4th My First Conference
September 24, 2020
Rijeka, Croatia

Fault Detection in Robotic Manipulators using Support Vector Machines

Sandi Baressi Šegota[1,*], Nikola Anđelić[2], Vedran Mrzljak[3], Zlatan Car[4]

[1]*Faculty of Engineering, University of Rijeka*
E-mail: sbaressisegota@riteh.hr

[2]*Faculty of Engineering, University of Rijeka*
E-mail: nandelic@riteh.hr

[3]*Faculty of Engineering, University of Rijeka*
E-mail: vmrzljak@riteh.hr

[4]*Faculty of Engineering, University of Rijeka*
E-mail: car@riteh.hr

Abstract

The detection of faults during the actions performed by robotic manipulators can be of great importance. A timely detection and appropriate stopping of robotic manipulator can prevent damage to the robotic manipulator itself, as well as surrounding equipment [1]. In the presented research the author uses a publicly available dataset to train a model of fault detection. The dataset consists of 463 datapoints – each containing 15 time series of measurements of directional forces (F_X, F_Y and F_Z) and torques (T_X, T_Y and T_Z); measured on the robot end effector [2]. Each of the measurement has one of fifteen different classes assigned to it. Out of these fifteen classes two represent normal operation, while thirteen represent a failure [3]. As the sort of the failure is not important in the control and stopping of robotic manipulator operation those classes are grouped in a class "0" – normal operation, and "1" – fault [4]. With these a binary classification model can be developed, with the goal of detecting a fault based on force and torque measurement. Machine learning (ML) models can have a fast classification performance [5], which is of great importance in preventing any damage caused and have previously been widely used in robotics. Support Vector Machines (SVM) are ML algorithms, which allow for classification by determining a separation between the instances in the feature space of the given problem, through the creation of support vectors [6]. The idea of support vectors is presenting the shortest possible distance between the hypersurface separating the classes and class instances [7]. Hyperparameters are values which define the properties of the machine learning algorithm, and have large influence on the algorithm performance, which is why the adjustment and testing of values is necessary [8]. The training is performed on a total of 120 hyperparameter combinations, with 10-fold K-fold cross validation being performed [9-11]. The quality of the solution is evaluated using Area Under Receiver Operating Curve (AUC) metric. The best solution achieved reaching mean AUC 0.95718±0.16233 ($N=10$) with hyperparameters {'C': 1.0, 'degree': 3, 'gamma': 'auto', 'kernel': 'poly'}. Mean time of detection is 10.000389±1.031651 [μs] ($N=100$).

Keywords

Machine learning, fault detection, binary classification, industrial robotic manipulator, support vector machine

References

[1] L. Seabra Lopes, “Robot Learning at the Task Level: A Study in the Assembly Domain.” Universidade Nova de Lisboa, Ph. D. Thesis, 1997.

[2] L. S. Lopes and L. M. Camarinha-Matos, “Feature transformation strategies for a robot learning problem,” in *Feature Extraction, Construction and Selection*, Springer, 1998, pp. 375–391.

[3] L. M. Camarinha-Matos, L. S. Lopes, and J. Barata, “Integration and learning in supervision of flexible assembly systems,” *IEEE Trans. Robot. Autom.*, vol. 12, no. 2, pp. 202–219, 1996.

[4] F. Khan, J. Ahamed, S. Kadry, and L. K. Ramasamy, “Detecting malicious URLs using binary classification through ada boost algorithm.,” *Int. J. Electr. Comput. Eng.*, vol. 10, 2020.

[5] P. C. Sen, M. Hajra, and M. Ghosh, “Supervised Classification Algorithms in Machine Learning: A Survey and Review,” in *Advances in Intelligent Systems and Computing*, 2020, vol. 937, pp. 99–111, doi: 10.1007/978-981-13-7403-6_11.

[6] W. H. Land and J. D. Schaffer, “The Support Vector Machine,” in *The Art and Science of Machine Intelligence*, Springer, 2020, pp. 45–76.

[7] Z. Gao and N. Y. Chong, “Efficient Robotic Grasp Learning by Demonstration,” in *RITA 2018*, Springer, 2020, pp. 87–99.

[8] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. MIT press, 2016.

[9] I. Lorencin, N. An\djelić, V. Mrzljak, and Z. Car, “Genetic Algorithm Approach to Design of Multi-Layer Perceptron for Combined Cycle Power Plant Electrical Power Output Estimation,” *Energies*, vol. 12, no. 22, p. 4352, 2019.

[10] T. Hastie, R. Tibshirani, and J. Friedman, *The elements of statistical learning: data mining, inference, and prediction*. Springer Science & Business Media, 2009.

[11] Z. Car, S. Baressi Šegota, N. An\djelić, I. Lorencin, and V. Mrzljak, “Modeling the Spread of COVID-19 Infection Using a Multilayer Perceptron,” *Comput. Math. Methods Med.*, vol. 2020, 2020.