AUTOMATIC PROCESS PATTERN RECOGNITION FOR MOBILE MACHINERY

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ABSTRACT

In nowadays-used mobile construction machinery, the knowledge of the usage profiles is in fact not available. This lack causes a design phase, which is characterized by assumptions. This affects every development step in which the application has a significant influence on the design, what in nearly every section is the case (e.g. dimensioning of structural-mechanical part, drive system development, hydraulic structure construction). This paper presents the development of a process pattern recognition (PPR). Process patterns are from an engineering perspective a class of uniform or similar working cycles. The developed system will answer the question which working-cycles the machine executes during its lifetime.

KEYWORDS: process pattern, pattern recognition, machine learning, usage profiles

1. INTRODUCTION

The versatile use of typical construction machinery in field is a crucial criterion during the development process. Nobody knows which tasks the operator executes and furthermore how sensitive they will be done. Additionally to this operator-guided process, the changing environmental conditions, which include the weather and the consistence of the working medium, have to be observed during the design-phase.

The researchers at the TU Dresden started in further projects to deal with these issues. In [6] a definition of so-called process patterns was introduced with the aim of developing a method capable of classifying load consequences. As mentioned before, process patterns are defined as a class of uniform or similar working cycles. This definition was applied within the context of the project by measuring the loads exerted on relevant components and allocating load consequences with a similarly damaging effect to specific process patterns. The resultant classes provided a basis for the determination of process-dependent instances of partial damage that can be superpositioned and extrapolated to a specific period of machine operation. A key prerequisite to realize this is the knowledge of the machine's probable operating parameters. Against this backdrop a method enabling the definition of usage profiles for mobile machines was developed [8]. The broad range of knowledge already available in the field of pattern recognition in parallel areas of application such as image and speech recognition was used as a foundation for the selection and adaptation of algorithms enabling the definition of customer usage profiles that in turn facilitate the realistic measurement of mobile construction machines when in operation. The resultant algorithms enabled the online recognition of working cycles and the allocation thereof to pre-defined process patterns during machine operation. Real-time data evaluation kept data storage requirements to a minimum despite the very long observation periods involved, as only the frequency with which individual patterns occurred needed to be recorded. The researchers could show, that this method basically enables the user to record the occurring working patterns. The extension of this method leads to the requirement of an automatically data preparation to get independent from the special sensor signals and makes the method applicable to different types of machines.

Based on the most typical wheel loader's pattern called y-cycle the whole development is presented in this contribution. In chapter 2 the basics of an HMM and its suitability for the application to the example is presented. Besides this chapter introduces the reader in the definition of the HMM and what the definition of the state and transition probabilities means. Furthermore the suitable sensor signals, which are necessary for a most accurate recognition rate, are discussed. After the validation of the developed method is shown, chapter 3 decribes the actual development with the extension of the method for the efficiency analysis and the structure of the recognition system. Finally, chapter 4 concludes the paper's content.

2. HIDDEN MARKOV MODELS AND THE Y-CYCLE

2.1. Hidden Markov Models

The first step included the choice of suitable algorithms for this application. The aim to detect patterns from signals is similar to parallel areas such as speech and image recognition. Every recognition-method has the similar structure, shown in Figure 1.

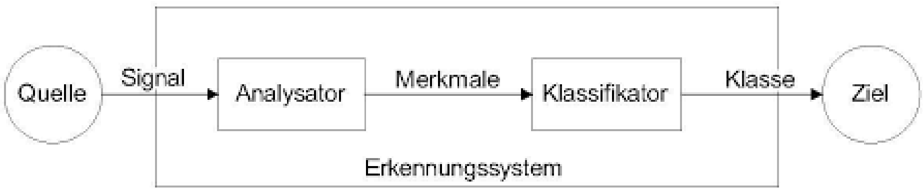

Figure 1. Structure of a recognition system [4]

The workflow contains the signal source, which is imported to the analyser, where the data preparation, e.g. frequency filtering, is being executed. After that a classification and the decision, to which class the signal is allocated is done. The main difference between the available algorithms is the conversion of the physical signal to the characteristic classification type. For this application the typical pattern recognition methods have been investigated. These were the template matching procedure (TM), artificial neuronal nets (NN), support-vector-machines (SVM) and hidden markov models (HMM), which are described in detail in [3].

HMMs meet the requirements. First of all that they offer the opportunity to deal with a continuing data stream. In the field of online application, this is the most important issue, which had to be fulfilled. Furthermore HMMs can manage the high variation of the duration of the working cycles, which occurs in nearly every successive cycle. The separation of the single working cycle out of one dataflow had to be ensured in the pattern recognition. With HMMs this is convertible.

HMMs are widely used within the context of word recognition ([5],[1]). This involves the overlaying of the speech signal with a window function and the calculation of the frequency spectrum. The maxima observed at characteristic frequencies within the spectrum depend on the tone spoken, and are summarised in a feature vector which is transferred to the HMM. A pre-trained vocabulary is then used in combination with the Viterbi algorithm to determine the word with the maximum level of probability. Their mode of operation makes HMMs highly suitable for the recognition of sequences of various lengths, with analysis of the previous signal history used to create a type of memory. The relatively simple mathematical operations involved and the compact description of process patterns with the aid of probability distribution make the procedure especially suitable for implementation on a microcontroller.

2.2. Model definition

This chapter will handle the theoretical basics of the HMM and the realization of the method regarding to the application as pattern recognition algorithm in mobile machinery. The shown example is a wheel loader's y-cycle.

The basic idea behind the HMM is to interpret the issue under investigation as a temporal sequence of so-called states. The machine can only be in one of the n possible states (Z). In addition, it is assumed that the state of the system at time t+1 is only ever dependent on the immediately preceding time t. Nevertheless it is not possible to either observe such states in practice or measure them using sensors. Observable variables (V) (sensor signals) are instead used to determine the hidden state of the system. Transferred to the y-cycle there are 4 states the machine could belong to: Driving into the heap of excavated material, driving out of the heap, driving to the point of unloading and driving from the point of unloading back to the point of loading (see Figure 2).

Figure 2. Wheel loader's y-cycle

It is possible to determine which of the 4 states the machine is currently in by analysing measured sensor signals (here: the force applied by the lifting cylinder and the driving speed) in combination with transition and output probabilities. These probabilities are the main parameters of the model definition. Transition probabilities $a_{i,j}$ describe the probability of the machine being in state j at time t if it was in state i at the previous time increment t-1 (equation (1)).

$$P\left(Z(t) = Z_j \middle| Z(t-1) = Z_i\right) = a_{i,j} \qquad (1)$$

If you have a system with n possible states, the transition probabilities are summarised in A, a nxn matrix. The diagonal elements describe the probability of the machine of staying in the same state in two following time steps. Above and underneath the diagonal elements are the probabilities of changing in the next or the prior state located.

In addition to the transition probabilities, the observation probabilities $b_{n,m}$ are the second element of HMMs, which have to be determined. They describe the probability of a specific sensor value being observed in the machine in the respective state. The observation probabilities are being summarised in B, a nxm matrix. This includes the n states and m possible sensor values.

Transition and observation probabilities are defined with the aid of training data. For each process pattern a HMM has to be trained. As mentioned before the shown pattern in this contribution is a wheel loaders y-cycle. The training is one of the basic problems for HMMs. Given are the observation sequence and the sequence of the states. The first aim is to fill the matrices A and B. This is realized with a simple counting-algorithm of the states, the observations and their transitions and to classify them into the frequency matrix. One main problem, which occurs before the training proceeds, is the definition of the state sequence. In contrast to typical applications of the HMM, e.g. speech recognition as shown in [7], the training problem could not be solved with the Baum-Welch-Algorithm or the Viterbi-training. Instead an instance counting is used to train the HMM. The goal to compute the HMM which produces a state sequence out of observations can be realized by counting the hidden state transitions and the output emissions and by determining the probabilities of the occurrence. To realize this, there is a need to assign the state sequence to the measured observation. Mieth showed in [8] a semiautomatic way to implement this by developing a special GUI used in this contribution.

Figure 3 shows a figure with the assignment of four states to the wheel loaders driving speed. This is the data basement for the described HMM training.

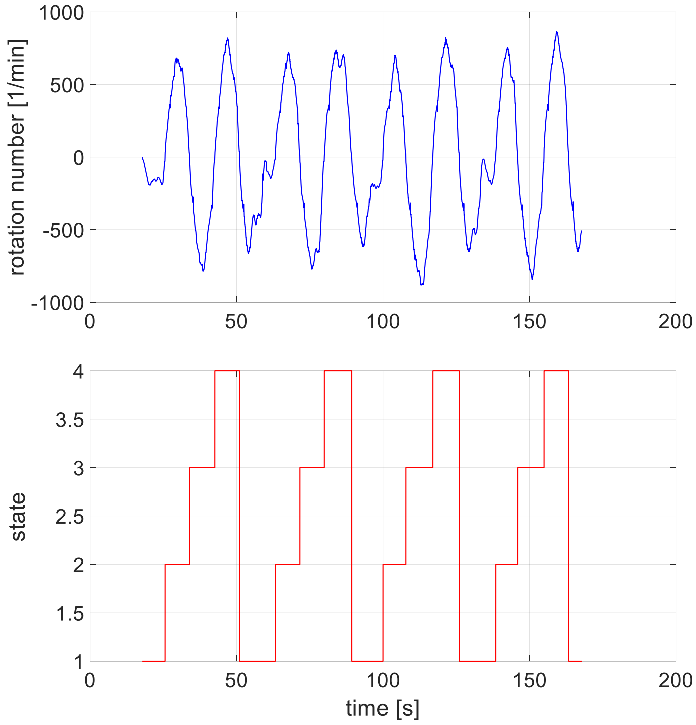

Figure 3. State distribution

$$A = \begin{bmatrix} a_{1,1} & \cdots & a_{1,n} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,n} \end{bmatrix}$$

$$A_{0.1} = \begin{bmatrix} 0000 \\ 0000 \\ 0000 \\ 0000 \end{bmatrix} \quad A_{0.2} = \begin{bmatrix} 1000 \\ 0000 \\ 0000 \\ 0000 \end{bmatrix} \quad A_{0.3} = \begin{bmatrix} 1000 \\ 0000 \\ 0000 \\ 0000 \end{bmatrix}$$

$$A_{0.4} = \begin{bmatrix} 0{,}75 & 0{,}25 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad A_{0.5} = \begin{bmatrix} 0{,}75 & 0{,}25 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$A_{0.6} = \begin{bmatrix} 0{,}75 & 0{,}25 & 0 & 0 \\ 0 & 0{,}5 & 0{,}5 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad A_{0.7\ldots0.9} = \begin{bmatrix} 0{,}75 & 0{,}25 & 0 & 0 \\ 0 & 0{,}5 & 0{,}5 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad A_{1.0} = \begin{bmatrix} 0{,}75 & 0{,}25 & 0 & 0 \\ 0 & 0{,}5 & 0{,}5 & 0 \\ 0 & 0 & 0{,}8 & 0{,}2 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$A_{1.1} = \begin{bmatrix} 0{,}75 & 0{,}25 & 0 & 0 \\ 0 & 0{,}5 & 0{,}5 & 0 \\ 0 & 0 & 0{,}8 & 0{,}2 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \boxed{A_{1.2} = \begin{bmatrix} 0{,}75 & 0{,}25 & 0 & 0 \\ 0 & 0{,}5 & 0{,}5 & 0 \\ 0 & 0 & 0{,}8 & 0{,}2 \\ 0 & 0 & 0 & 1 \end{bmatrix} = A}$$

time [s]	states
0,1	1
0,2	1
0,3	1
0,4	2
0,5	2
0,6	3
0,7	3
0,8	3
0,9	3
1,0	4
1,1	4
1,2	4

Figure 4. Synthetic example for instance counting transition matrix A

Figure 4 shows an abstract overview, which illustrates the training after the state definition with the instance counting method. The counting for the observation sequence is not described in detail, because it is done a similar way.

During the recognition subsequently the trained HMM determines the states with the highest level of probability at each time increment as well as the overall probability of the state sequence up to that point with the aid of the Viterbi algorithm.

2.3. Suitable sensor Signals

As mentioned before the wheel loader y-cycle suitable sensor signals for the recognition were the force applied by the lifting cylinder and the driving speed. These were not random chosen but in fact determined before applying the trained HMM. It was the next task to find the variables, which yielded the most accurate prediction of hidden states. This was achieved with the aid of a discriminant analysis according to Fisher, which was used to investigate the spread of two variables. A variable was deemed to be suitable if the spread of the measured values between two different states was significantly greater than the spread yielded by the sensor within a state. The discriminant analysis is based on the assessment of variances of the information of the class affiliation. The sensor signals n are merged to the defined states S and the spread s_w within one state is calculated with equation (2).

$$s_w = \frac{1}{n-S} \sum_{i=1}^{S} \sum_{j=1}^{n_i} \left(x_{ij} - \bar{x}_i\right) * \left(x_{ij} - \bar{x}_i\right)^T \qquad (2)$$

x_{ij} ... data point j of class i

$\bar{x}_i$ ... median of data points of class i

The spread s_b between the classes is calculated with the equation shown in (3).

$$s_b = \frac{1}{S} \sum_{i=1}^{S} (\bar{x}_i - \bar{x}) * (\bar{x}_i - \bar{x})^T \qquad (3)$$

If the spread between the states is higher than within the states the quotient D, called fisher-criteria, is getting higher than 1 and the signal is suitable.

$$D = \frac{s_b}{s_w} \qquad (4)$$

For the existing measurement data of the y-cycle the force applied by the lifting cylinder and the driving speed gave the best results (Figure 5) and will be used for the recognition.

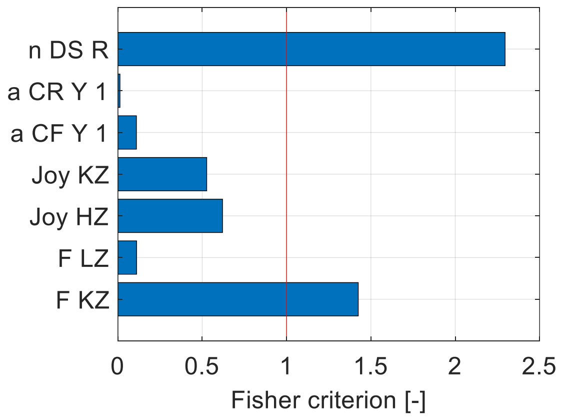

Figure 5. Result discriminant analysis

2.4. Validation

The algorithm required for pattern recognition and the processing of training data in preparation for the training of the HMM was realised in the MATLAB environment. The validation was executed with different data sets of the wheel loaders y-cycle measured in a former project. The installed machine was a Liebherr L 576. The data sets are characterised by different drivers and due to this varying sequence times of the single cycle. This issue enables the investigation of the operator leverage. Because every process in the field is operator-guided this is a very important point.

This contribution bases on the work of Mieth. He showed in [8] that the pattern recognition in the described way is basically possible. He used the former mentioned GUI to assign states to the sensor signals and hereupon teaches the HMMs. After that, he implemented them on a ESX-3M control device from Sensortechnik

Wiedemann. For the validation, he uses a machine model integrated in a HiL test bench in combination with the control device. An interface was integrated into the machine model in order to enable the machine operator to interact with them using control devices in the form of a joystick and pedals. Additionally to this virtual validation, he implemented the control device on an excavator. He investigated his algorithms with two different operators. The cycles were carried out in a random order but in roughly equal numbers. This made it possible to compare the time curves recorded for the sensor signals against the results yielded by the recognition system, thus enabling the determination of the rates of recognition achieved. The recognition rates achieved 80 to 83 % in the case of process pattern excavating and 76 to 85 % in the case of process pattern scraping. The testing of the actual machine yielded a recognition rate of the working cycle excavating of 76%. The recognition rate was slightly lower than at the preliminary examinations. This could be attributed to a large extent to the fact, that during the validation measurements, machine states repeatedly occurred that were only insufficiently covered by training data.

For the validation of the HMMs described in this paper first the influence of the data set and with that the described operator leverage is shown. Therefor the states were assigned to every of the 4 data sets by the manual GUI like Mieth uses it and after that with every data set a HMM was trained. This approach is a kind of supervised learning. The next step was to apply the 4 data sets to the trained HMM and calculate the recognition rate. The referred way to determine suitable signals was applied and the mentioned sensor signals were used for the recognition. The results are shown in Table 1.

Table 1. Results HMM training and application

		Data set (train)				
		1	2	3	4	
Data set (use)	1	96,6	93,3	50	23,3	Recognition rate [%]
	2	56,7	90	33,3	33,3	
	3	50	0	50	36,7	
	4	13,3	73,3	73,3	80	

Different data sets lead to different recognition rates. A replicable relationship between train data and use data was not detectable. Although the states were previously assigned to the data sets, the recognition rate alternates between 100% to 0% and this was not suitable for a detection system.

2.5. Between conclusion and problems

The examination of the method showed, that in former contributions the HMMs lead to adequate recognition rates if states will be assigned in a manual way to the training data. Furthermore, the investigation of the y cycle’s data set with the data-preprocessing leads to different recognition rates with a big spread. Both issues are crucial for the extension of the data-preprocessing in a way, that the states have not been assigned manual to the data set, that the determination of suitable sensor signals has to be simplified or better avoided to meet the effect of the train data and in the end the training has to be automated. All these issues will lead to an unsupervised learning of unknown patterns and the later detection of them and thereby to an automatic system for process pattern recognition.

3. QUADRANT METHOD

3.1. Development

The approach, described in the following chapters, was first chosen due to the requirement of the independence of certain sensor signals. The second issue described, the automatically assignment of the states, can also been realised with this method. The basic idea is the regard of every single load and its working point in the speed-force- respectively speed-torque-diagram. Not the absolute values are examined, but only the appearance in the quadrant of the particular diagram of the load in every time step is observed (Figure 6).

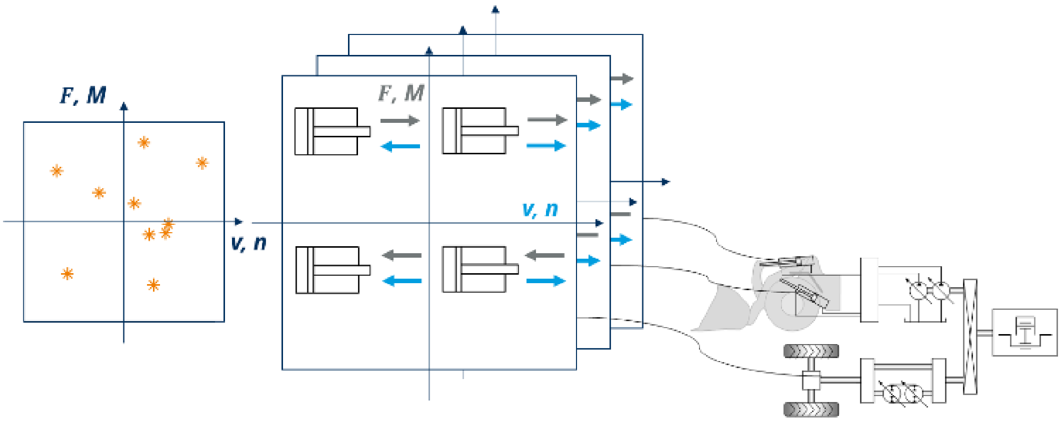

Figure 6. Quadrant method

By regarding the wheel loader, the lifting cylinder for example can be grouped into ascending with pulled load, ascending with pushed load, levelling with pulled load and levelling with pushed load. The approach includes all on mobile machine installed actuators (cylinder and hydraulic motors). At the wheel loader three actuators can be adducted. These are the drivetrain motor, the bucket cylinder and the lifting cylinder. In every time step, the combination of each actuator's quadrant will be determined. This accounts for $5^3 = 125$ possible combinations. Table 2 shows an example of the determination of the combination distribution at the first six time steps.

Table 2. Determination of the combination distribution

		load						**combination**
		1		2		3		
Time step	1	1	1	1	-1	0	0	1
	2	1	-1	1	1	0	0	2
	3	1	-1	-1	1	-1	1	3
	4	1	1	1	-1	0	0	1
	5	1	1	1	1	0	0	4
	6	1	-1	1	1	0	0	2

These are the four mentioned quadrants and additionally the idleness both of the cylinders and the motor. It was defined, that if one of the regarded actuator's potential (speed) or flow variable (force, torque) is equal zero, the variable, which is unequal zero, will be set zero. This is possible because in both cases the power is calculated to zero (equation 5).

$$P = F, M(flow) * v, n(potential) \qquad (5)$$

This leads to five possible positions for every actuator. With three actuators this leads to 125 possible combinations. By computing the combination in every time step a distribution is achieved, which is the substructure both of the training and of the application of the HMM. The first of the defined goals, the independence of certain sensor signals is attained. The next step is the elimination of the manual assignment of the states to the observed sensor signals. For this purpose, a classification into four classes of the determined combinations is executed. The result is a four-state-distribution which is trained on the HMM. This is a possibility to assign the states to the sensor signals or in this case to the combination distribution without doing this manually. The idea behind this procedure is the occurrence of the same quadrant combinations within the process patterns. Due to that, the calculated state distribution (Figure 7) is repeatable. This described method was implemented as an algorithm in the MATLAB environment. With the resulting data (Figure 7) a HMM was trained.

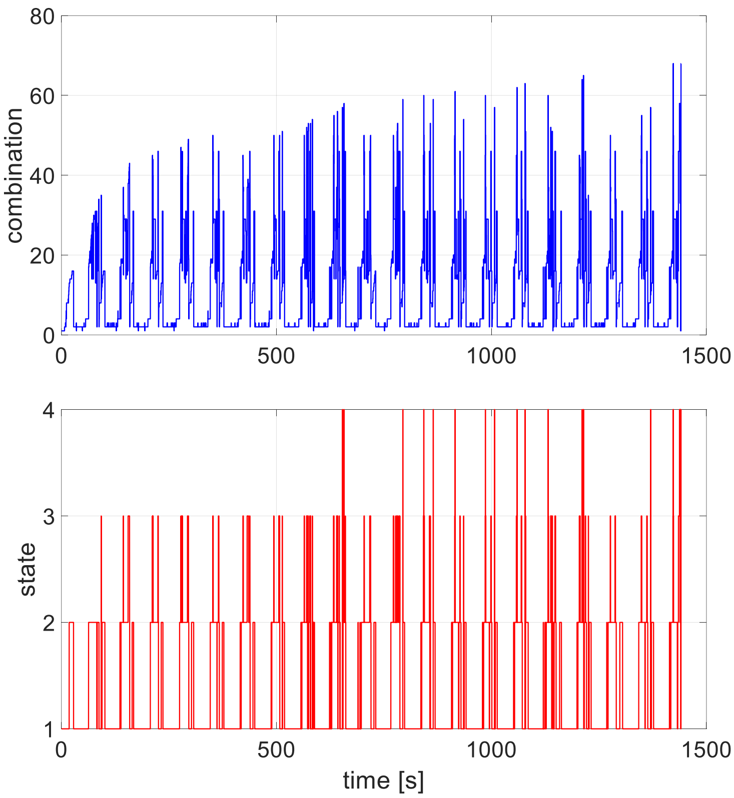

Figure 7. Results quadrant method

3.2. Validation of the quadrant method

To get comparable results the data sets of the wheel loaders y-cycle were taken again and the combination distributions were calculated with the developed algorithm. After that, the HMMs were trained and applied with these data sets. The calculation with the computed recognition rates of the trained HMMs shows Table 3.

Table 3. Results HMM training and application after quadrant method

		Data set (train)				
		1	2	3	4	
Data set (use)	1	100	100	100	100	Recognition rate [%]
	2	100	100	100	100	
	3	100	100	100	100	
	4	100	100	100	100	

By using the preprocessed data every train data set with every use data set achieves 100% of the recognition rate. This is first of all an improvement of the results in 2.4 and a promising substructure for the further development of the recognition system.

3.3. Application of the quadrant method

3.3.1. Efficiency evaluation

The manual assignment of the data-preprocessing and thereby the states definition of the sensor signals is a working method, if a big amount of data of one specific process pattern applied on one specific machine is available for the training of the HMM. The quadrant method is focussing both on a machine comprehensive application of the HMM and on the creation of an interface for an efficiency evaluation. Within the second part of the research project an efficiency model was developed, which is not described in detail in this paper. The point of contact to the described method is that the evaluation of the efficiency can only be answered with the knowledge of the usage profiles. With the detected patterns, an efficiency evaluation can be executed. Only the working point distribution is necessary. The quadrant method provides, besides the mentioned issues, the opportunities that working points are considered in the step before determining the combinations of the actuators. The combining of the usage profile with the efficiency model is simply realisable. This is a further application of the quadrant method and shows the potential of this approach.

3.3.2. Macro HMM and detection system

The development of a detection system and thereby the interface of the efficiency model is described in this chapter. The training of an HMM with automatized generated states and combinations distributions was shown in 3.1. However, the recognition system has to detect different patterns and besides has to learn unknown patterns, what correlates with an unsupervised learning. In [2] Balke mentioned therefor a macro HMM, which is suitable for the detection of different patterns. The structure of such a macro HMM of a wheel loader with the process patterns y-cycle, pushing, idling and driving is shown in Figure 8.

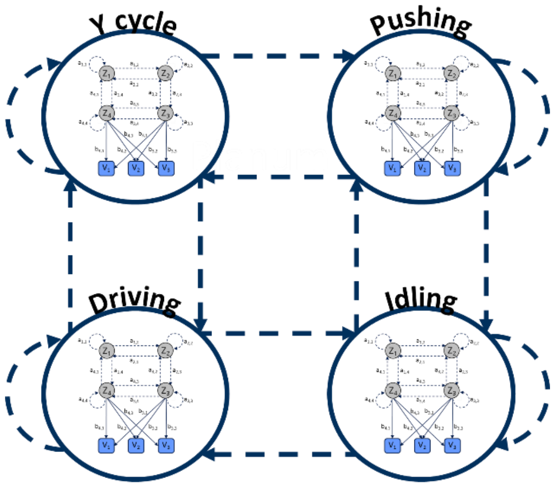

Figure 8. Structure of a macro HMM

In a macro HMM an important issue is how the HMMs are passed during the calculation. Either in a serial way with starting and end conditions for every HMM in the macro HMM or parallel like shown in the following chapter. Because no further data sets of the wheel loader with other process patterns were available other data of different machines were taken to set up a macro HMM. Three different process patterns were finally used. In addition to the mentioned y-cycle, two different data sets of two excavators were applied with the patterns digging and levelling. As an important edge condition the number of states, which were calculated with the quadrant method, has to be the same in every data set, which is applied in the macro HMM. This is the case, because every data set is parallel calculated in every HMM of the macro HMM and after that a comparison of the state distributions calculated by the HMM and the quadrant method is executed. Also as an intermediate step a classification of the combinations before computation had to be conducted, as the size of the observation matrix is determined with the training the applied data set has to have the same size. If these conditions are met, the recognition system (Figure 9) is able to calculate.

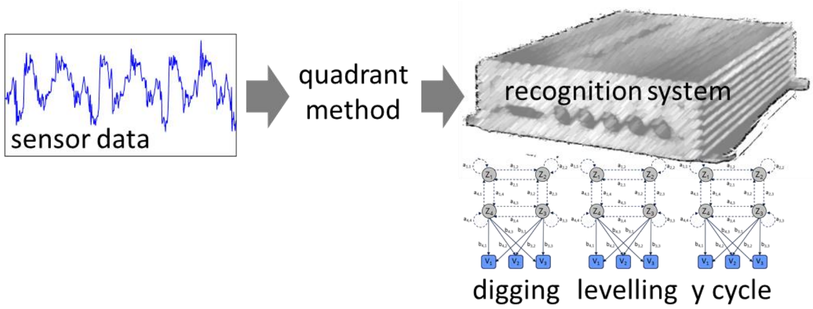

Figure 9. Structure of the recognition system

In the next chapter the criterions, which are used to detect the correct process pattern, are discussed. At first the probability of the most probable path of every HMM in the macro HMM is considered. This probability is calculated with the observation sequence, which presents the classified distribution of the combinations determined with the quadrant method. The HMM which produces the highest probability is the excepted pattern. For the second criterion the distribution of the path with the highest probability is taken. The preprocessing with the quadrant method enables the comparison of the computed path with the path the quadrant method calculated. The comparison includes the calculation of the variance of both distribution in every time step and the mean value computation. The least value represents the probable pattern. For the third criterion both state distributions are used again and the correlation coefficient of both is determined. The highest value is assigned to the most probable pattern. Because the pattern detection was very defective, these three different criterions were introduced. In the calculation the criterions are weighted. The values for this weighting were determined in an iterative process.

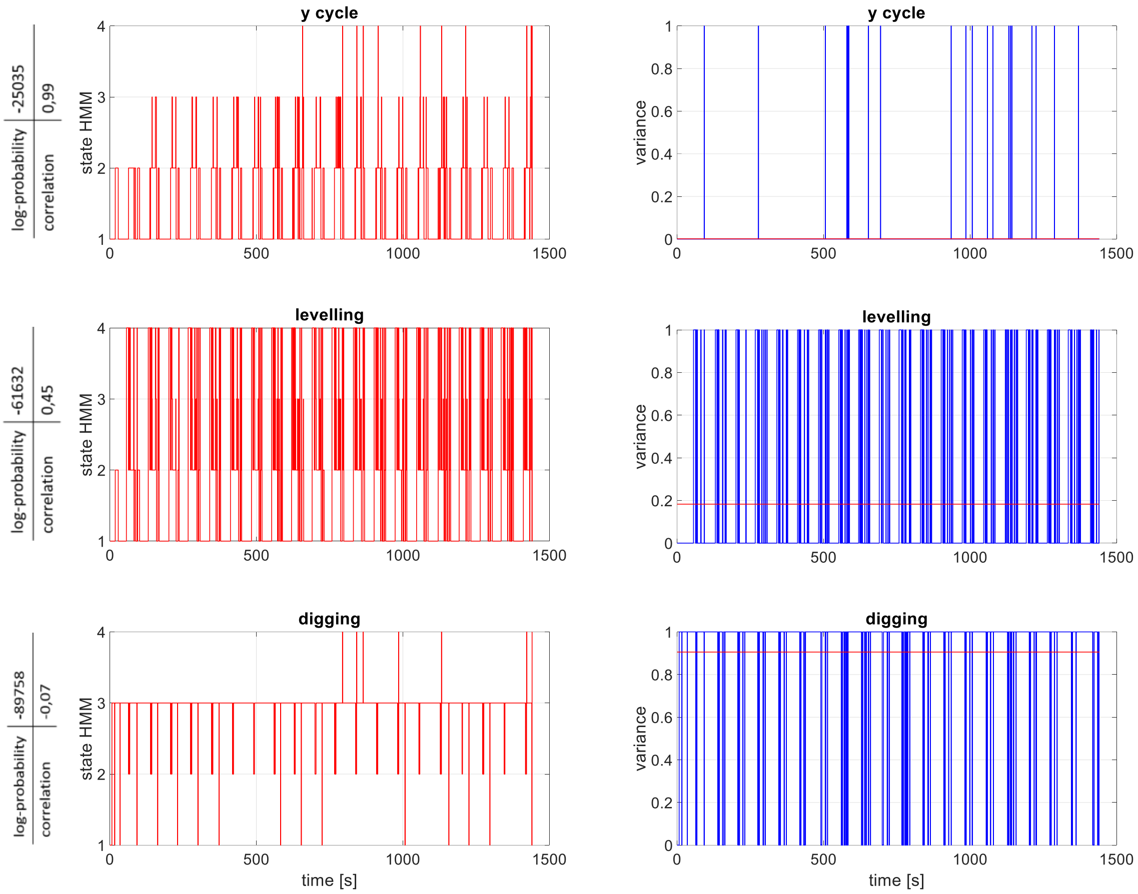

Figure 10. Results of the single HMMs with one of the y-cycles data set

Figure 10 shows the results of the single HMMs of the recognition system applied with one of the y-cycle's data set. The combination distribution (Figure 7) is best calculated by the HMM trained with y-cycle's data. The variance of both the computed and the state distribution determined with the quadrant method is shown on the right side. As you can see the y-cycle's HMM has the least variance and thereupon the least mean value (red line). Also the probability of the most probable path and the correlation coefficient have the highest values in the y-cycle's HMM. In this case, every of the three defined criterions are matched for the right process pattern.

In further investigations with other data sets the results of the detection were consistently positive. Every pattern was detected from the data sets. Each of the 4 y-cycle were detected and also the levelling and the digging. The y-cycle's HMM was trained with only one of the four data sets. The 3 other data sets, the HMM never saw before, were confident detected. The same results were achieved by using data of another unknown third excavator with the pattern digging.

When occurring an unknown pattern the system gives out a warning and the possibility to learn this new pattern. If this new pattern is done again the system will be able to detect it. Thus the recognition system becomes more intelligent with every new pattern.

4. CONCLUSIONS AND OUTLOOK

The paper shows on the one hand the realization of a method for the recognition of known patterns for a specific machine. On the other hand the extension of this method with a suitable data-preprocessing and with that the possibility of the detection and the learning of unknown patterns are given. Additionally the system is applicable to every single machine. Furthermore the shown method will be refined to an online procedure. The first problem, which has to be solved, is the consideration of a small time window or better every time step. The algorithms for cycle counting have also to be improved for an online application. Main problems are the determination of the start and end times of the patterns. At the moment the system can only detect different patterns. A first attempt to identify these times by examining the decrease of the calculated probability in the HMM leads to promising results. The further development of these aspects will be the next step.

Generally the process pattern recognition concept presented is exercisable across a wide range of applications. It facilitates the targeted optimisation of both development tasks and reverse engineering. The application of the concept in other engineering disciplines is also conceivable, like shown as a means of assessing the efficiency of a drive system using knowledge of process pattern-specific energy-related circumstances within the machine gained over a long observation period.

The representative usage profiles for mobile construction machines yielded by the concept unquestionably offer huge added value for both machine manufacturers and their suppliers. The intelligent adaptation of control and drive parameters during machine operation represents another potential area of application due to the real-time capability of recognition systems of this type. The fact that the concept is based on the use of standard sensors and control devices simplifies the transfer thereof to a variety of conventional construction machines.

5. ACKNOWLEDGEMENT

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