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ON-LINE PAYLOAD DETERMINATION OF A MOVING LOADER USING NEURAL NETWORKS

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Abstract: This paper describes a method that combines Kalman-filter and neural network to form an efficient data fusion technique for estimating payload in the bucket of a moving loader. Kalman-filter is used to find the signal levels from noisy measurement data before the data is fed to the neural network. Neural network is then used to form the nonlinear connection between the indirect measurements describing the load and the actual load in the bucket. The results show that the used combination of these different methods offers a viable solution for estimating the payload. *Copyright © 2002 IFAC.*

Keywords: Kalman-filter, neural networks, payload estimation, intelligent mine

1. INTRODUCTION

In near future *intelligent mine* concept (Dasys *et al*, 1999; Singh, 1997) will become more and more important. The idea is to automate mining including e.g. computer-based mine planning, information, communication and maintenance systems, production planning and simulation. A reliable method for measuring the payload is an important aspect also in automating the whole mine production process.

One way to do the weighing is to use a scale. The scale should recognize different vehicles and the payload measurement would be done by driving over the scale. The problem is how to determine the actual payload, when the weight of the driver, the amount of fuel, the wearing of the components (e.g. bucket) etc. affect the result. In addition, the measuring time is quite short because the machines can not be stopped for weighing. Also calibration of the scale can be time consuming and expensive. However, the biggest problem is that different machines can all have different driving paths. Even the driving paths of the individual machines can vary from work cycle to another. Thus the positioning of the scale can be difficult. Also the repositioning of the scale when the machines are moved to a new place can be difficult. These problems are solved by integrating the weighing system to individual loaders.

When weighing is done onboard the loaders, the information can be used, besides controlling the production process, also to monitor individual machines and individual tasks and to plan the maintenance actions. This way also the payment of salaries for the drivers can be based on transported ore tons. In addition, information of the payload helps to load the trucks and railroad cars to their maximum rated capacity without the risk of overloading.

This paper concentrates on the payload weighing problem of moving LHD (load-haul-dump) machines (figure 1) manufactured by Sandvik Tamrock Corporation, but the results can be generalized to other similar hydraulic machines. LHDs are especially designed for underground mining (they have low profile, large bucket volumes and suitable weight distribution). There are many tasks related to production and development of the mine where these machines can be used. From the weighing point of view, the most important task is the ore transportation from the stope to the primary crusher.

Very few reported scientific contributions exist in the field of weighing the payload of moving LHD machines. However, there exist several patents on the topic e.g. (Kyrtsos and Worrell, 1990). There are also commercially available products (e.g. by Tamtron Inc. or Pfreundt Inc.). The purpose of this work was to improve the accuracy of the existing methods, by using neural networks together with a proper data preprocessing method. As far as the authors know this is the first time when Kalman-filtering and neural networks are combined to form an efficient data fusion technique.

This paper is divided as follows: in section 2 the problem at hand is described. In section 3 follows the description of the used measurements and their behavior. After that the data preprocessing method is discussed in section 4. Section 5 presents the used neural networks. The results are given in section 6. Finally, in section 7, some problems in practical weighing applications are discussed together with some remarks on current research and the paper is concluded.

2. PROBLEM DESCRIPTION

The objective of this work was to estimate the payload in the bucket of an ore transportation machine. The weight determination is done onboard. Since no direct measurements of the weight can be done, indirect measurements must be used.

The presented method is based on the measurements of hydraulic pressures in boom lifting cylinders (figure 2). The boom is stopped to a certain position while weighing. The main problem is that for the sake of effectiveness the ore weighing has to be carried out during the machine's work cycle i.e. while the machine is moving between loading and dumping points. The movement indirectly corrupts measurements with noise. Moreover, the system induced nonlinearities have to be compensated in order to get satisfactory results. To enable the compensation, some additional measurements were carried out as will be discussed in section 3.

Because the relation between the load in the bucket and the measurements is nonlinear and partly unknown, neural networks are used to calculate the load from the measured values. Inputs to the neural networks are signal levels calculated from the measured signals. Signal levels from the noisy measurement data are found using Kalman-filter.

Fig 1. LHD machine Toro450D manufactured by Sandvik Tamrock Corporate.

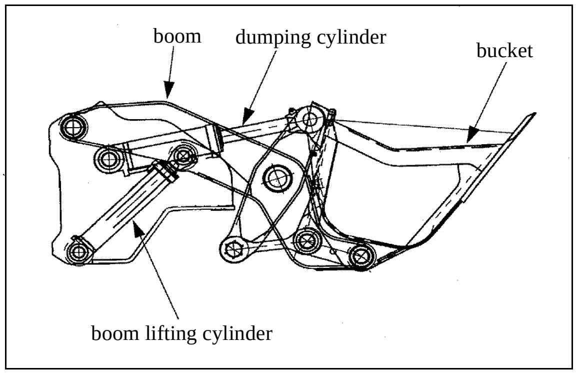

Fig 2. Structure of the machine front.

3. MEASUREMENTS

Due to the fact that the loader is moving during the weighing, many external factors can affect the pressure signal levels and thus cause errors in weighing results. To compensate the effect of these factors, several additional measurements were carried out. Used measurements were inclination angle, boom position and temperature of hydraulic oil. Also some other measurements such as driving speed, gear information, and engine rpm were carried out. However, simulations indicated that only the first three measurements contain significant information. Examples of the signals' behavior during a measurement are given in figures 3-7.

Before weighing the boom is in its lowest position pulled against a stopper. When weighing is started, boom is lifted a little and then stopped to a specified level. Boom lifting can be seen as a stepwise change in the boom lifting pressure (figure 3). The change in boom position measurement is similar to changes in pressure signals during the weighing i.e. there is a stepwise change also in the boom position value when the boom is lifted to its setpoint value (figure 4). Despite the setpoint value the boom position varies between lifts and this is why it has to be measured. Factors causing the variations around the setpoint are

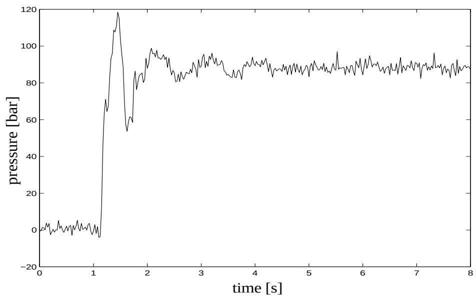

Fig 3. Upper pressure during boom lifting. Pressure at the other side of the cylinder piston makes a step down at the same time as the pressure value rises on the other side.

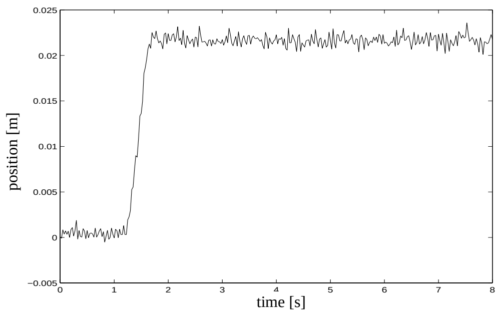

Fig 4. Boom position during weighing.

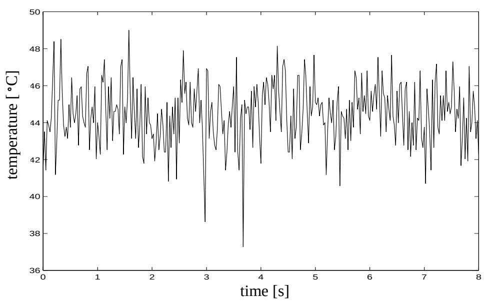

Fig 5. Temperature of hydraulic oil during weighing.

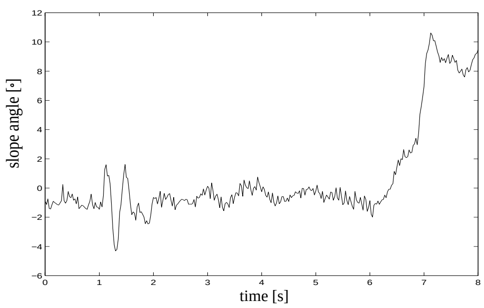

Fig 6. Example of the changes in inclination angle during weighing.

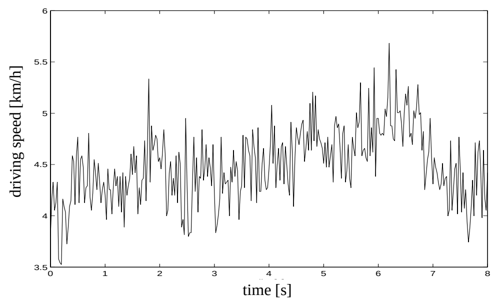

Fig 7. Example of driving speed signal during one weighing.

for example engine rpm and load in the bucket. Boom position is the most important additional measurement having the biggest influence on the accuracy of the weighing results.

The variations in pressure result from inertia of the mass when stopping the boom to the setpoint height for measurements. Driving on a rough surface can cause similar effects at any point of the measurements as the vehicle hits or clears a bump. The amplitude and the frequency depend on the load in the bucket and on the previously mentioned external factors. Because the whole machine instead of just the boom is oscillating and the hydraulic oil is not very compressible, the same fluctuations can not be seen in boom position measurement.

Figure 5 represents a measurement of the temperature of hydraulic oil. In figure 6 an example of a slope angle measurement is given. Slope angle is the second most important additional measurement after boom position. In figure 6 oscillations between 1 and 2 seconds are from the same origin that the oscillations in pressure signals after stopping the boom. Other changes in the signal are due to changes in the surface when the machine is moving i.e part of the changes are due to actual changes in the signal levels and part of the changes represent noise. An example of driving speed signal is shown in figure 7.

4. DATA PREPROCESSING

When using neural networks, it is very important that the data fed into these systems is properly preprocessed. In this case only the final values of the signals i.e actual signal levels during the weighing are of interest. During every weighing these levels are estimated and the estimated values are then fed into the neural networks as the inputs in order to calculate the corresponding payload in the bucket.

Because the signals can vary significantly during a measurement, it is difficult to determine the actual signal levels. Especially the machine inclination measurement is difficult because part of the variations represent noise and thus should be neglected and part is due to actual changes on the state. Another problem is that the work cycle of the machine can be very short which limits the measuring time. Short measuring time together with varying oscillation frequency of the signals prevents for example simple mean value calculation to be used in signal level determination.

In the final system the preprocessing problem is solved by using dynamic discrete-time linear Kalman-filter (Bar-Shalom, 1993; Gelb 1974). Also other methods, such as median filtering and low pass filtering, were tested. However, when the results gained with different methods were compared in various situations, it was clear that Kalman-filter was the fastest and also the most accurate method. Kalman-filter is a computational algorithm that processes the state of the system by utilizing knowledge of the system and measurement dynamics, assumed statistics of system noises and measurement errors, and initial condition information. It is an optimal estimator in minimum mean square error sense. In figure 8 is depicted the structure of one recursive round of state estimation.

State estimation is updated using state prediction together with the innovation (i.e. residual between actual measurement at the time and the predicted value of the measurement) weighted with filter gain value:

$$\hat{x}(k+1|k+1) = \hat{x}(k+1|k) + W(k+1)\nu(k+1)\,, \quad (1)$$

where $\hat{x}(k+1|k+1)$ is the updated state, $\hat{x}(k+1|k)$ is the predicted value of the state, $\nu(k+1)$ is innovation and $W(k+1)$ is the filter gain.

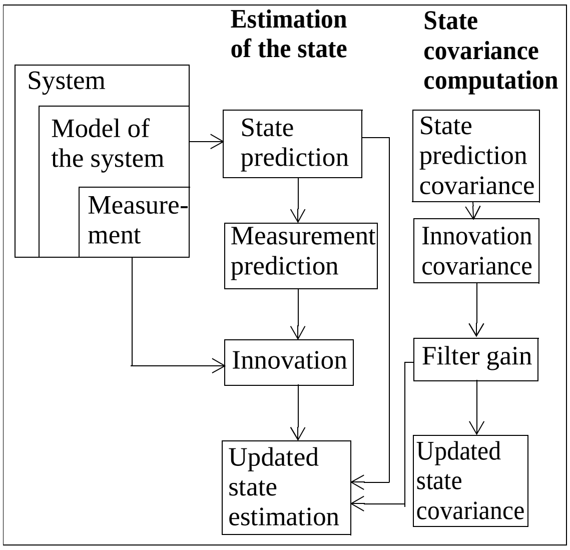

Fig 8. One cycle in state estimation of a linear system.

In this application separate Kalman filters are formed for each measurement presented in figures 3-7, each filter having only one state. This way both the state transition matrix and measurement matrix, that are needed in the state computation, have scalar value 1 and the covariance matrices reduce to scalar variance values for each filter.

In figures 9-11 results of the state estimation are shown for measurements during one weighing for pressure, inclination angle and driving speed. When estimating the pressure the state is deemed to be more accurate than the new measurements. This way the oscillations of the signal can be ignored (filtered) and the actual signal level can be found. In driving speed estimation the new measurements are considered to be more reliable than the predicted state. This way the estimate reacts more rapidly to the changes in the signal.

Estimating the state of the slope angle is the most difficult task. This is because part of the changes in the signal are due to the actual changes in the state and part is oscillation which is defined as an error and should be filtered out. This means that a compromise between trusting the measurements and trusting the model is more difficult to find.

In Figures 9-11 it can be seen that the estimate follows the signal and filters out the unwanted oscillations. The true state can be read after a couple of seconds.

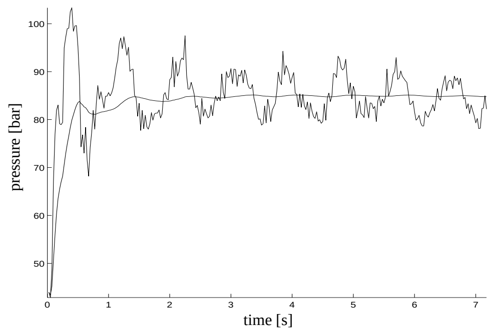

Fig 9. Kalman filter in estimating the pressure.

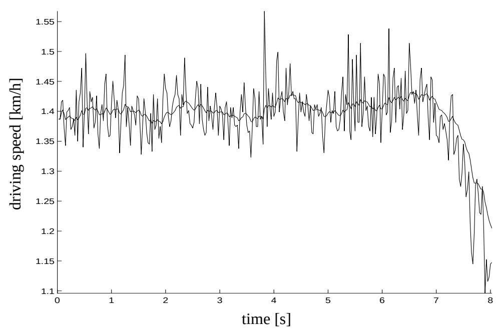

Fig 10. Kalman filter in estimating the driving speed.

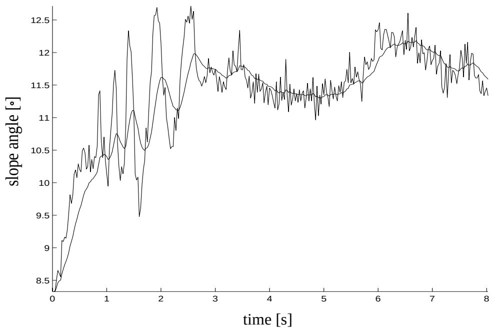

Fig 11. Kalman filter in estimating the slope angle.

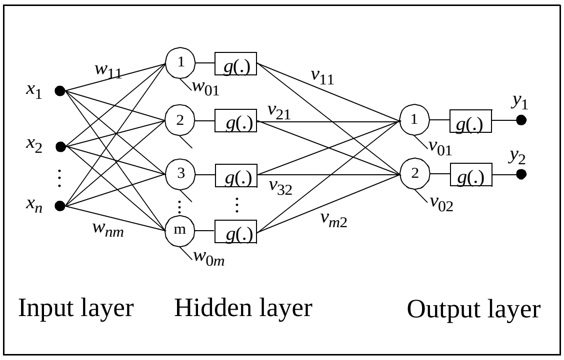

Fig 12. Example of MLP type of neural network.

5. NEURAL NETWORK

Almost 600 weighings were done to get enough measurement data to train the neural network (Bishop, 1995; Jang, 1997). During the measurements driving conditions - for example driving speed, inclination angle etc. - were changed. Eleven different known weights were used in the bucket while measuring.

Using Kalman filter the measurement signals were preprocessed to get signal levels for the neural network inputs. State estimates after 3 seconds of filtering were used. Preprocessed data was then divided into two different sets: training set and validation set. Validation set was used to stop the training of the network (with training set) before the network looses its ability to generalize.

Because the actual weight in the bucket during every weighing was known, supervised learning methods were used in network training. The chosen network structure was fully connected feed-forward (FF) type of network. Both Multi-Layer-Perceptron (MLP) and Radial-Basis-Function networks were tested. Also several different learning algorithms, for example Levenberg-Marquardt (LM) and resilient backpropagation (Rprop), were used.

After some simulations the final network structure was chosen to be an MLP-network with one hidden layer and a Levenberg-Marquardt learning algorithm. With this structure different input combinations and different amounts of hidden nodes were tested. The structure of an MLP network with one hidden layer, n different inputs and two outputs is shown in figure 12. In the hidden layer there are m hidden nodes which act as summing elements for the weighted sum between inputs of the layer and the weights w and v. $g(.)$ is an activation function which in this case is hyperbolic tangent.

6. RESULTS

All the results shown here are obtained using validation data set. In figure 14 is shown an example of weighing results with a neural network where the inputs were pressures from both sides of the boom lifting cylinder, boom position, inclination angle and temperature of hydraulic oil. In the figure measurements of the weight 11660 kg (highest level) are totally new to the system i.e. these measurements were not used during the training of the network.

As can be seen from the figure, system has retained its ability to generalize and the weighing results are satisfactory also for the new data. In figure 15 is depicted the relative errors in each measurement for the neural network used in figure 14. From the figure it can be seen that for the neural network relative errors are between -3.86 and 3.20% for 95% of the data.

Best network size was between 9 and 15 hidden nodes. Different error calculations gave slightly different results concerning network size and best input combination. Best total error (0.004%) was obtained

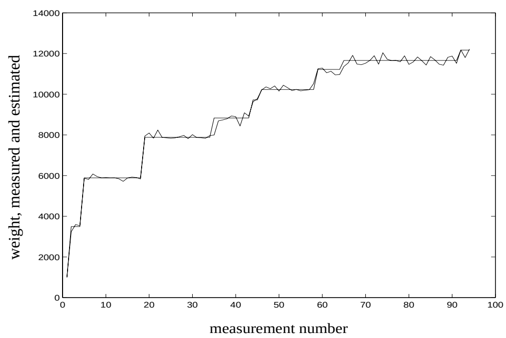

Fig 14. Weighing results with a neural network.

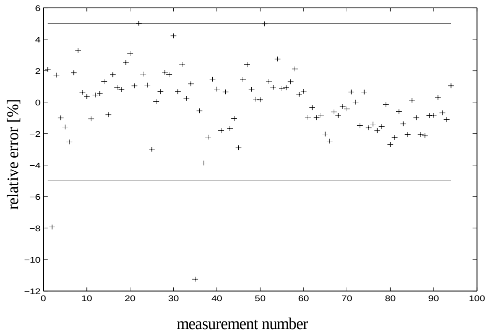

Fig 15. Relative error for the weighing results from the neural network.

when inputs to the network were pressures, boom position, inclination angle and the temperature of hydraulic oil (see figure 14). Nine hidden nodes were used in this case. Best mean of relative errors (1.68%) on the other hand was obtained using 10 hidden nodes and pressures, slope angle and boom position as inputs to the network. These results can be seen from the table 1 below.

Table 1: Results for neural networks with different input combinations

Input combinations	RMSE	Total error	Relative error	Error bounds
[1 2 3 4 5 7]	179	0.01	2.04	-4.2, 4.6
[11 3 4 5 7]	182	-0.25	1.90	-4.91, 4.87
[1 2 3 4 5]	178	0.004	1.69	-3.86, 3.20
[1 2 3 5]	170	-0.27	1.98	-4.03, 4.30
[1 2 4 5]	670	-0.45	5.66	-13.6, 15.0
[1 2 3 4 7]	178	0.18	1.73	-5.37, 4.53
[1 2 3 4]	178	-0.04	1.68	-3.71, 4.46
[1 2 3 4 5 6 7]	183	-0.10	2.12	-5.55, 4.29
[1 2 3 4 5 6 10]	188	0.24	2.32	-6.38, 6.05

In the table are shown the root mean square error, total error (%), relative error (%) and error bounds (percentage for 95% of the data) for the weighing results when different input combinations to the network are used. The explanations for numbered input combinations are: 1=pressure (upper), 2=pressure (lower), 3=inclination angle, 4=boom position, 5=oil temperature, 6=rpm, 7=driving speed, 10=gear.

7. CONCLUSIONS

In this paper a neural network based method for determining the weight in the bucket of a moving loader is presented. The most important thing in using neural networks is to preprocess the data before feeding it into the network. Here Kalman-filters with one state are used for each measurement. Depending on the problem also Kalman filters with several states can be implemented.

The results indicate that neural networks together with Kalman-filter offer viable solution for estimating the payload. The results were obtained for Toro450D, which is an LHD machine manufactured by Sandvik Tamrock Corp. However, results can be generalized.

Although results obtained with neural network based methods give good results, there are some problems that have to be solved before these algorithms can be implemented to the actual weighing system. Such problems are for example the huge amount of training data needed for the networks. In this case approximately 600 measurements were carried out which took several days. In practice it is impossible to use such a long period to tune the weighing system of each individual machine. Also the calibration and tuning the weighing algorithm after changing a component in the machine is problematic. The algorithm should also take into consideration the long term changes in the function of the machine like the wearing of components.

REFERENCES

Bar-Shalom Y., Li X-R. (1993). *Estimation and Tracking: Principles, Techniques and Software*, 514 p. Artech House, Norwood.

Bishop C., M. (1995). *Neural Networks for Pattern Recognition*, 482 p. Clarendon Press, Oxford.

Dasys A., Geoffroy L., Drouin A. U.S. Patent 5941921. *Sensor Feedback Control for Automated Bucket Loading.* Assigned to Noranda Inc., Canada, application number 750278, filed 19.03. 1997, date of the patent 24.08.1999. 18 p.

Gelb, A. (1974). *Applied Optimal Estimation*, 374 p. The M.I.T. Press, Massachusetts Institute of Technology, Cambridge, Massachusetts.

Jang J-S. R. (1997). *Neuro-fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*, 614 p. Prentice Hall, Upper Saddle River.

Kyrtsos T., Worrell D., A. US Patent 4919222. *Dynamic Payload Monitor.* Assigned to Caterpillar Inc., application number 344458, filed 15.03.1989, date of patent 24.04.1990, 11p.

Singh, S. (1997). The State of the Art in Automation of Earthmoving. *ASCE Journal of Aerospace Engineering.* **Vol. 10, no 4**, 30 p.