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Virtual Artificial Sensor to identify abnormal combustion phenomena in gasoline engines

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Abstract:
This article deals with the identification of abnormal combustion phenomena in gasoline engines by reconstructing physical values, which cannot be detected directly or only at high costs. Therefore methods from the field of Artificial Intelligence and statistics are combined in a Virtual Artificial Sensor (VAS) to create a basis for important Electrical Control Unit (ECU) algorithms. The influence of databases with an extremely uneven data distribution and data spectrums of high-variance is investigated. Standard measurements from various engines are processed to ensure a high generalizability of the model and the comparability to the results of the ECU. A noticeable increase of robustness against interferences resulting in an improved quality and a reduced parameterization effort is achieved by using the VAS.

Key words: generalizability, robustness, quality, effort

Introduction

Increasing the efficiency of gasoline engines to reduce both, emissions and consumption, call for reliable detection of abnormal combustion phenomena in order to ensure optimum operation.

Due to the continuing development of internal combustion engines, such as downsizing, turbo charging, and multiple fuel injections, engines and their combustion processes are becoming more and more complex and as a result also the control and calibration is increasingly demanding. A consequence of this is an increased probability of abnormal combustion occurrences (e.g. knocking, pre-ignitions or misfiring), which, amongst others, have a negative influence on the engine efficiency and on the exhaust gas composition. Best possible detection of abnormal combustion phenomena requires physical measurement values, which cannot be determined directly by the sensors to do the extreme physical stress and the short service life, or is anything, only at very high costs. The automotive industry therefore uses hard-wearing, durable and cost-efficient sensors that detect the effects of abnormal combustions indirectly. In consequence of the indirect measurement method useful information is superposed by electrical and mechanical disturbances, which impair the quality of the combustion analysis. The variance of these interferences is an additional challenge that aggravates a robust and generalizable combustion analysis and reaches the performance limits of current detection methods.

The evaluation of the sensor signal determined in this way is frequently done according to the state-of-the-art principle of the reference value model. In doing so, the combustion to be evaluated is compared with the preceding combustions. The methods of digital signal processing, such as filtering and integrating in fixed time intervals, serve to determine the decisive features of every combustion process. The Final evaluation of the combustion is performed by using fixed and calibrated thresholds.

Related Work

The feasibility of using Support Vector Machines (SVM) and Artificial Neural Networks (ANN) to detect knocking by means of combustion analysis was investigated in the course of a research project between the Robert Bosch GmbH and the Institute for Integrated Sensor Systems at the Technical University of Kaiserslautern ([2],[3]). The frequency points, determined by applying a Fast Fourier Transformation (FFT) on the structure borne noise signal from the engine, serve as feature space in this research project. In the process, the frequency spectrum is restricted to the specified bandwidth of the used structure-borne noise sensor that ranges from 5 to 25 kHz. The thus obtained results show an increased robustness towards interferences.

The calculation of the used features, the parameterization effort for the modelling, and the required specialized knowledge in the field of artificial intelligence, as well as the traceability of the complex non-linear models renders the use of this method impossible for today's calibration processes and for Electronic Control Units of the current generation.

A decrease of the computational effort relating to the results of the already mentioned research project by reducing the model complexity for an implementation of the algorithms on a Rapid-Prototyping-System was investigated as preliminary stage to the VAS in [1]. The quality of the results that were achieved by using linear models is comparable to those of the complex non-linear models of the research project.

VAS Approach

The VAS approach is a variable and modular system structure that expands the linear model for the regression analysis from [1], which has already been verified with regard to its efficiency, by a non-linear model part. Here, the non-linear functions are adjusted to the boundary conditions, i.e. the computational performance, and the arithmetic of the future ECU generation by Robert Bosch GmbH. In contrast to the linear model, the fixed signal processing is designed to be variable and intelligent. Self-adapting thresholds instead of fixed thresholds are used in the detection algorithm in the VAS. By calculating adjusted quality criteria the training is (partly) automated, since variable model parameters are optimized on the basis of these criteria.

The digital signal processing is modified such that the VAS does not use all available input data or features for modelling, but rather identifies suitable features during the training process using a time-frequency analysis, which already show an increased correlation with the target value. Thereby interferences are reduced already prior to the training of the model.

The linear model of the VAS describes the basic system behaviour. The advantages are reduced memory requirement and computational effort for the model. Moreover, the linear model usually has a higher generalization capability compared to the very specific non-linear model, which tends towards overfitting during the training process due to the unevenly distributed database that are characteristic of combustion analysis.

The non-linear expansion compensates interferences on the model and is only used if no sufficient quality can be achieved by means of the linear model.

Adjustment of the detection method to the respective problem is achieved by an algorithm, the basic functions of which follow the lines of the method regarding the pressure-based knock detection described in [4]. Adaptation of the detection threshold to the operating-point dependent engine behaviour is achieved by including the basic characteristics of the combustion engine. This ensures more sensitive detection while at the same time reducing the calibration effort.

A combination of criteria from the fields of classification, regression, and combustion analysis is used for the evaluation of the detection quality. Thereby, it is possible to perform further grading, although the classification is ideal, which in turn for the determination of the best possible model for the improvement in engine efficiency.

The described variable and modular structure allows for an adaptation of the VAS to further conceptual formulations of the combustion analysis, such as misfire detection or pre-ignition detection. An application for the classification beyond the field of combustion analysis, for example for the field of language or object detection, is thereby also ensured, without performing further generalizations of the VAS model.

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Implementation

The current implementation stage of the VAS under Matlab comprises two areas, the VAS structure and the VAS training, which will be described below using the example of knock detection. The used data, for training and verification, is based on standard measurements for the calibration of the knock detection. These measurements are taken at different operating points, which are defined by engine speed and load. The structure-borne noise signal of the engine, scanned with 200 kHz, serves as input for the VAS. The reference value for the knock detection is the maximum value of the band-pass filtered cylinder pressure signal in a frequency range of 4 to 40 kHz.

The VAS structure comprises several modules that are divided into two groups, VAS periphery and VAS core (shown in Fig. 1).

The VAS periphery is the interface to other components of the engine management, such as the sensor technology at the input and the control at the output of the VAS. The main modules of the periphery are the digital signal processing of the sensor signals and the detection algorithms. The components are exchangeable and their characteristics can be adjusted to the respective tasks.

The portfolio of the implemented signal processing for calculating the features comprises, amongst others, filtering, FFT, and Wavelet Transformation. In the process, special importance is attached to the time-frequency transformations, since they are used during the training process for an automated reduction of the features.

The detection algorithms are essentially influenced by a can- and a must-detection threshold. In the value range between these two thresholds, the finally effective threshold adapts itself. In the process, the basic characteristic of the combustion, formed by using the mean value of all not detected combustions (not knocking), is added to the can-detection threshold, while the must-detection threshold limits it to its maximum value.

The VAS core serves the modelling and is composed of a linear basic model and a non-linear correction model.

The linear model part is mathematically determined by a principal component analysis (cp. [5]) that always generates the same model for a fixed database. The model characteristic can be depicted and evaluated by experts in the field of combustion analysis regarding its functionality and quality.

The correction model, consisting of an ANN with Radial Basis Functions as activation, compensates non-linear influences that are caused, amongst others, by interferences. The intervention on the result of the linear model is limited in order to protect the system against irregular behaviour, which can occur, for example, in case of new unknown input data. Due to computational effort, the amount of artificial neurons is limited to a maximum of ten.

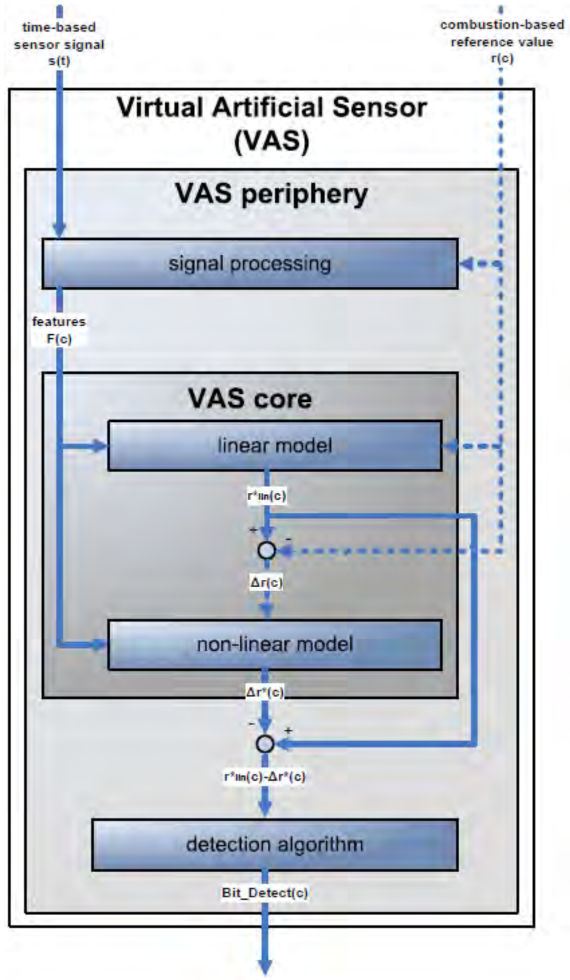


Fig. 1. Graph of the VAS structure where the reference value (dashed line) is only used during the training process

The VAS training is done in three steps, starting from the signal processing to the linear basic model to the non-linear correction model. For this, 50% of the overall database is used.

In the first step, those frequency ranges that contain relevant information are identified by means of a time-frequency analysis. For every detected frequency range, additionally a time range is determined by thresholds to reduce interferences on the useful signal (see Fig. 2).

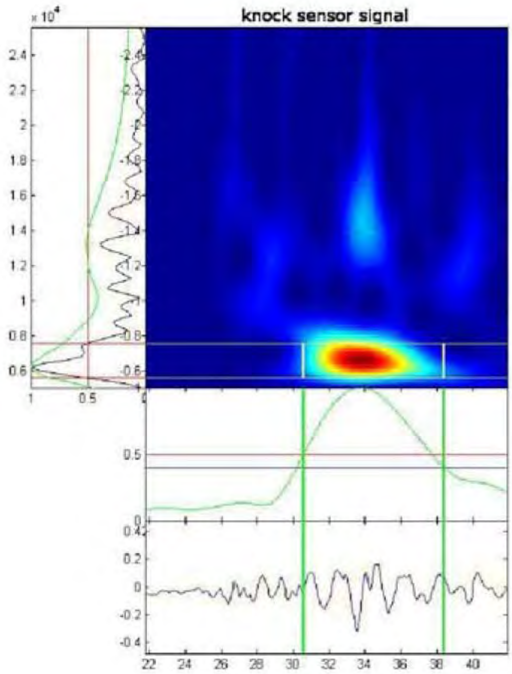


Fig. 2. Graph of time-frequency analysis for knock detection to reduce interferences. The identified frequency and time range is marked.

The second step concerns the training of the linear model, which is determined by a principal component analysis of the training database followed by a linear regression of the main components representing knocking.

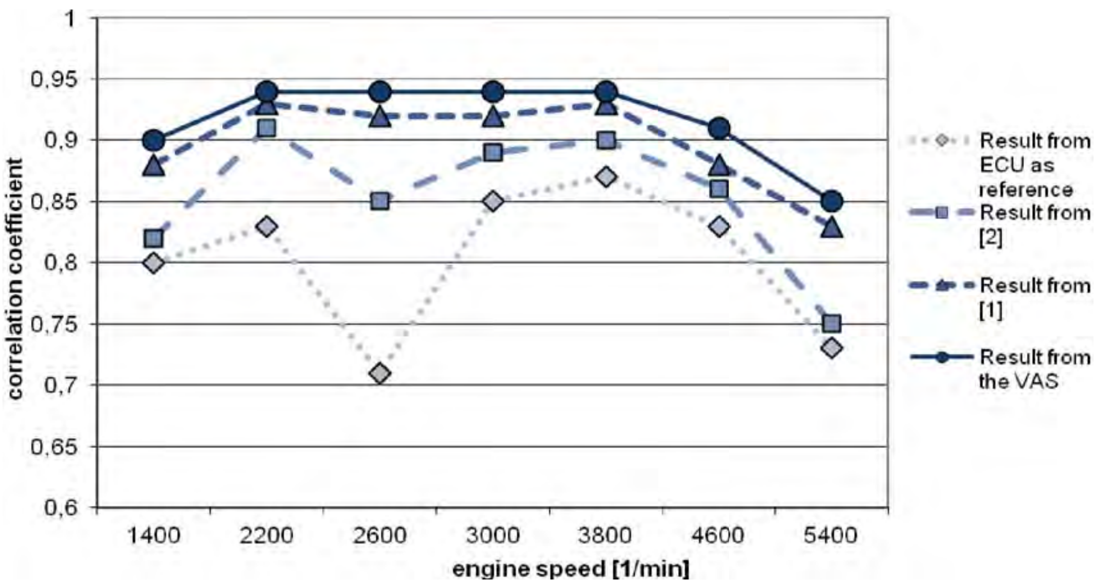
During the third and final step, the non-linear model is trained. In doing so, the difference between target value and output of the linear model constitutes the new target value and the features from the training of the linear model are again used as input here. This training is optimized to correct data points with a high deviation. The Levenberg-Marquardt algorithm (cp. [6]) is used for the training of the ANN. This algorithm is suitable for databases that are statistically unequally distributed.

Results

As compared to the results of the current knock detection and to the results of [1] and [2], the results of the VAS show an enhanced correlation (see Fig. 3) and an increase in particular of the knock detection quality (see Fig. 4).

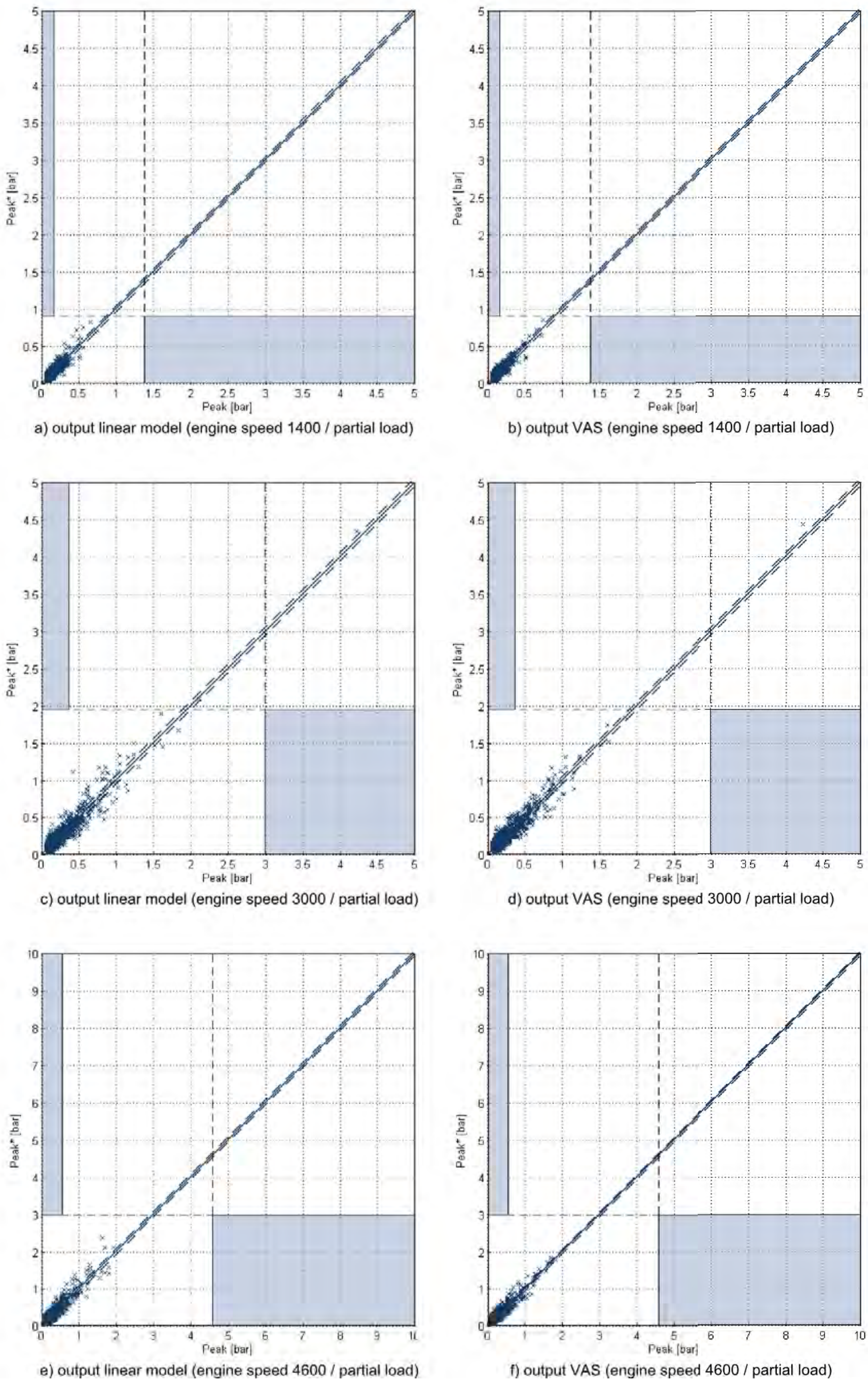
The computational effort for the algorithms, especially for the signal processing, is lessened. The combination of quality criteria from the field of regression analysis and proven criteria from the field of combustion analysis leads to an improved training process and to better results.

Fig. 3.



Correlation graph for the various investigated knock detection methods at different engine speeds

Fig. 4.



Examples of output (Peak) of the linear model and the VAS correlated with the reference value (Peak) for different engine speeds with regression line (solid) and standard deviation (dashed)*

Conclusion and Future Work

The enhanced knock detection quality, with simultaneous lesser computational effort, that is achieved by the VAS brings the approach of a detection of abnormal combustion phenomena by means of the sample detection methods closer to the series production application.

Ongoing projects investigate whether it is possible to lessen the computational effort of the signal processing by using automatically calculated filters instead of transformations, while keeping up the quality. Implementing the VAS algorithms on the Rapid-Prototyping System according to [1] will be effectuated in a next step, so as to confirm the simulation results during real engine operation. The applicability of the VAS for the detection further combustion abnormalities will be verified on the basis of the misfire detection.

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