26th International Conference
ENGINEERING MECHANICS 2020
Brno, Czech Republic, November 24 – 25, 2020

ANOMALIES DETECTION IN TIME-SERIES DATA FOR THE INTERNAL DIAGNOSTICS OF AUTONOMOUS MOBILE ROBOT

Vechet S., Krejsa J.*, Chen K. S.**

Abstract: *Autonomous mobile robots are complex mechatronic machines which consists of numerous hardware and software modules working asynchronously to achieve desired behaviour. As there are many frameworks which helps to overcome the flat learning curve the problem of internal diagnostics arises. While users and developers are able to focus only on solving the high level problem algorithm or methods the internal states of the system are hidden. This helps to separate the users from solving hardware issues, which is helping until everything works properly. We present an algorithm which is able to detect anomalies in time based behaviour of the robot to improve the users confidence that the internal robot framework works correctly and as desired. The algorithm is based on probabilistic patterns detection based on Bayesian probabilistic theory.*

Keywords: Anomalies detection, Bayesian networks, Diagnostics, Robot Operating System.

1. Introduction

The Robot Operating System (ROS) is set of tools, modules, drivers, communication stacks and other libraries which aim is to help developers the build and autonomous mobile robot with focus on application. The inter-process communication is based on publisher-subscriber architecture, it can handle data logging, visualization, path planning (Masek, 2015), navigation (Krejsa, 2010) and partial in system diagnostics.

While the ROS has internal diagnostics itself (Vechet, 2019) the main purpose of this module is to diagnose problems with executing of given nodes not to diagnose already running nodes nor perform any time based behavioral analysis.

The aim of this work is to present a method to looking for anomalies in time-series data read on communication channels within the robot so we can monitor the trends in data towards anomalies which may mean the system failure in near future.

2. Problem definition

The problem we try to solve is to monitor any time-series data which are presented within the system. The data needs to be represented as a number which can be easily discretized to N values. These are further processed by proposed probabilistic engine to boolean (two valued) result which means the normal data stream or there is an anomaly detected. This high-level information can be further processed with superior control system. Moreover, this anomalies detection can be performed asynchronously on all presented time-series data stream in the system so we can perform detailed status monitoring.

3. Probabilistic approach

The anomalies detector is based on calculating a posterior probability of two consequent data readings from organized dataset *{data_0, data_1,...,data_n}* which is assigned to two groups *{OK,NML}* which represents

* Assoc. Prof. Stanislav Vechet, PhD., Assoc. Prof. Jiri Krejsa, PhD.: Institute of Thermomechanics AS CR, v.v.i., Technicka 2, 616 69, Brno, Czech Republic, vechet.s@fme.vutbr.cz,

** Prof. Kuo-Shen Chen: National Cheng Kung University, Department of Mechanical Engineering, No. 1, Ta-Hsueh Road, Tainan 701, Taiwan

doi: 10.21495/5896-3-508

correct data (group OK) and anomaly data (group NML). To sort the data reading we use an assumption that the system is working correctly on start and during operation time it can degrade. The degradation can be caused by slow mechanical damage or fatigue. The posterior calculation uses Bayesian conditional probability equation:

$$P(group = \{OK, NML\}|data_k, data_{k-1}) =$$
$$\eta^{-1}P(data_k|data_{k-1}, group = \{OK, NML\})P(group = \{OK, NML\}) \qquad (1)$$

where:

- *OK* – data are correct,
- *NML* – data are incorrect with some anomalies,
- $data_k$ – data measured in time step k,
- $data_{k-1}$ – data measured in previous time step k-1,
- $P(group = \{OK, NML\}|data_k, data_{k-1})$ posterior probability,
- $P(data\_k|data_{k-1}, group = \{OK, NML\})$ transition probability of data samples belongs to given group.
- $P(group = \{OK, NML\})$ pprior probabilities.

The posterior probability can be represented graphically as a 2D matrix projection to visually compare signal properties (Fig. 1).

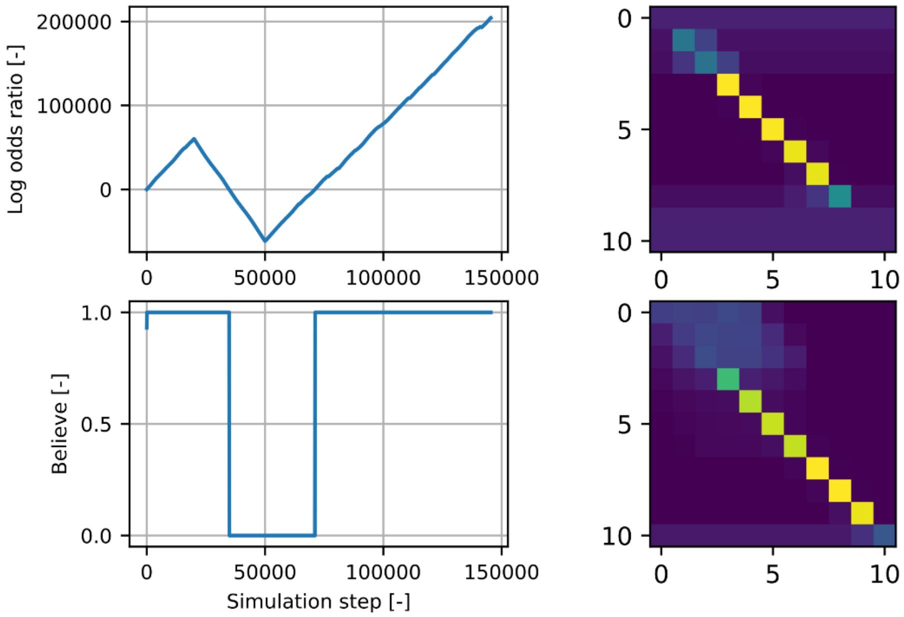

Fig. 1: Graphics representation of the posterior probability for correct data (right top), incorrect data (right bottom) and the anomaly detection (left bottom) calculated from log odds ratio (left top).

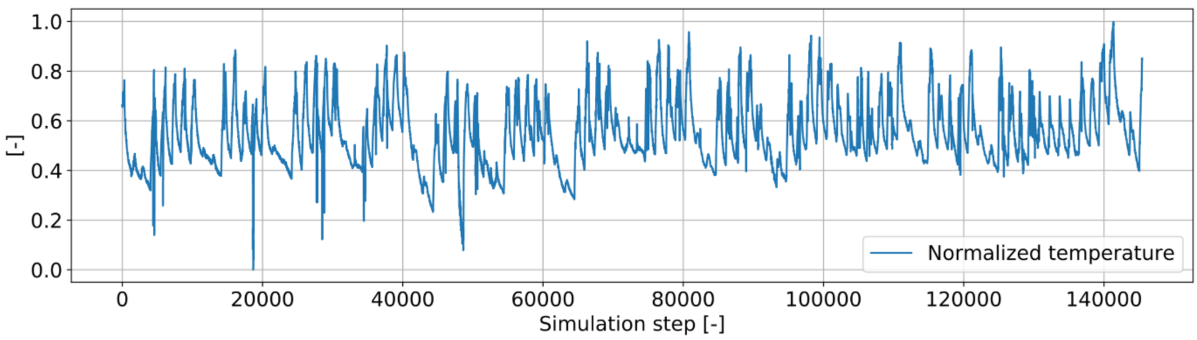

Fig. 2: Example of normalized original (correct) signal measured on tested machine.

4. Simulation experiments

For simulation experiments the real temperature data were measured on mobile robot and normalized in further processing (Fig. 2).

A noisy artificial signal represented as a harmonic signal with white noise was then used for replacement of a chunk of the original data. The harmonic signal can be seen in Fig. 3.

After we have defined the original (or correct) signal a disturbance was inserted into the prepared data-set (see Fig. 4). This simulates the situation where the original signal assumed as correct degrades to undesired measurements which needs to be marked as possible anomaly.

When the signals shown in Fig. 4 is used for continuous posterior calculation based on Eq. (1) the resulted graphic representation can be seen in Fig. 1 (right column). The top right image represents the correct data and right bottom image the erroneous data.

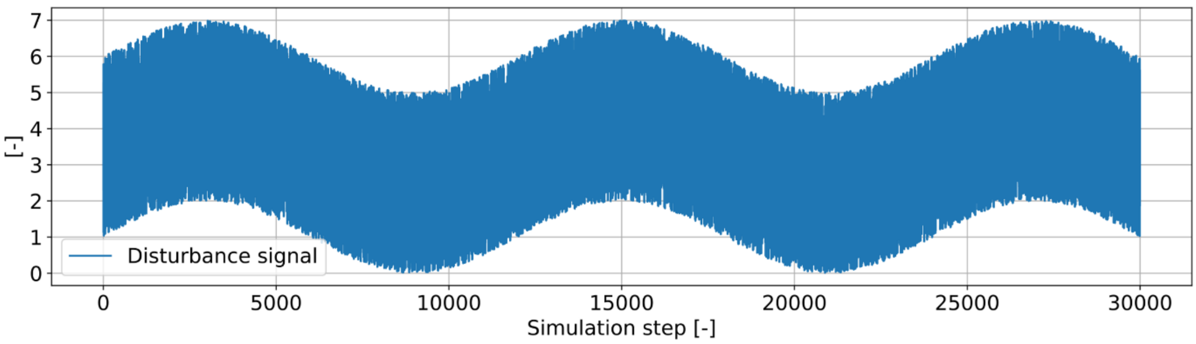

Fig. 3: Example of generated artificial disturbance signal.

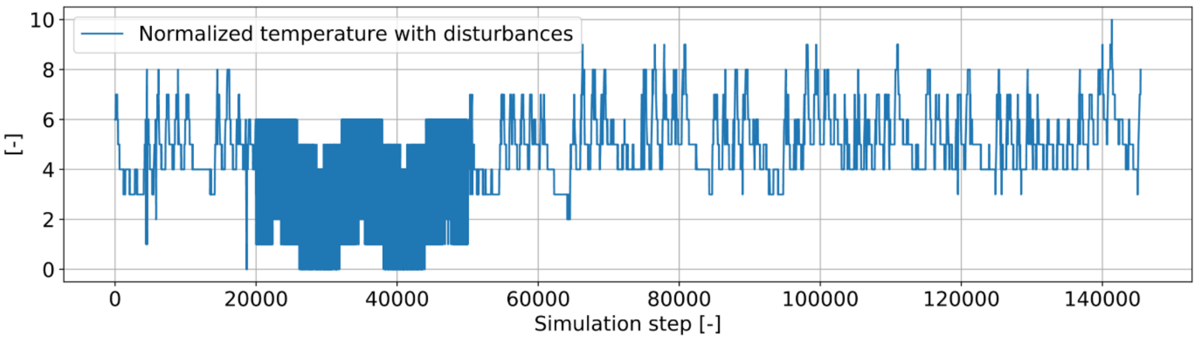

Fig. 4: Experimental signal where the part of original data was replaced by disturbances in time steps <20000, 50000>.

Based on the shown graphical representations is clearly seen that the posterior probability gives us different patterns for different signals. However, for the decision if the signal contains anomalies or not we need another method. We use a calculation of log odds ratio which give us single real number $(-\infty, \infty)$. If the number is higher than zero the signal is correct, if the number is equal or lower that zero than the anomaly was detected.

$$\mathrm{l}_\mathrm{k} = \mathrm{l}_{\mathrm{k}-1} + \log\left(\frac{P(group = OK|data_k, data_{k-1})}{1-P(group = OK|data_k, data_{k-1})}\right) - \log\frac{P(group=OK)}{1-P(group=OK)}, \quad (2)$$

where l_k, l_{k-1} are log odds ratios calculated from posterior and prior probabilities given by Eq. (1).

5. Conclusion

We present a method to detect anomalies in measured data on time basis. Presented results will be applied in various robotic system within our laboratory (autonomous mobile robots BREACH, Leela and Bender II) to see how it works in real world applications.

Further work is focused to combine our diagnostic methods developed separately into one scalable diagnostic system which can monitor the machine health in real-time.

Acknowledgement

The results were obtained with support of Mobility Plus Projects with Ministry of Science and Technology of AS CR, v.v.i., project no. MOST-20-06.

References

Hrbacek, J., Ripel, T., Krejsa, J. (2010) Ackermann mobile robot chassis with independent rear wheel drives. In Proc. of 14th International Power Electronics and Motion Control Conference (Epe-Pemc), doi:10.1109/Epepemc.2010.5606853. WOS:000319521600268.

Korb, K. B., Nicholson, A. E. (2010) Bayesian Artificial Intelligence, Second Edition, CRC Press, Inc., Boca Raton, FL, USA, ISBN 1-58488-387-1.

Krejsa J., Vechet S., Chen K. (2014) Multiple Indoor Robot Localization using Infrared Beacons, In Proc. of 20th International Conference Engineering Mechanics, pp. 336-339, WOS: 000364573900077.

Krejsa, J., Vechet, S. (2010) Odometry-free mobile robot localization using bearing only beacons. In Proc. of 14th Inter. Power Electronics and Motion Control Conference (Epe-Pemc), doi:10.1109/Epepemc.2010.5606893. WOS:000319521600308.

Krejsa J. and Vechet S. (2018) Fusion of Local and Global Sensory Information in Mobile Robot OutdoorLocalization Task. In: Proc. of 18th International Conference on Mechatronics – Mechatronika, Brno, pp. 296-300.

Mašek, P.; Růžička, M. (2015) A Task Planner for Autonomous Mobile Robot Based on Semantic Network. In Advanced Mechatronics Solutions. Advances in Intelligent Systems and Computing. Switzerland: Springer International Publishing, pp. 637-642. ISBN: 978-3-319-23921- 7. ISSN: 2194-5357.

Merritt, D. (1989) Building experts systems in Prolog. Springer-Verlag, New York. ISBN:978-1-4613-8913-2.

Robot Operating System, available online at www.ros.org, retrieved 2019.

Věchet, S., Hrbáček, J., Krejsa, J. (2016) Environmental Data Analysis for Learning Behavioral Patterns in Smart Homes. In Proc. of 17th International Conference on Mechatronics – Mechatronika, Prague: Czech Technical University in Prague, pp. 386-391. ISBN: 978-80-01-05882- 4.

Vechet, S., Krejsa, J. (2019) Real-time diagnostics for ROS running systems based on probabilistic patterns identifications. In Proc. of 25th International Conference Engineering Mechanics 2019, Svratka, Czech Republic, 13-16 May 2019, pp. 383-386, ISBN 987-80-87012-71-0.