Machine-specific Approach for Automatic Classification of Cutting Process Efficiency

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Abstract. The identification of an inefficient cutting process e.g. in self-propelled harvesters is a great challenge for automatic analysis. Machine-specific parameters of the process have to be examined to estimate the efficiency of the cutting process. As a contribution to that problem a simple method for indirect measurement of the efficiency is presented and described in this article.

To establish a general algorithm, the vibration data of a harvesting machine were extracted. The data from two sensors were recorded while gathering whole crop silage and while standing still in operation mode. For every data stream, a spectral analysis and a feature extraction was performed.

For the development of the algorithm, exploration techniques of Machine Learning were implemented. Artificial Neural Networks were optimized using subsets of the recorded data and then applied to the independent validation data to compute the efficiency of the cutting process. The established algorithm is able to identify the process efficiency without using additional machine-specific parameters.

The validation results are presented as confusion matrices for each data set and the case-specific population of the generated Artificial Neural Networks. The described algorithm is able to automatically determine an inefficient and machine-specific cutting process as an additional information using vibration data only.

Keywords: classification, condition monitoring, cutting process, machine, sensors, artificial neural network, vibration measurement

1 Introduction

The development and integration of simple and adaptive algorithms into embedded systems is demanded by further technology evolution [1]. The automatic generation of models for analytic approaches can be performed by evolutionary optimization and further techniques of Machine Learning. As an example a standalone embedded diagnostic system for automatic analysis of cutting processes should be developed. As an essential part of this system the automatic approach of data analysis is presented in this work. An inefficient cutting leads to a poor process quality and to a higher energy consumption for example in self-propelled field harvesters [2]. Additionally a frequently grinding of the chopping blades leads to higher costs and requires more machine downtime [2]. So the cutting process efficiency in self-propelled field harvesters should be analysed to determine the perfect point of grinding. In advantage to [3] it is required that the analysis does not need any additional machine specific information or to know about the type of crop.

2 Material and Methods

Relationships between the measured data and recognized states can be found by strategies of Machine Learning. By using meaningful data and features efficient models of classification can be generated for example by Evolutionary Algorithms. Next to the machine-specific vibration data additionally the telemetry of the machine was available. The telemetry is only used for control purposes and not used by the automatic classification algorithm. The built in accelerometers are normally used to control the positioning of the cutting system after the process of grinding the chopping blades. The grinding process requires the harvester to stand still. But while harvesting the sensors are not needed by the machine. The machine generates vibration during operation. The vibrations seem to be different in relation to the sharpness of the chopping blades and in common to the efficiency of the cutting process [3][4][5]. The cutting process was divided into three different states *inefficient*, *normal* and *efficient*.

2.1 Data Aquisition

The whole data were collected throughout two case studies using a Claas Jaguar 950 as shown in figure 1. The self-propelled harvester was used to gather whole crop silage in the field in the first case A. In the second case B it was in working mode without gathering crop and it was standing still. In a first step in both cases data were collected while using not grinded chopping blades. These data were rated as a *inefficient* cutting process. After the first data recording the harvester runs grinding cycles for the whole chaff cutting assembly. The next data sets were collected after grinding and these data were rated as a *normal* cutting process. Grinding cycles for the whole chaff cutting assembly were performed again. Afterwards the last data sets were recorded and marked as *efficient* cutting process. So independent data sets were generated for evaluation. For every state of the cutting process in case A and B approximately 180 to 220 epochs of data were recorded. In the first case one grinding cycle was performed between the states of the process and in the second case two cycles. The vibration data were recorded at a sampling rate of 51.2 kHz with a *NI USB-4431* device at two different positions near the rotating chopping blades. By using two accelerometers two different data channels were observed. The features were extracted offline. The feature base was defined by several variants of the Spectral Edge Frequency (SEF). The SEF is mainly used in monitoring and classification of electroencephalographic patterns in anaesthesia [6][7]. The original signals and feature values were directly used for analysis. The data sets were divided into epochs for training, test and validation of the Artificial Neural Networks (ANN).

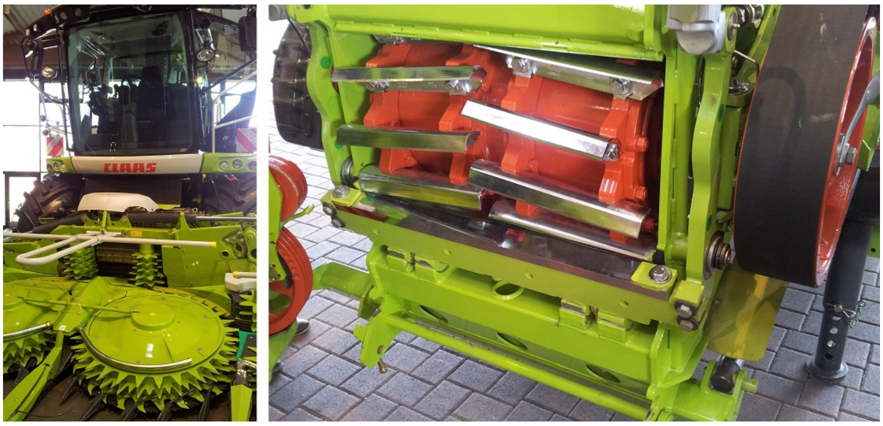

Fig. 1. Self-propelled field harvester (left) and its chaff cutting assembly with 2x12 chopping blades (right). Two built in accelerometers are used to evaluate the cutting process for two channels.

2.2 Requirements

The long term aim is to develop an independent embedded system which is automatically self learning using the described algorithm in this article. To ensure the feasibility in a first step a software system was developed to analyse the vibration data and the cutting process. The first results concerning this work are described in this article. The software should be able to generate process-specific models within a *Training* procedure. In addition the generated models should be used to classify data within an *Application* procedure to confirm the quality. The number of states of the cutting process depends on the classification task. The optimization of the models is performed automatically.

2.3 Software Development Process

To establish an automatic optimization and classification approach a standalone software system named *EMiL-Analyzer* was developed. The software system was new programmed and based upon the experiences in software programming for the systems partially described in [6] and [7]. The software development was bound locally. The Evolutionary Development Model for Software was chosen to react to changes of requirements rapidly [8][9]. Additionally the software was programmed using components for later reuse and maintenance. The main components consist of data management, spectral analysis, feature extraction, evolutionary optimization, artificial neural networks and the user interface. The Software *EMiL-Analyzer* is still working in offline mode and provides the analysation and modeling algorithm as described below. An automatic online mode for classification tasks was prepared.

2.4 Evolution and Modelling

The relationship between the recorded data and the states of the cutting process is modelled using Artificial Neural Networks (ANN). The training of these models is performed with error backpropagation. The structure of the ANN and parameters of the backpropagation algorithm are optimised using an Evolutionary Algorithm. Multilayer Perceptrons with two hidden layers and sigmoid activation functions were optimized. Because the number of states could be changed in subsequent studies, neural networks were chosen to optimize. The implemented Evolutionary Algorithm uses a elite population of individuals. The size of this population was 10, the number of child individuals was 5. The number of generations for all cases was 40. The rate of recombination for cross over of chromosomes was 0.7, the rate of mutation of a gene position was 0.3. The mutation of genes is performed as described in [7]. The procedure of automatic generation of models, i.e. ANN for classification of efficient cutting processes, is called *Training* in this work. The later use of the models is called *Application*. Both procedures are explained in the following and illustrated in figure 2.

The data sets, which were recorded throughout the two different cases, were divided into subsets for training, test and validation. The subsets of training and test were used for the procedure of *Training* of the ANN. To calculate the performance as presented in tables 1(a-d) the independent subset of validation was used. In the following the procedure of *Training* is explained:

1. Initialisation of the elite and the child population with a given number of individuals and ANN (one ANN corresponds to one individual). The structure of the ANN ist randomly initialized.
2. Training of the ANN with error backpropagation using the vibration training data and the corresponding process classification.
3. Evaluation of the ANN using the vibration test data and the process classification. Calculation of $q_{1,i}, q_{2,i}, q_{3,i}$ and $q_{4,i}$ as described in the next paragraph for each ANN i.
4. Calculation of the fitness f_i of the individuals using the quality of the ANN as a weighted sum: $f_i(q_{1,i}, q_{2,i}, q_{3,i}, q_{4,i}) = 0.3{*}q_{1,i} + 0.2{*}q_{2,i} + 0.2{*}q_{3,i} + 0.3{*}q_{4,i}$ where i indicates the individual and the corresponding ANN.

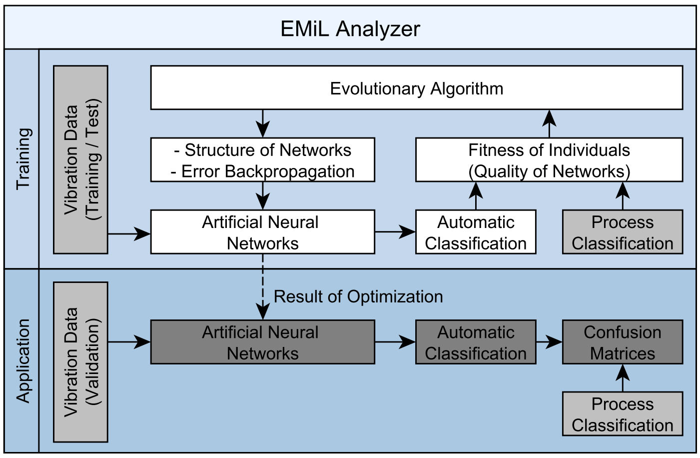

Fig. 2. The developed software *EMiL-Amalyzer* provides a built in optimization procedure *Training* and a procedure of *Application*. Within the *Training* procedure populations of ANN are optimized using an Evolutionary Algorithm. Within the *Application* the resulting ANN are used to classify unknown vibration data as a *inefficient*, *normal* or *efficient* cutting process. For performance evaluation confusion matrices are calculated.

5. Storage of the best individuals into the new elite population. Generation of new child population using the operators of selection, recombination and mutation. Continue with step 2 until generation limit is reached.

Finally the procedure of *Application* is described:

1. Evaluation of the validation data for every generated ANN. Within a real application of the system in future this data will be recorded online and rated automatically by the ANN.
2. Calculation of confusion matrices as presented in tables 1(a-d) for validation only.

2.5 Evaluation of the Artificial Neural Networks

The Artificial Neural Networks are evaluated within the evolutionary optimization using the quality criteria which were presented in [6] and [7]. These criteria are used to compute a fitness value for each individual within the evolution. A neural network is an attribute of an individual next to the fitness value. The first criterion evaluates the quality of the absolute accordance over all epochs or datavectors and is defined by

$$q_1 = \frac{\sum_{n=1}^{N} I_n}{\sum_{n=1}^{N} S_n} \tag{1}$$

with N as the number of states, S as the number of the desired data vectors for each state n and I as the number of the correct recognized data vectors for each state n. To evaluate the accordance for every single state n a second criterion is defined by

$$q_2 = \frac{1}{N} \sum_{n=1}^{N} \frac{I_n}{S_n}. \tag{2}$$

The result of q_2 is an average value based on the number of states N. The third criterion q_3 is defined by the geometric mean of the state-specific accordance and calculated with

$$q_3 = \sqrt[N]{\prod_{n=1}^{N} \frac{I_n}{S_n}}. \tag{3}$$

At least the criterion q_4 is presenting the worst accordance of all states with

$$q_4 = \min_{n=1,2,\ldots,N} \left(\frac{I_n}{S_n} \right). \tag{4}$$

To obtain an individual-specific fitness value, a weighted sum is calculated using the values of the quality for each neural network. The fitness value is connected to an individual, which itself represents the corresponding neural network within the evolutionary optimization process.

3 Results

Optimized populations of Artificial Neural Networks were generated to classify the states of a cutting process. Therefore a standalone software for automatic generation and application of this networks was developed. The optimization of other models of classification is also prepared in this software. An Evolutionary Algorithm was implemented to generate the mathematical connection between the recorded vibration data and the states of a machine-specific cutting process. To validate the generated ANN an independent subset of vibration data was used. The prediction of the states of the cutting processes of this subset shows a very high concordance as presented in the tables 1(a-d).

The general confusion is on a very low level. Additionally in the tables 1(a) and 1(b) the reached performance is very similar for channel 1 and 2. The same result is recognisable in the tables 1(c) and 1(d) for the second case study. The use of two independent channels allows additional control of the validation.

4 Conclusion and Future Works

Next to the obtained objectives several other results can be concluded. It was shown that the feature Spectral Edge Frequency is suitable for machine diagnostics. The SEF is normally used to classifiy patterns of electroencephalograms

(a)

A Channel 1		*Automatic Classification*		
		inefficient	normal	efficient
Process	inefficient	**94.4%**	0.0%	1.9%
	normal	0.0%	**74.1%**	25.9%
	efficient	0.0%	3.0%	**97.0%**

(b)

A Channel 2		*Automatic Classification*		
		inefficient	normal	efficient
Process	inefficient	**100.0%**	0.0%	0.0%
	normal	1.9%	**87.0%**	0.0%
	efficient	0.0%	4.5%	**95.5%**

(c)

B Channel 1		*Automatic Classification*		
		inefficient	normal	efficient
Process	inefficient	**100.0%**	0.0%	0.0%
	normal	0.0%	**88.9%**	11.1%
	efficient	0.0%	0.0%	**100.0%**

(d)

B Channel 2		*Automatic Classification*		
		inefficient	normal	efficient
Process	inefficient	**100.0%**	0.0%	0.0%
	normal	0.0%	**87.0%**	13.0%
	efficient	0.0%	0.0%	**100.0%**

Table 1. Median tables of confusion matrices generated by the resulting populations of artificial neural networks. The values of the tables are calculated for each case A and B and for each channel 1 and 2. For each table the performance of 15 ANN was evaluated using the independent validation data.

througout anaesthesia procedures [6][7][10]. Furthermore, very similar accordances for channels 1 and 2 were calculated for each of the cases as presented in tables 1(a-d). The use of two channels allows an additional internal control of the generated calculation results of the algorithm. The presented process of training should also work for different machines. The generated models for classification are machine specific in every case. Throughout this work only one machine was evaluated, so further research should consider different machines and crops. The optimizing evolutionary algorithm should be expanded with the implementation of additional evolutionary selection procedures, other classification models like fuzzy rules and an automatic feature selection. To increase the performance and robustness of the populations of neural networks the approach of cooperation as presented in [6] and [7] should be integrated too. The implementation of Multi-objective Evolutionary Algorithm as presented in [7] should lead to an additional increase of performance. A forecast of a change of the cutting-process efficiency should be added to present a time-based point of grinding. In future research the data recording, data preprocessing and the presented algorithm should be implemented into an embedded system [11][12].

The project was supported by funds of the German Governments Special Purpose Fund held at *Landwirtschaftliche Rentenbank*.

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