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

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

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 is 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.*

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 (see 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 behavioural 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 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:

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

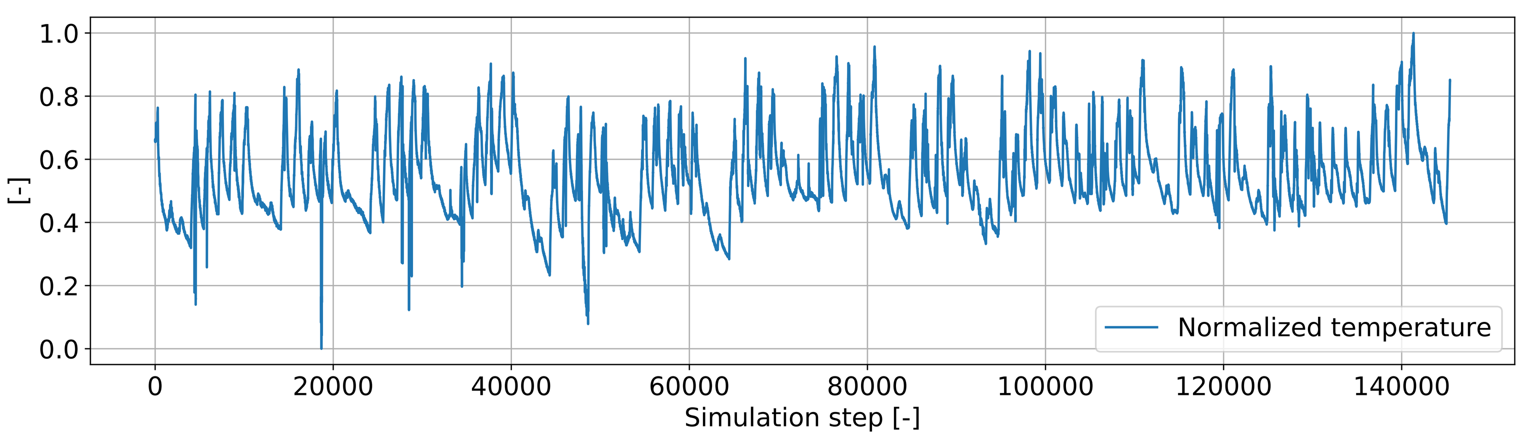
where

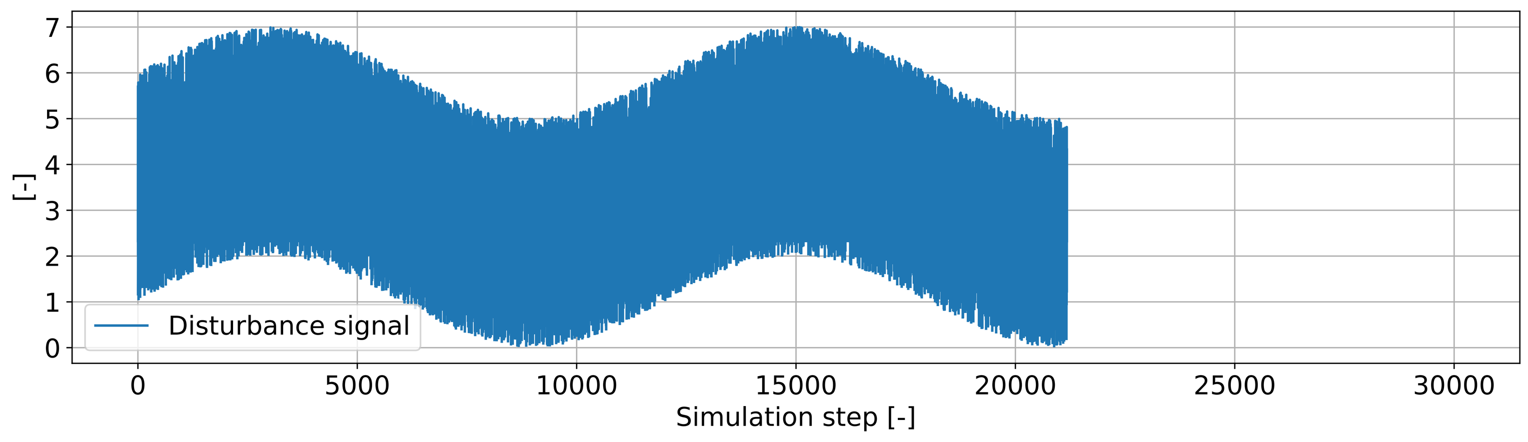
- OK - data are correct,
- NML - data are incorrect with some anomalies,
- $data_k$ - data measured in time step k
- $data_{k-1}$ - data measured in previous time step $k-1$
- $P\left(group = \{OK, NML\} | data_k, data_{k-1}\right)$ - posterior probabilities,
- $P\left(data_k | data_{k-1}, group = \{OK,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

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

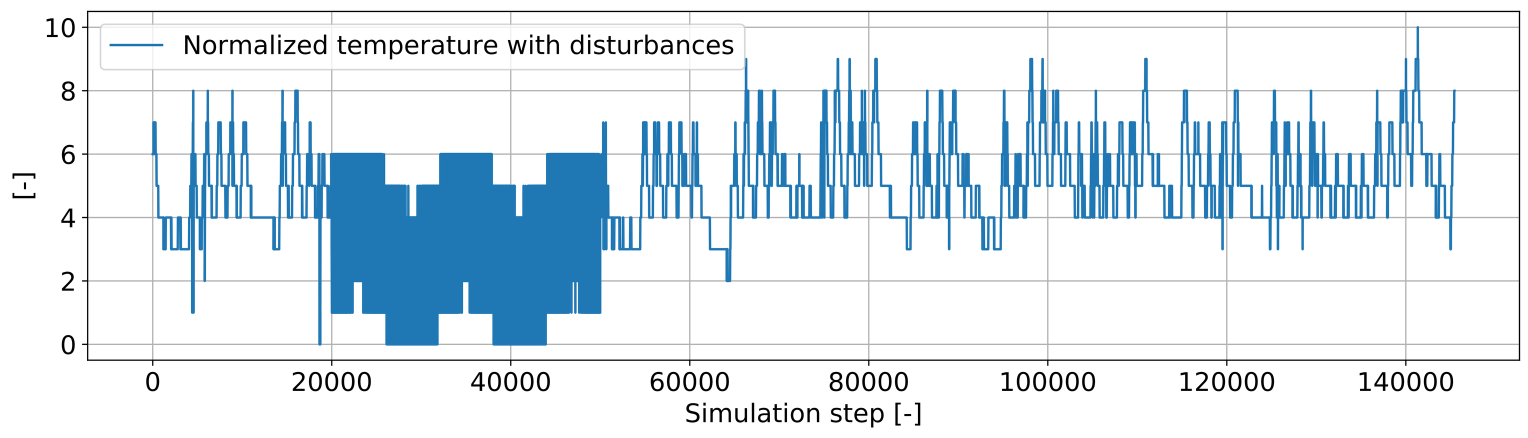
4 Simulation experiments

For simulation experiments the real temperature data were measured on mobile robot and normalized in further processing.
A noisy artificial signal represented as a harmonic signal with white noise was than used for replacement of a chunk of the original data.

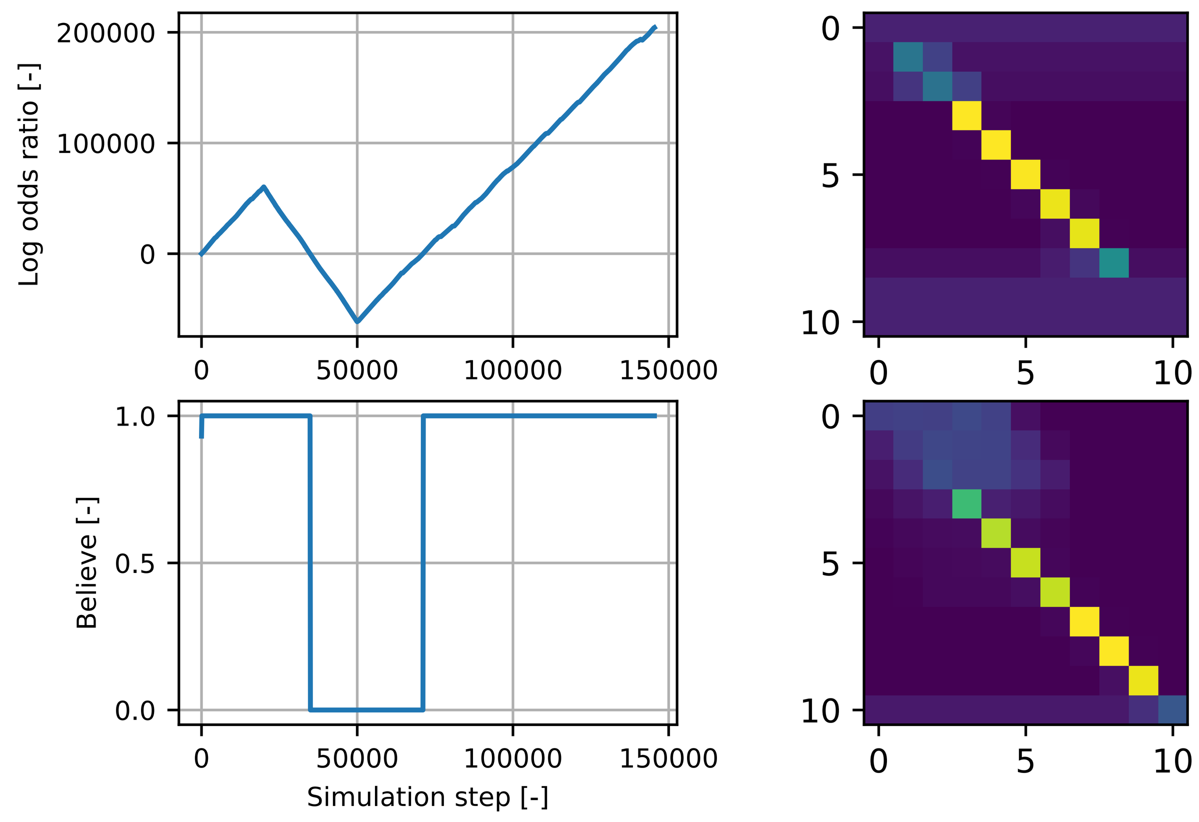




After we have defined the original (or correct) signal a disturbance was inserted into the prepared data-set. This simulates the situation where the original signal assumed as correct degrades to undesired measurements which needs to be marked as possible anomaly.



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



Based on the shown graphical representations is clearly seen that the posterior probability give 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.

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

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

5 Conclusions

We present a method to detect an 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.

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* Assoc. Prof. Stanislav Vechet, Ph.D., Assoc. Prof. Jiri Krejsa, Ph.D.: 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