

Recognition of Operating States of a Wheel Loader for Diagnostics Purposes

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ABSTRACT

In this paper, the operating states of a wheel loader were studied for diagnostics purposes using a real time simulation model of an articulated-frame-steered wheel loader. Test drives were carried out to obtain measurement data, which were then analyzed. The measured time series data were analyzed to find the sequences of operating states using two different data sets, namely the variables of hydrostatic transmission and working hydraulics. A time series is defined as a collection of observations made sequentially in time. In our proposed method, the time series data were first segmented to find operating states. One or more segments build up an operating state. A state is defined as a combination of the patterns of the selected variables. The segments were then clustered and classified. The operating states were further analyzed using the quantization error method to detect anomalies. The recognized operating states define the operation of the machine so the analysis can be focused on specific sections and situations in time series and to identify which kinds of operating situations generate anomalies. Simulated leakages in the main hydraulic components of the hydrostatic transmission and the working hydraulics were used as anomalies to study the changes in the recognized operating states and the magnitude of the quantization error.

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INTRODUCTION

The diagnostics of machinery require analysis of the time series of sensor and control signals. In order to analyze the time series data, different operating states which describe the transients of the measured variables need to be first detected. After that, some higher level description should be used to further analyze these operating states.

Finding operating states from the measured time series data requires segmentation of the time series data. Segmentation [1,2] is a method which allows the dividing of time series data into smaller groups of data sets which describe the patterns of the measured variables. In segmentation, the time series data are transformed into piecewise representation. A segment is a contiguous subset of a time series.

Time series segmentation is often used as a pre-processing step in time series analysis applications. Time series segmentation is exploited in a wide range of applications: for example, medical diagnostics, analysis of financial time series, speech processing, or sensor signal analysis [1]. Typically, in modern machinery there is already

a lot of information available about the operation of the machine, e.g. process and control data through communication buses, which can be used in analysis. In addition to this, condition monitoring specific sensors can also be added to the system. When all this information from communication busses and additional sensors are recorded, it leads to the generation of a huge amount of data. High dimensionality complicates the processing of time series data, especially from the pattern recognition point of view [3].

After segmentation, the segments have to be organized into groups of similar members so that data can be classified against these groups. This grouping process is often referred to as clustering [4,5]. A cluster is a collection of objects which are similar between them and are dissimilar to the objects belonging to other clusters. These clusters are then interpreted to be operating states. Diagnostics can now be focused on these operating states or even a single interesting operating state. Most information in regard to the detection of anomalies is usually obtained from operating states which have the biggest changes in the analyzed variables [6].

RESEARCH PLATFORM AND SIMULATOR SYSTEM

The studied wheel loader, called GIM-machine, is a modified version of the Avant multipurpose wheel loader. It has been designed to serve as a platform for different types of research to be conducted. The frame of the machine is original, but the control system, electronics and hydraulics have been changed for research purposes. The research platform is shown in [figure 1](#).



Figure 1. Research platform.

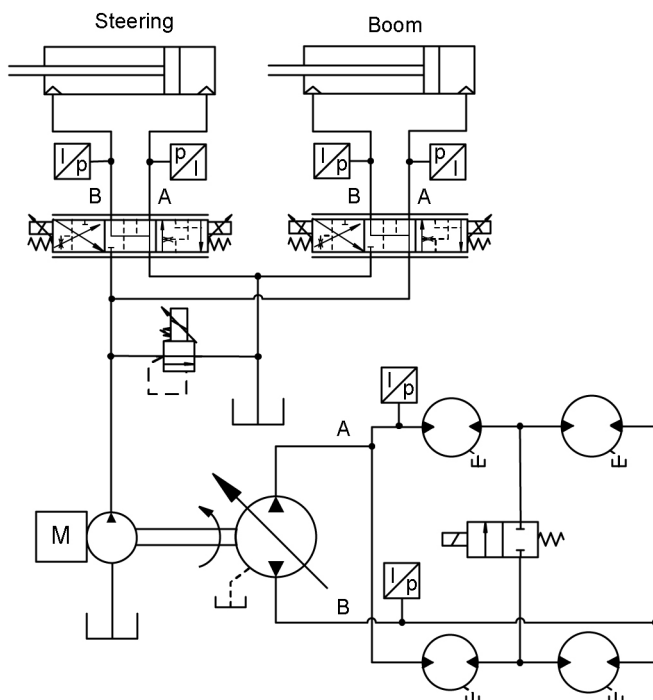


Figure 2. Simplified hydraulic circuit.

[Figure 2](#) shows a simplified hydraulic circuit of the hydrostatic transmission (HST) and the working hydraulics of this research platform. The hydrostatic transmission is implemented with an electronically actuated variable

displacement pump and fixed displacement motors. Steering is executed by a hydraulic cylinder. The stroke of the steering cylinder is controlled by means of an electronically actuated proportional valve as well as other cylinders (boom, telescope and bucket) in the working hydraulics. The telescope and the bucket have been left out of the figure for purposes of clarity. Separate fixed displacement pumps are used for the steering and for the working hydraulics.

A real time Hardware-In-the-Loop (HIL) simulation model [7] for the GIM machine has been developed utilizing Matlab/Simulink environment for the GIM research project (www.gim.tkk.fi). It is used mainly in the development of the control and the hydraulic systems of future autonomous mobile machines. The model and its sub models, such as the hydraulic component models, are verified by laboratory measurements and the model has proved its capability to even tune the control parameters of the control system. From this perspective, it is also very well suited for fault diagnostic research. In this paper, this real time HIL simulation model has been utilized.

TIME SERIES ANALYSIS

At the training phase of operating state recognition it is usually easy to make predetermined work movements and to direct the analysis and teaching measures only onto data which is collected in this way. However, after the training stage the work machine will be run in the sequences determined by its operating situations, in which case the measurement data are obtained from previously undefined driving situations. Situations which appear occasionally and correspond to the training data have to be separated from the measured time series data; in other words, certain operating states that have been defined in advance. The recognition of specific operating states is emphasized because the system, and the measurement data which is obtained from it, behave naturally in a quite different way in different driving situations, and especially when there are separate operators.

In the choice of operating states to be analyzed, a noteworthy point is the appearance of the effects of anomalies at different stages of the driving sequences in the measurement data. Earlier research results [6] have indicated that the biggest effects of anomalies will be at the transient stages of the system, where changes in the pressure and volume flows are at their biggest. After the transient stage, the effect of anomalies on the measurement results disappears, or at least decreases significantly. Thus, the analysis should be directed only to that part of the measured data where the deviations can be detected as being the clearest. Then most information in regard to the detection of anomalies of this kind is obtained from these operating states. Based on these earlier results, test drives were defined here to include fast accelerations, decelerations, and lifting and lowering the boom.

In the method used in this study to find interesting operating states from the time series data, the data are

segmented to find operating states. After the segmentation, pre-processed segments are clustered into different operating states. A state is defined as a combination of the patterns of the selected variables. After the clustering process, analysis can then be focused on specific operating states. The operating states were further analyzed using the quantization error method. The method is illustrated in [figure 3](#) and will be explained in more detail in the following sections.

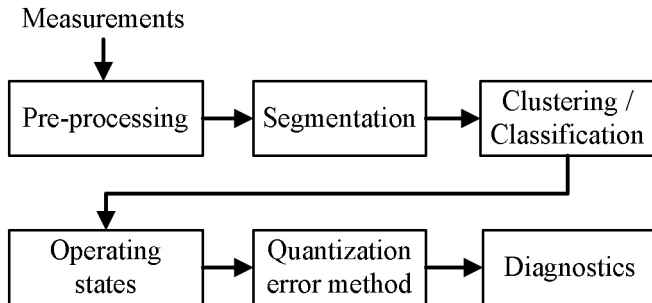


Figure 3. Time series analysis and state recognition.

Preprocessing of Time Series Data

The data have to be scaled before segmentation so that all variables have an equal effect on the segmentation result. The representative statistics of the data are needed in order to be able to scale the measurements. To do that, all the variables of the data should have enough variation. The data range and distribution used to compute the statistics should correspond to those of the whole data set.

Segmentation of Time Series Data

In segmentation, the time series data are transformed into piecewise linear representation. A segment is a contiguous subset of a time series. In this study, the time series data are segmented using the sliding window method with piecewise linear regression [2]. In this method, curves are approximated with lines. It is also possible to use other feature extraction techniques which can describe the segmented sections more precisely, for example, discrete wavelet transform [6,8].

New samples are added to the segment until cumulative squared estimation error exceeds a predefined threshold. Several measurements can be segmented together. Thus, they have common cost function and the cost is computed by summing all the measurements. The measurements together define the edges of segments.

Segmentation algorithms work either in a batch mode (offline) or online. The latter are needed for applications with harsh timing constraints (e.g. monitoring), but they are also suited for applications where a huge amount of data must be processed [1]. The sliding window segmentation method is well suited to online segmentation, because only the preceding samples are needed to define the edges. There are several modifications of the sliding window segmentation algorithm and there are other more efficient segmentation methods, but unfortunately most of them are not very suitable

for online analysis. This is because the methods expect that the whole sequence will be available at the time of segmentation.

Clustering/Classification of Segment Features

After segmentation, pre-processed segments are clustered and classified. Clustering is the process of organizing objects into groups whose members are similar in some way. A cluster is therefore a collection of objects which are similar between them and dissimilar to objects belonging to other clusters. Clustering can be performed using hierarchical methods or k-means algorithm [4].

The parameters of piecewise linear regression lines are used as features. One choice is to use the slopes of lines as features. Also, the offset and the length of the segment can be used as additional features. The number of segment clusters has to be defined, or a validation index should be used to select a suitable amount of clusters [5]. It is not necessary to cluster all the available segments, as some of them can be classified using cluster prototype vectors defined using a representative set of segments. Each cluster is presented by a d-dimensional prototype vector (also known as: weight, codebook, model, reference) $m=[m_1, \dots, m_d]$, where d is equal to the dimension of the input vectors. It is useful to save these prototype vectors in order to classify another set of segments or to analyze classes or classification results later.

Quantization Error Method

The recognized operating states can be analyzed more thoroughly using the quantization error method [6,9]. It is based on distance calculation between the input sample vector (segmented feature vector) and the prototype vectors of operating states. Using this method it is possible to pinpoint when and where anomalies appear because each operating state corresponds to a certain operation of the machine.

MEASURED DATA FOR ANALYSIS

The test cases were defined and test drives were carried out to obtain measurement data from different operating states, which were then analyzed. The controlling functions were performed manually the first time and all the control signals were recorded. After this, the recorded control signals were used instead of manual driving. In this way it was possible to repeat the driven test drive and compare the results of the state recognition method and magnitude of the quantization error in the case of simulated faults (internal leakages) in the main hydraulic components of the hydrostatic transmission and working hydraulics, namely the HST pump and control valve of the boom cylinder [10,11]. An additional load of 300 kg was used in the test drives. [Figure 4](#) shows an example of a drive path on a test field with the simulator.