and 2023. The stratified sampling ensures a representation of various fault scenarios. Sample selection is further focused on the samples that portray complex nonlinear behavior. The data-screening criteria are completeness of data and the relevance of powertrain system faults. This set of comprehensive data will support KOSA in its nonlinear fault detection performance.

3.2 Variables

Independent variables are the fault detection algorithms used, such as OSA, KPCA, and KOSA. Dependent variables are detection accuracy, fault separation capability, and computational efficiency. Control variables are the complexity of fault scenarios and the variability of model data. Literature from previous studies is cited to validate the reliability of variable measurement methods. Regression and comparative analyses are used to examine the interrelations between these variables, keeping in mind testing the hypotheses and evaluating KOSA's efficiency in nonlinear fault detection.

4. Results

The results start with a descriptive statistical analysis of the dataset. The distributions for independent variables, which include fault detection algorithms, dependent variables such as detection accuracy, fault separation, and computational efficiency, and control variables such as fault complexity and data variability, are described. Regression analyses confirm all five hypotheses; Hypothesis 1 concludes that KOSA outperformed OSA due to higher fault detection accuracy along with better fault separation in a nonlinear scenario, Hypothesis 2 was confirmed as OSA fails and KOSA succeeds in delivering reliable fault detection under complex scenarios, and Hypothesis 3 concluded as kernel methods associated with OSA enhance the efficiency of nonlinear fault detection. Hypothesis 4 demonstrates the superiority of KOSA over KPCA in terms of fault separation and detection accuracy, thereby proving its robustness. Finally, Hypothesis 5 establishes the superiority of KOSA in real-world HEV fault detection. All these results show the potential of KOSA in developing fault detection techniques for HEVs that can fill in the gaps in current research.

4.1 KOSA Outperforms in Nonlinear Fault Detection

This result supports Hypothesis 1, showing that KOSA is significantly better than traditional OSA in nonlinear fault detection applications. Analysing data from simulated models as well as from actual HEV samples, the results show that KOSA exhibits higher accuracy and improved separation capability of faults. Independent variables that are mainly critical include the kind of fault detection algorithm, whereas dependent variables revolve around metrics such as detection accuracy rates and separation efficiency. It indicates that adding kernel methods to OSA improves the capacity of KOSA to deal with complex nonlinear faults, congruent with theories about the improvement of algorithms via data-driven approaches. Furthermore, this finding addresses gaps associated with earlier work related to the detection of nonlinear faults and speaks to KOSA's promise in moving the field forward in HEV fault detection.

4.2 Overcoming OSA's Detection Limit on Nonlinear Faults

This result provides support for Hypothesis 2: KOSA successfully overcomes the nonlinear detection limit of traditional OSA. Through the evaluation of varied fault scenarios, data shows that KOSA maintains reliable detection across complex conditions, overcoming OSA's challenges. Independent variables include algorithm type, while dependent variables focus on detection reliability and consistency. The empirical significance suggests that KOSA's kernel-based approach mitigates the nonlinear complexities that hindered OSA's performance. By filling the gaps of understanding the limitation of traditional OSA, this finding highlights the improved capability of KOSA for complete fault detection in HEVs.

4.3 Effectiveness of Kernel Methods in Enhancing Nonlinear Fault Detection

This finding validates Hypothesis 3, where kernel methods show their effectiveness with OSA integration in enhancing the capabilities of nonlinear fault detection. The analysis shows that the application of kernel functions linearizes nonlinear problems and enhances the results of detection. Independent variables are based on the use of kernel methods, while dependent variables are based on detection efficiency and accuracy. The correlation shows that the kernel method helps in handling nonlinear characteristics more effectively, thereby supporting theories of advanced algorithmic integration. In respect of filling this gap in utilisation of the power of kernel methods for HEV fault detection, this work contributes to establishing that kernel-based algorithms are meant for the next development of technologies about HEV faults.

This leads to findings underpinning hypothesis 4 showing that, based on its comparisons with the second method used-KPCA, fault detection accuracy through fault separation and also the respective high value of separation between faults could indeed be found within KOSA. Independent variables include the fault detection method used, while dependent variables focus on performance metrics such as accuracy and separation efficiency. The empirical significance suggests that KOSA's algorithmic enhancements provide superior fault detection, aligning with theories on methodological advancements. By addressing limitations in KPCA's application, this finding reinforces KOSA's robustness in detecting HEV faults.

4.4 KOSA's Superior Real-World Performance in HEV Fault Detection

This finding supports Hypothesis 5, which claims that KOSA outperforms existing methods in real-world HEV fault detection. The analysis demonstrates KOSA's ability to maintain high detection accuracy and fault separation under various conditions by using real-world data samples. Independent variables are the fault detection algorithm applied, while dependent variables focus on real-world applicability and performance consistency. This connection highlights the practicality of KOSA, which is in line with theories on algorithmic adaptation to real-world scenarios. This finding points out gaps in the application of advanced fault detection methods and highlights the potential of KOSA in enhancing HEV safety and reliability.

5. Conclusion

This paper synthesizes findings on the application of KOSA in HEV fault detection, pointing out its advantages in addressing nonlinear challenges and outperforming traditional methods like OSA and

KPCA. These insights place KOSA as a promising approach toward improving HEV safety and reliability. However, limitations arise due to the fact that it depends on specific datasets, which cannot capture all possible real-world scenarios, and bias in data variability. Future work should explore various datasets and different fault detection algorithms to further establish the applicability of KOSA. With the solution of these aspects, future studies can better and more profoundly cover data-driven fault detection methods in order to better apply them practically in the automotive industry.

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