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DATA ANALYSIS PROCESS OF WORKING HYDRAULICS OF SMALL MOBILE MACHINE

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Abstract

Changing work sequences and the operational environment makes the condition monitoring of mobile work machines more challenging compared with industrial systems. This sets special demands in regard to the analysis of the data measured from the machine during operation. A forklift, reach stacker, is used here as a research platform to study the operation of the data analysis process of working hydraulics of small mobile machine. The focus in the data analysis process is on feature extraction and classification parts. Discrete wavelet analysis is used to extract features which are then classified using the Self-Organizing Map (SOM). In addition, the sensitivity of data analysis process is studied. A simulation model of the lifting movement of the forklift is made to study the effects of changes in the fault levels of the performance of the data analysis methods.

Keywords: mobile machine, data analysis, condition monitoring, hydraulics, forklift

1 Introduction

The analysis of hydraulic systems consists of several phases between physical inputs and the final decision about the state of the system. This process (Duda 2001) is shown in Fig. 1. A sensor measures a physical quantity and converts it into a signal which can be read by an observer or by an instrument. A feature extractor extracts features from the measurement data which are then used in classification. After this a classifier uses the extracted features to assign sensed inputs to a category. Finally, a post processor uses the output of the classifier to make a decision about the state of the system, and it can also decide what actions to take.

In this study a forklift, reach stacker, is used as a research platform to study the operation of the data analysis process, where the focus is on feature extraction and classification parts, including the post processed state of the system. Even though a fairly specific machine is used here, the used methods can be adapted to several mobile machines.

The oil hydraulic components from the work hydraulics of the forklift have been replaced with water hydraulic ones (Krogerus, 2008a). The water hydraulic components are not designed for this kind of mobile machine, which sets special requirements for the condition monitoring of such a system. The role of condition monitoring in general is emphasized with water hydraulic components and systems because of problems caused by the pressure medium.

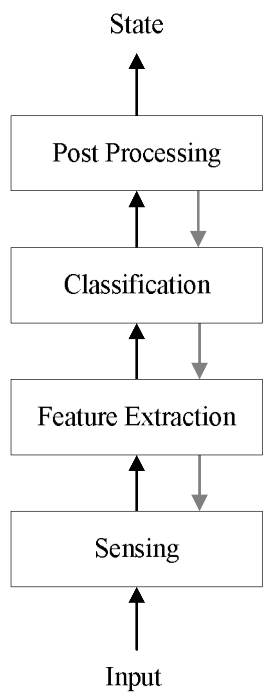

Fig. 1: *Process of data analysis (Duda, 2001).*

The studied data analysis methods, which have been previously tested in laboratory systems (Krogerus, 2007; Krogerus, 2008b) were implemented as an automated process for a forklift and tested in actual use. The research platform is shown in Fig. 2.

Fig. 2: *Research platform (forklift).*

2 Data Analysis Methods

The preprocessing of the measurement data usually involves extracting relevant and discriminating information, and in so doing, reducing data dimensionality. This process is often called feature extraction. Variables that are used to discriminate different system states from each other are called features (Hiirsalmi, 2003). Furthermore, it is important to preprocess any raw and/or dynamic data to improve the performance of the analysis made based on these features. In this study, discrete wavelet analysis is used in feature extraction.

After feature extraction, these extracted features are classified into different categories. The classification procedure used in this study consists of two levels. On the first level, the fault situations are not known, and only data from the normal situation is used to train the classifier. On the second level, the classifier is trained with normal and fault situation data. The SOM, with unsupervised learning, is used in the classification.

In this study, the SOM Toolbox (SOM Toolbox, 2010) was used to create and use the neural network, and Mathworks' Wavelet Toolbox (Mathworks Inc., 2010) was used in wavelet analysis.

2.1 Wavelet Analysis

In hydraulic systems, measured signals contain numerous non-stationary or transitory characteristics such as drift, trends, abrupt changes, and beginnings and ends of events. These characteristics are often the most important part of the signal. Wavelet analysis allows the use of long time intervals where more precise low-frequency information is needed, and shorter regions where high-frequency information is desired.

Wavelet analysis can often compress or de-noise a signal without appreciable degradation. The basic idea of wavelet analysis is to adopt a wavelet prototype function, called an analysing wavelet or mother wavelet. The original measured signal is broken up into shifted (translated) and scaled (dilated) versions of the wavelet function. With some wavelets, but not all, there is an additional function associated, called the scaling function. In this study, discrete wavelet transform (DWT) and Daubechies-4 wavelet function is utilized. DWT has been implemented using filters (Mallat, 1989). This filtering algorithm, usually called Mallat algorithm, yields a fast wavelet transform. Eq. 1 and 2 show calculation of wavelet coefficients by convolutions with dilated filters $\bar{h}$ and $\bar{g}$, where a_j is a signal before decomposition, a_{j+1} are approximation coefficients and d_{j+1} are detail coefficients.

$$a_{j+1}[n] = a_j * \bar{h}_j[n] \tag{1}$$

$$d_{j+1}[n] = a_j * \bar{g}_j[n] \tag{2}$$

In fact, every other sample of these convolutions is taken when a_{j+1} and d_{j+1} are computed. The wavelet function is determined by the high-pass filter $\bar{g}$ and the scaling function is determined by the low-pass filter $\bar{h}$. The wavelet function is associated with the details and the scaling function with the approximations of the wavelet decomposition. Repeating this process is referred to as multilevel one-dimensional DWT, which is used to extract the wavelet coefficients. The basic principle of the multilevel one-dimensional DWT using filters, followed by a down sampling is shown in Fig. 3. Because the original signal or function can be represented at a certain accuracy using only approximation coefficients, data analysis can be performed using just the approximation coefficients (Mallat, 1999).

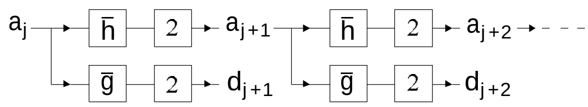

Fig. 3: *The basic principle of multilevel one-dimensional DWT using filters followed by factor 2 down sampling (Mallat, 1999).*

2.2 Self-Organizing Maps

After feature extraction, approximation coefficients are used as inputs to SOMs in the classification of different system states.

A SOM consists of neurons organized on a regular low-dimensional grid, usually 2-dimensional. In this study, hexagonal lattice structure and sheet shape SOMs are used. SOMs learn to recognize groups of similar input vectors in such a way that neurons physically near each other in the neuron layer respond to similar input vectors. Similar system states have similar feature vectors, and therefore it is possible to separate different system states. Each neuron is presented by a d-dimensional weight vector (prototype vector, codebook vector) $m = [m_1, \dots, m_d]$, where d is equal to the dimension of the input vectors. A schematic representation of a SOM is shown in Fig. 4.

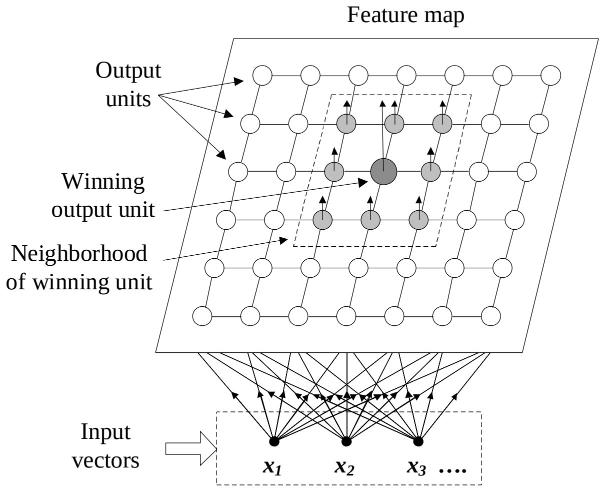

Fig. 4: *Schematic representation of SOM (Karray, 2004).*

SOMs can be used in different ways to monitor the status and condition of hydraulic components and systems. These are, for example, quantization error (Ahola, 1999; Alhoniemi, 1999; Krogerus, 2006), categorization (Krogerus, 2006), feature extraction, forbidden area of neurons (Zachrison, 2008) and parameter estimation. In this study, on the first level, the so-called fault-detection map is used and the fault detection is based on quantization error. Kasslin et al. (1992) argue that the quantization error method is the best one when only data from the normal situation is used in training. On the second level, the categorization method is used to identify specific faults and their levels. The second level can also be divided into two different parts, in which case the faults will be first identified, and after that their levels. Fig. 5 shows the first and second level data analysis process using SOMs.

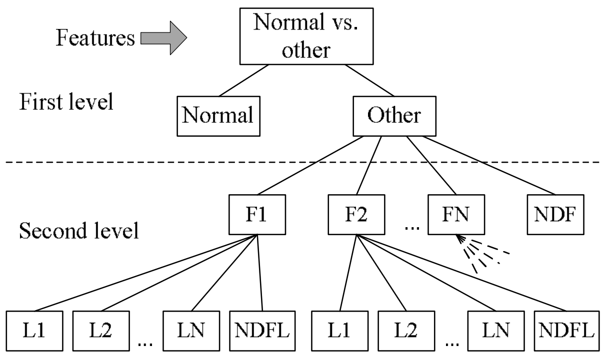

Fig. 5: *First and second level data analysis process using SOMs. F1 to FN are different faults, L1 to LN are different fault levels, NDF is not a defined fault and NDFL is not a defined fault level.*

In the quantization error method only data from the normal situation of the system is used in training and it is based on the distance calculation between the best-matching unit (BMU) and input vector. Euclidian distance measure is used here. The neuron whose weight vector is closest to the input vector x is called the BMU. Map units which are hit (a neuron has been chosen, at least once, as a BMU in the training phase) during the training are labelled after it as a normal situation. If clustering of input data is ascertained, semantic labels may be attached to certain units of the topological map. After this, a certain threshold is set, which determines the greatest distance on which recognition occurs. So when the network is tested, the distances between sample vectors from the testing data and all the weight vectors of the SOM, which are labelled as normal, are calculated. If the minimum distance is bigger than the threshold value set beforehand, then this sample vector is treated as a new event.

After new events have been detected and proved to be fault situations, these can also be trained to the SOM on the second level. Then these fault situations can be identified in the future using the SOM as a categorizer, which uses data from normal and fault situations in the training phase. In this method data are clustered to certain areas in the neuron layer, and semantic labels can be attached to certain units of the topological map, after training the map, which correspond to the state that has the most hits at a specific neuron.

Before using SOMs the feature vectors need to be normalized because large variable values would have a bigger meaning without this operation. Since the SOM algorithm is based on distance calculation, typically Euclidian distance, input vectors with large values would dominate the organization of the map. In this study, logistic transformation (SOM Toolbox, 2010) is used, which ensures that all values are within the range [0, 1]. The data are first scaled as in variance normalization: see Eq. 3, where $\bar{x}$ is the mean of **x** and s is the standard deviation of **x**. After that it is transformed with the logistic function, see Eq. 4.

$$\boldsymbol{x}_s = \frac{\boldsymbol{x}_i - \bar{x}}{s} \tag{3}$$

$$\boldsymbol{x}_l = \frac{1}{(1 + e^{-x_s})} \tag{4}$$

There are two variants of the SOM training algorithm in the Toolbox. In traditional sequential training data samples are presented to the SOM one at a time and the algorithm gradually moves the weight vectors towards them. In batch training the data are presented to the SOM as a whole and the new weight vectors are weighted averages of the data vectors. In this study the batch algorithm is used because it is much faster in Matlab.

Defining the number of map units is an essential part of the analysis. In the SOM Toolbox (SOM Toolbox, 2010), the default number of map units is defined according to Eq. 5, where m is the number of map units and n is the number of data samples. In this study, the number of map units is defined like this in Section 4 but in Section 6 smaller maps are used on the second level.

$$\mathrm{m} = 5\sqrt{\mathrm{n}} \tag{5}$$

It has been proved that the SOM algorithms can be initialized using random values for the weight (codebook) vectors, and still these vectors will be ordered in the long run. However, it is not the best or fastest way, and it is better if the initial values are already ordered.

In this study linear initialization (Kohonen, 2001) is used.

In the batch training algorithm, in each training step, the data are partitioned according to the Voronoi regions of the map weight vectors. This means that each vector belongs to the data set of the map unit to which it is closest. After this the new weight vectors are calculated according to Eq. 6, where $c = \arg\min_k\{\|\boldsymbol{x}_j - \boldsymbol{m}_k\|\}$ is the index of the BMU of data sample $\boldsymbol{x}_j$ and n is the number of data samples (Vesanto, 2000).

$$\boldsymbol{m}_i(t+1) = \frac{\sum_{j=1}^{n} h_{ci}(t)\boldsymbol{x}_j}{\sum_{j=1}^{n} h_{ci}(t)} \qquad (6)$$

The new weight vector is a weighted average of the data samples, where the weight factor of each data sample is the neighbourhood function $h_{ci}(t)$ at its BMU c.

3 Structure of Studied Mobile Machine and Monitored Component

The working hydraulics of a mobile machine is now studied to demonstrate the operation of the data analysis process. A forklift was chosen as a research platform to perform these studies. Different levels of internal leakage of the lifting cylinder are used here as fault situations, which were studied also in (Krogerus, 2007; Krogerus, 2008b). Although the position signal of the lifting cylinder is available here, which could also be used for leakage detection, it is not used here because idea is to develop more general method for condition monitoring which could be applied to wide range of mobile machines and faults. The data analysis process can be extended to include several hydraulic components, or even the whole system.

The hydraulic circuit of the work hydraulics of the forklift and location of the pressure sensors that were used in data analysis process are shown in Fig. 6.

The leakage between the annulus and piston sides of the lifting cylinder was created here by opening a bleed valve between the actuator ports. Three different leakage levels were used in this study and these were adjusted approximately to 0.5/1.0/2.0 l/min to the extending and retracting strokes using a flow meter. These flow values are the maximum leakage values during the extending and retracting strokes.

The size of the double-acting lifting cylinder was 63/40-1000. The supply pressure in these tests was 90 bar. No additional load was used in testing, but the weight of the forks was 101 kg, and the sledge, which slides between the masts, was 93.5 kg. More detailed information about the forklift is given in (Krogerus, 2008a).

The lift movement is actuated by an operator, who controls the work movements with potentiometer joysticks.

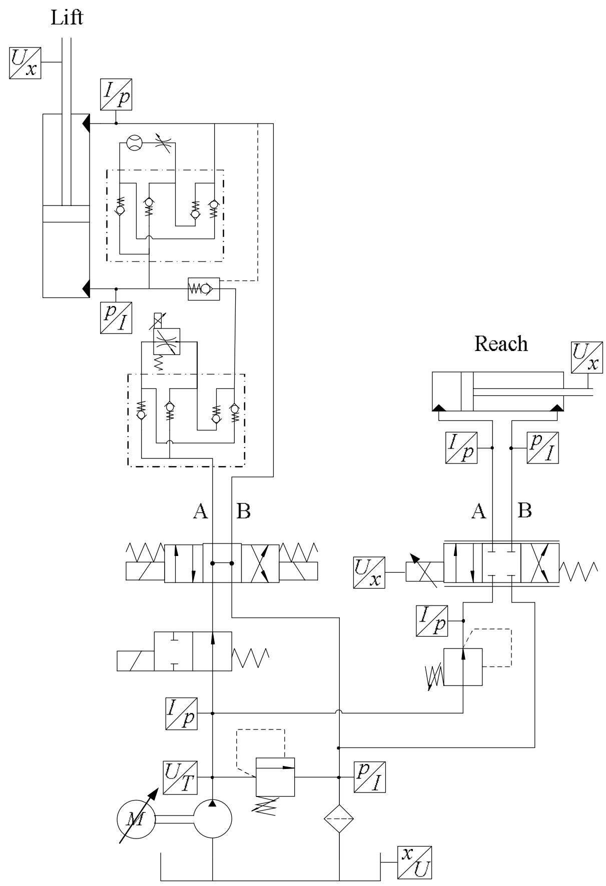

Fig. 6: *Hydraulic circuit of work hydraulics of forklift and pressure sensors used in data analysis.*

The pressure sensors were used to measure the pressure, in normal and different fault situations, from the actuator ports A and B of the lifting cylinder during the extending and retracting strokes of the cylinder. Other sensors shown in Fig. 6 were not used here for data analysis.

4 Measured Data for Analysis

The forklift was operated in normal and fault situations in the extending and retracting strokes, which were chosen as separate sequences, and parts of them are finally used in the data analysis. The starting and stopping of the sequence measurements used in data analysis was carried out manually. Otherwise the data analysis process was automated.

There were four different system states to measure, namely the normal state and three cylinder leakage levels. The same sequence was measured 20 times in each case. One half was used in training, and the other half in testing. The sampling frequency was 100 Hz.

In the choice of data to be analysed, a noteworthy point is the appearance of the effects of different faults at different stages of the driving sequences in the measurement data. Earlier research results (Krogerus, 2007; Krogerus, 2008b) have indicated that the biggest effects of different fault situations will be at the transient stages of the system in which the changes in the pressure and volume flows are at their biggest. After the transient stage, the effect of fault situations on the measurement results disappears, or at least decreases significantly. Thus, an attempt was made to reduce the amount of data to be analysed by directing the analysis only to that part of the measured data in which the deviations can be detected to be the clearest. 50 measurement points from the beginning of the sequence and 50 points after the control signal of the lifting movement has been cut off were taken into the data analysis. Selecting the training and testing data from the sequence measurements is illustrated in Fig. 7 and examples (training data used in this study) of measured pressures A and B from the extending stroke in normal and faults situations are shown in Fig. 8.

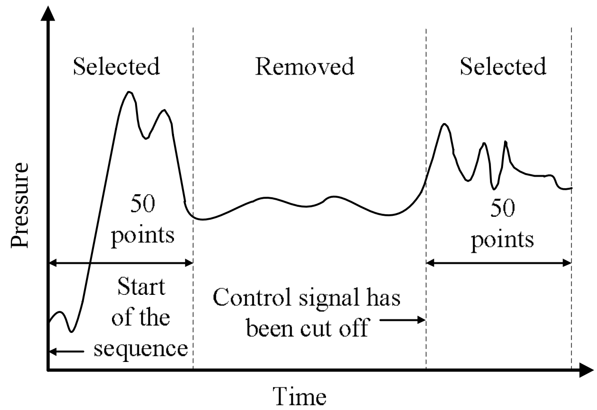

Fig. 7: *Selecting the training and testing data from sequence measurements.*

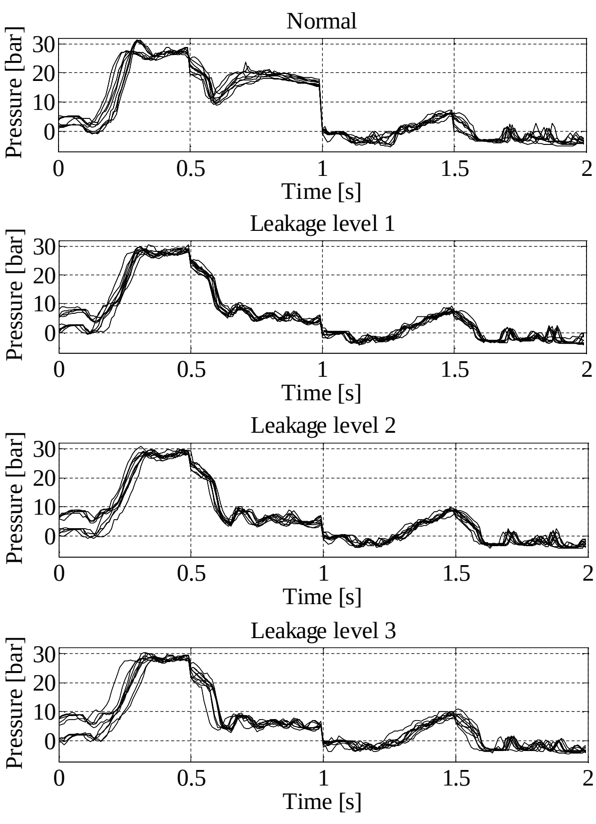

Fig. 8: *Examples of measured pressures A and B from extending stroke in normal and fault situations.*

In data analysis, one training vector includes the values of the extracted features of pressure A and pressure B from the actuator ports of the lifting cylinder. Level 5 discrete wavelet transform was used in extracting approximation coefficients from the measured pressures. Transform level was optimized based on classification results. In the extending and retracting strokes 9 coefficients were extracted from the merged signals of pressure A and B, altogether 200 points, so 9 values form one training vector.

There is a lot of overlap in the measurements between different states, see Fig. 8. There are different reasons for this, but the biggest is that there were variations in the rotation speed of the hydraulic pump between different instances of use and this caused a lot of variations between different measurement times. In this development version of the research platform the rotation speed of the pump is not measured so that it could be used in the data analysis, and the magnitude of the fluctuation was not discovered until the final stage of the research. Otherwise it could be instrumented and used also in the data analysis, and in such a way that the effect of fluctuation could be eliminated. Also the mechanical structure of the lift, especially the sledge between the masts, has an influence on the measurement results, mainly because of changing friction situations, which also apply to water hydraulic cylinders. Besides all these, the frequency converters of the forklift cause intensive interference on the measurement. Taking everything into consideration, the data analysis of this kind of system is much more challenging compared to previous laboratory systems (Krogerus, 2007; Krogerus, 2008b).

4.1 Sequence Recognition

When mobile machines are used in normal operation, the sequences driven are determined by the operating situations in which case the measurement data that are used in data analysis is obtained from undefined driving situations. Situations which appear occasionally and correspond to the training data with certain accuracy need to be separated from all the data measured. The definition and identification of driving sequences is important because the system, and the measurement data obtained from it, behave naturally in a quite different way in different driving situations, and especially when there are separate operators.

Individual sequences which are suitable for use in data analysis can be separated from the practical driving situations on the basis of the speed and direction information contained by the control signals. The control signals acceptable for data analysis can be filtered from other data by setting certain limit values for the rise, decay and duration times, and the magnitude of the control signal. Also a certain range is defined for change in the control signal after it reaches the maximum level. The idea of limit values of sequence recognition is shown in Fig. 9.

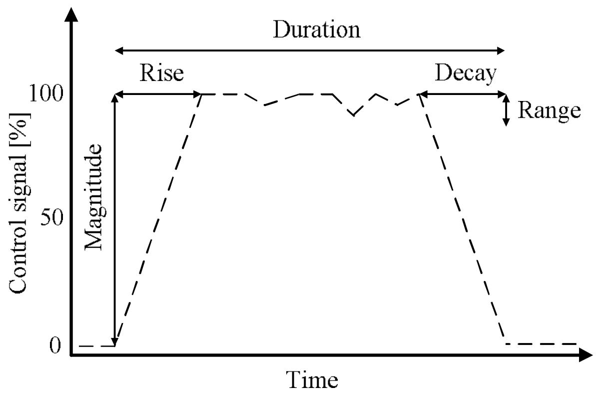

Fig. 9: *Limit values of control signal in sequence recognition.*

If the sequence is acceptable according the predefined limits, then the chosen parts of this sequence are analysed. The limit values were chosen on the basis of the test drives, where several sequences were recorded and examined to find as tight values as possible for the behaviour of the control signal so that it will be possible to perform the controls in question manually through the joysticks. In these test drives the controller joystick was quickly turned to its extreme position. This causes the rejection of several sequences in real applications, but most valuable information is achieved from these kinds of sequences. The chosen limit values are shown in (Krogerus, 2011).

5 Classification of the State of the System

The different system states: normal and three fault states, were classified using the extracted information from the pressure signals separately in the extending and retracting strokes.

Fault detection based on quantization error was used on the first level and the categorization method on the second level to define specific faults and their levels.

5.1 First Level

On the first level, 10 sequences from the normal situation were used in the training and 10 sequences from each system state in testing. It should also be noticed here that not all sequences passed the sequence recognition phase. This was because of too high rise or decay times, when there are less than 10 sequences in the actual data analysis.

On the first level, two different maps were trained. One was for extending strokes and the other for retracting strokes. The number of map units in both maps is 5 x 3. The thresholds in testing are 0.7 and 0.84. Table 1 presents the quality of the state recognition on the first level in the case of the extending and retracting strokes. From the results it can be seen in general that normal state and high fault levels are detected quite well. Some of the smaller levels of faults, especially in the retracting stroke, are classified as normal states because the difference between this small fault level and normal state is so small.

Table 1: Quality of state recognition on the first level in the case of extending and retracting strokes. N is normal, ND is not defined, L1 to L3 are different leakage levels of cylinder. Dark grey areas are classified correctly.

	Detected state of the system			
	Extending		Retracting	
State	N	ND	N	ND
N	8	1	7	3
L1	2	8	8	2
L2	0	9	5	5
L3	0	9	1	9

The threshold for extending and retracting strokes is a sensitive parameter because small fault levels are so close to normal state that the threshold had to be defined so that smaller fault levels would be detected as normal states. It was noticed during testing that when the level of the fault goes higher, the distance increases, which clearly shows the increase in fault level.

5.1 Second Level

The second level was divided into two parts. The faults were first defined, and after that their levels. Only cylinder leakage is studied here but in the case of several faults those could be separated in the first part of the second level. For example, in (Krogerus, 2011) different valve faults, namely impaired dynamics and erosive and abrasive wear of the valves, were studied.

The sequences where minimum distance was bigger than the threshold value on the first level were classified on the second level as a fault and furthermore different fault levels. On the second level, 10 sequences from each system state besides the normal state were used in the training.

In the first part on the second level, the number of map units in the extending strokes is 8 x 5, and in the retracting stroke 11 x 4. Table 2 presents the classification results of the specific fault situations. The faults were detected quite well. Normal state is also shown here because some of the sequences from the normal situation were classified as not defined on the first level. Table 2 shows which sequences classified as other than normal states on the first level were identified here as fault states.

On the second part on the second level, two different maps were used. The number of map units in the extending strokes is 5 x 2, and in the retracting stroke 3 x 3. The sizes of the maps in relation to the amount of training data are smaller here than on the first level and on the first part of the second level, which defines the fault. Better results were obtained with these smaller maps.

Table 2: Quality of state recognition on the first part of the second level in the case of extending stroke. N is normal, L is leakage, ND is not defined, L1 to L3 are different leakage levels. Dark grey areas are correct states.

	Identified state of the system					
	Extending			Retracting		
State	N	L	ND	N	L	ND
N	8	0	1	7	0	3
L1	2	8	0	8	2	0
L2	0	9	0	5	3	2
L3	0	8	1	1	8	1

Table 3 present the classification results of the levels of the fault situations. The levels of the faults are not recognized as well as the specific faults. The biggest problems are in the low levels of cylinder leakage in the retracting stroke. In general, higher fault levels are better detected correctly, but there are also some exceptions, such as level 1 of cylinder leakage in the extending stroke, which is better detected than at levels 2 and 3.

Table 3: Quality of state recognition on the second part of the second level in the case of extending and retracting strokes. N is normal, L1 to L3 are different leakage levels, NDF is not a defined fault and NDFL is not a defined fault level. Dark grey areas are correct states. Light grey areas are correct faults, but level is wrong.

		Identified state of the system					
	State	N	L1	L2	L3	NDF	NDFL
Extending	N	8	0	0	0	1	0
	L1	2	7	0	1	0	0
	L2	0	3	2	4	0	0
	L3	0	2	0	6	1	0
Retracting	N	7	0	0	0	3	0
	L1	8	0	0	0	0	2
	L2	5	0	0	3	2	0
	L3	1	0	1	7	1	0

6 Sensitivity Analysis of the Data Analysis Process

Sensitivity of the data analysis process is really important when only discrete fault levels are used in the training phase, as in this case. Small changes in the fault level can have an effect on the final result of the analysis. Also fault levels that are between the trained ones should be detected as the closest fault level.

6.1 Simulation Model

Based on earlier studies of the forklift, it was noticed that there were changes between different instances of use. Therefore, a simulation model of the lifting movement of the forklift, based on physics equations, was made because it is stable between different instances of use and the repeatability of the tests is good. By means of this model the effects of changes in the fault level to the performance of the data analysis process were studied. Using this simulation model data were generated which were then used in training and testing of the data analysis methods. Matlab Simulink (Mathworks Inc., 2010) was used for the simulation.

The model was verified with supply pressure, cylinder chamber pressures, pressure between directional valve and Wheatstone bridge connection, and position and velocity of the cylinder. More detailed information about the simulation model and the verification process is given in (Krogerus, 2011).

After verification, measurement noise was added to the simulated pressure signals A and B, which were used in the data analysis. White noise was used to simulate the measurement noise.

Pressure dependent laminar flow was used to model the leakage in the cylinder to study the effect of the fault level changes in the data analysis process; see Eq. 7.

$$Q_{\mathrm{i}} = \mathrm{K}_{\mathrm{leak}}(p_{\mathrm{A}} - p_{\mathrm{B}}) \tag{7}$$

6.2 Simulated Data Used in the Sensitivity Analysis

The simulation model was driven to obtain 10 sequences for training and 10 sequences for testing from each state that were used in training and testing. A specified control sequence was used that is similar to the sequences measured in the test drives of the forklift. Table 4 show the levels of fault which are used to study the effect of fault level change. When the effect of the changes in the fault level was studied, data only from the normal situation was used in training on the first level. The fault levels that were used in training or testing are marked with X in the table.

Table 4: Levels of fault and their use in sensitivity analysis.

Level	Fault type and magnitude	Training		Testing	
		1st	2nd	1st	2nd
1	Leakage 0.50 l/min	-	X	X	X
2	Leakage 0.75 l/min	-	-	X	X
3	Leakage 1.00 l/min	-	X	X	X
4	Leakage 1.50 l/min	-	-	X	X
5	Leakage 2.00 l/min	-	X	X	X

The variables used in the data analysis were pressures A and B from the actuator ports of the lifting cylinder. The sampling frequency with the pressure measurements was 100 Hz. Training and testing data were selected in the same way as in Section 4.

Before classification, level 2 discrete wavelet transform was used in extracting approximation coefficients. Lower level transform were used than with in Section 4 because transform level was optimized based on classification results. The extending and retracting strokes were processed separately. The parts of the pressure signals A and B were first merged, resulting in a signal of 200 points. Then, 52 coefficients were extracted from the merged signal. Therefore, a training vector consists of 52 values.

6.3 Classification Results of the Sensitivity Analysis

Leakage levels L1, L3 and L5 are used in the training and levels L1 to L5 in the testing. The levels were determined by the maximum leakage during the driven sequence and were the following: 0.5, 0.75, 1.0, 1.5 and 2.0 l/min. Levels L2 and L4 were studied in terms of how well they are classified as a normal or fault state on the first level of the SOM and how well they were classified as the closest possible fault level on the second level of the SOM.

On the first level, two different maps were trained. One was for the extending strokes and the other for the retracting strokes. The number of map units on the first level is 4 x 4 in both maps. Figures 10 and 11 show the distances between the BMUs and the testing vectors. In the extending stroke the threshold was set to 1.9 so that all the normal state sequences were classified correctly. This, however, results in few sequences of the smallest fault level being classified as normal. The distance clearly increases when the fault level becomes higher. In the retracting stroke the difference between the normal and fault situation was clear. This is because in the normal situation in the beginning of the retracting stroke pressure A was higher than in cases of leakage. During the sequence differences between different states were smaller. However, the differences between the fault levels were very small.

Table 5 shows the quality of the state recognition on the first level. 94 % of the sequences are classified correctly in the extending stroke if the threshold is set to 1.9. Respectively, in the retracting stroke 100 % of the sequences are correct if the threshold is set to 2.5.

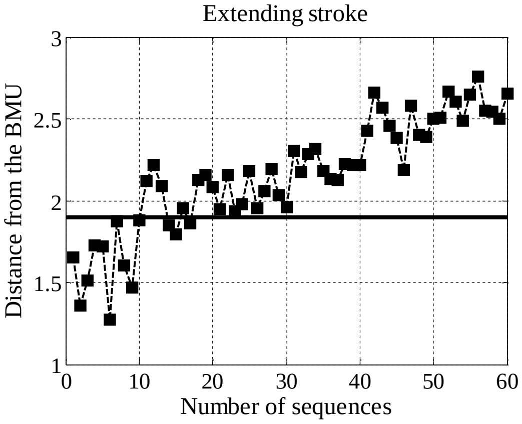

Fig. 10: *BMU distances from extending strokes. Sequences are in order normal, fault levels 1, 2, 3, 4, 5.*

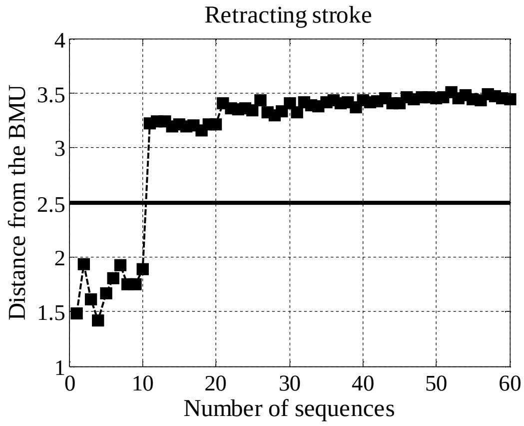

Fig. 11: *BMU distances from retracting strokes. Sequences are in order normal, fault levels 1, 2, 3, 4, 5.*

Table 5: Quality of state recognition on the first level in the case of extending and retracting strokes. N is normal, ND is not defined and L1 to L5 are different leakage levels. Dark grey areas are classified correctly.

	Detected state of the system			
	Extending		Retracting	
State	N	ND	N	ND
N	10	0	10	0
L1	3	7	0	10
L2	0	10	0	10
L3	0	10	0	10
L4	0	10	0	10
L5	0	10	0	10

On the second level, the number of map units in the extending stroke is 2 x 5 and in the retracting stroke 3 x 3. The second level is not divided here into two different parts. Instead, the levels of faults are directly classified on the second level because only fault levels are studied. Table 6 shows the results of the quality of the state recognition on the second level. The levels that are not used in training are better classified, as the closest fault level, in the extending stroke. In the retracting stroke about half of the sequences that are not used in training are correctly classified, and half of those are classified as a not defined fault level (NDFL). 90 % of the sequences in the extending strokes are classified correctly with fault levels that are used in training, and 90 % of the sequences classified as the closest fault level with fault levels that are not used in training. Respectively, in the retracting stroke 100 % of the sequences are correct in the case of the fault levels that are used in training and 55 % of the sequences classified as the closest fault level in the case of fault levels that are not used in training.

Table 6: Quality of state recognition on the second level in the case of extending and retracting strokes. N is normal, L1 to L5 are different leakage levels and NDFL is not a defined fault level. Dark grey areas are correct states. Light grey areas are closest correct states.

	Identified state of the system							
	Extending				Retracting			
State	L1	L3	L5	NDFL	L1	L3	L5	NDFL
L1	7	3	0	0	10	0	0	0
L2	5	5	0	0	2	3	0	5
L3	0	10	0	0	0	10	0	0
L4	0	4	4	2	0	3	3	4
L5	0	0	10	0	0	0	10	0

Conclusions

The main goal of this research was to study the operation of the data analysis process in a small mobile machine and also the sensitivity of this process.

A forklift was chosen as a research platform. This kind of testing environment proved to be a more difficult environment compared to previous laboratory systems (Krogerus, 2007; Krogerus, 2008b). The results of the analysis, related especially to state recognition concerning the specific faults and levels of different faults, were not as good as with those in laboratory systems.

The result of the analysis on the first level was good, which means that deviations from the normal state were detected well. However, there were some problems with small levels of faults. In practical applications this would mean that a fault can be reliably detected after it exceeds a certain level, which needs to be determined for each case. To raise the level of the results, better measurements would still be needed, but the overall performance of the data analysis methods proved to be good.

Usually, data from fault situations are not available at the beginning of the life cycle of the hydraulic system unless there is data history available from similar systems that have similar symptoms near an emerging fault situation. More often, only deviations from the normal situation in measured variables are detected during an operation where the quantization error method is used, and the actual fault can be confirmed with certainty after more specific examination. Therefore, the first level in the classification process using SOMs is the most important in the actual system.

After confirmation of the fault situation, information from this state can be used in the future to detect and identify this specific fault situation and its level. The rate of change in the fault level tells how fast the level of the fault is increasing and how long the system can still be used.

Sequence recognition based on a limit of values of the control signal was proved to be suitable to select appropriate sequences for use in data analysis, which would be comparable to ones that have been used in the training phase. As an alternative to this kind of approach, test sequences could be specified and driven; for example, in the beginning of the working day when the machine is started. Also, different repetitive work scenarios, other than presented in this study, can be specified for different machines.

To study the sensitivity of the data analysis process, a simulation model of the lifting movement of the forklift was made. This model was used to produce data for analysis purposes. It was noticed from the results of the analysis that it is possible to use only a few fault levels in the training phase and still maintain the performance of the data analysis process. These results prove the generalization capability of the used data analysis process.

The usability of the results is one of the most important parts of this kind of study. Based on the results of the mobile test platform shown here and the previous test systems, it can be claimed that by using wavelet coefficients of pressure transients as features which are then classified into different categories it is possible to detect and identify fault situations and their levels during normal operation of the hydraulic system. However, before the analysis methods researched in this study can be fully exploited in commercial applications there are still challenges. The most essential include:

- Deeper analysis of different operators and different applications should be made so that the limit values of the sequence recognition would be better optimized.
- Data selection for the analysis should be optimized for different applications so that the right number of measurement points is taken into analysis.
- Threshold optimization of the SOM needs to be done for different systems separately. General threshold values cannot be used. Automation of this process is proposed.

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Nomenclature

a	Wavelet scaling parameter	[-]
a_j	Signal before decomposition	[-]
a_{j+1}	Wavelet approximation coefficient	[-]
a_{j+2}	Wavelet approximation coefficient	[-]
c	Best-matching unit (BMU)	[-]
$\bar{g}$	High-pass filter in DWT	[-]
$\bar{h}$	Low-pass filter in DWT	[-]

h_{ci}	Neighbourhood kernel around winner unit	[-]
I	Current	[A]
K_{leak}	Flow gain	[m^4·s/kg]
$\boldsymbol{m}$	Weight vector	[-]
m	Number of map units	[-]
n	Number of sample vectors	[-]
p	Pressure	[Pa]
p_A	Pressure in A line	[Pa]
p_B	Pressure in B line	[Pa]
Q_i	Internal leakage of cylinder	[l/min]
t	Discrete time	[-]
t	Time	[s]
T	Temperature	[˚C]
U	Voltage	[V]
x	Position	[m]
$\bar{x}$	Mean of vector $\boldsymbol{x}$	[-]
$\boldsymbol{x}$	Data/input vector	[-]
$\boldsymbol{x}_s$	Variance normalized feature vector	[-]
$\boldsymbol{x}_l$	Logistic normalized feature vector	[-]

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