Learning-based Detection of Leg-Surface Contact using Position Feedback Only

Jiří Kubík, Rudolf Szadkowski, and Jan Faigl
Department of Computer Science, Faculty of Electrical Engineering
Czech Technical University in Prague
Technická 2, 166 27, Prague 6, Czech Republic
{kubikji2,szadkrud,faiglj}@fel.cvut.cz
WWW home page: `https://comrob.fel.cvut.cz/`

***Abstract*—In this work-in-progress report, we present experimental results of lightweight learning-based leg-contact detection methods for a small hexapod walking robot with position feedback only. The detection of the leg contact with the surface is addressed as anomaly detection using predicted and measured positions of the leg's joints in the leg swing phase. A polynomial regressor and three-layer neural network are evaluated regarding the prediction error and computational requirements using realistic datasets collected with the real hexapod walking robot.**

I. Introduction

In rough terrain locomotion with multi-legged robots, the crucial part of the locomotion control is a timely and reliable sense of the leg contact with the terrain or obstacles. It is specifically important for position-based leg control, where the internal model of leg dynamics can be utilized to estimate the foot-contact [1]. However, in adverse environments such as cave systems, the robot leg dynamics can change for various reasons, such as increased leg weight by mud deposits or increased friction by sludge in the servomotors, and the leg can be damaged. Therefore, the dynamics model needs to be adjusted to such changes to support reliable contact sensing.

The model-based contact detection method uses an inverse dynamics model to estimate contact force [2]–[6]. The model accuracy relies on the identification of kinematic and dynamic parameters of the robot; hence, their applicability might be cumbersome [7] and become outdated as the robot properties change over time. On the other hand, machine learning-based approaches estimate input-output relation directly from the training data, including phenomena omitted by the analytical models. Moreover, the generalizing and online learnable systems can adapt to non-stationarities and changes in the system caused by external factors such as the multi-legged walking robot deployment in the underground environment as in Fig. 1.

We propose to develop a lightweight learning-based contact detection method using only position feedback from the servomotors. In [8], the general inverse leg dynamics black-box models were benchmarked and deployed on a single leg, which was initially shown as a promising approach. However, the detector constructed upon the best-benchmarked model did not yield reliable results supporting locomotion over rough terrains [9]. Therefore, we hypothesize that limiting the regressor operation range to a specific context of the leg swing phase increases the robustness and reliability of the detection. The developed solution has been studied for the real hexapod walking robot SCARAB (depicted in Fig. 1) actuated by 18 servomotors Dynamixel AX-12A with position feedback only.

Fig. 1. Six-legged walking platform SCARAB deployed in an adverse underground environment, where the robot struggles with mud changing the weight of the legs.

The remainder of the report is organized as follows. The addressed problem of foot contact prediction is formally stated in Section II. The proposed context-based detection method is described in Section III. Results of the experimental evaluation and comparison with other existing approaches are reported in Section IV. Concluding remarks are summarized in Section V.

II. Problem

The multi-legged robot locomotion can be based on the coordinated repetitive motion pattern called *gait*. Within each *gait cycle*, legs follow the prescribed trajectory and alternate between the *stance phase* supporting the body, and the *swing phase*, where the legs move to new footholds. An inverse dynamics model can be integrated into an adaptive force threshold-based locomotion controller to detect the leg contact with the surface using the position feedback only [1]. For position feedback only, it is possible to detect deviations from the collision-free dynamics model [10]. By comparing the measured and predicted values, we can detect motion anomalies. Then, the anomaly in the collision-free leg dynamics can be interpreted as a foot contact detection that regulates the gait phase of the leg.

In the case of the considered robotic platform SCARAB, two data types are available to model the robot dynamics at any given discrete time-step k and for each joint i. The data are the measured joint positions $\theta^i_{\text{real}}(k)$ and desired joint positions $\theta^i_{\text{des}}(k)$ set by the locomotion controller, respectively. The measured and desired joint positions are recorded for N and N' past time steps, respectively. Furthermore, the M future time steps of desired joint positions are available at each time step. We formulate the foot-contact detection as a time-series prediction of the i-th joint position $\theta^i_{\text{pred}}(k+1)$ from the current and historical data

$$\begin{aligned}\theta^i_{\text{pred}}(k+1) = \tilde{f}(k, \boldsymbol{\theta}_{\text{real}}(k-N), \ldots, \boldsymbol{\theta}_{\text{real}}(k), \\ \boldsymbol{\theta}_{\text{des}}(k-N'), \ldots, \boldsymbol{\theta}_{\text{des}}(k), \ldots, \boldsymbol{\theta}_{\text{des}}(k+M)),\end{aligned} \tag{1}$$

where $\boldsymbol{\theta}_{\text{real}}(k)$ denotes the measured joint positions vector of all joints coupled with the i-th joint; similarly we define $\boldsymbol{\theta}_{\text{des}}(k)$. The function $\tilde{f}$ is then approximating θ^i dynamics at the next time step $k+1$ out of the N measured positions, $N'+M$ past and future desired positions, and the current time step k.

III. Method

In multi-legged locomotion, the robot legs are moved in repetitive patterns defined by the utilized gait. Therefore, the particular leg trajectory can be divided into *gait segments* based on the trajectory shape. For the foot contact detection, the most relevant segments are those in which we expect the contact of the leg with the surface, which is further referred to as *contact (gait) segments*. In this work, we consider a 3-DoF leg and a triangular shape foot-tip trajectory shown in Fig. 2.

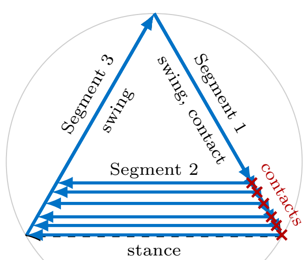

Fig. 2. The schematic depiction of a triangular-shaped leg trajectory with three segments. The contact is expected to occur in trajectory Segment 1 when the leg is descending. The leg supports the body in Segment 2, which length can vary because the contact can occur anywhere along segment 1. The leg ascends in Segment 3, closing the leg's repetitive motion.

For the fixed prescribed shape of the contact segment reference trajectories with the period p, the control signal $\theta^i_{\text{des}}(k) = \theta^i_{\text{des}}(k+n\cdot p),\ n \in \mathbb{N}^0$ is purely dependent on k. Hence, the values of $\boldsymbol{\theta}_{\text{des}}$ bring no additional information and can be omitted because of limited deployment context. Besides, assuming stochastic system with a low variance and the same initial conditions for each contact segment with the period p, $\boldsymbol{\theta}_{\text{real}}(k+n\cdot p), n \in \mathbb{N}^0$ would be similar to each other up to a random error e_{p} caused by inaccuracies. The values of $\boldsymbol{\theta}_{\text{real}}(k-N), \ldots, \boldsymbol{\theta}_{\text{real}}(k)$ is assumed to contain low additional information compared to the information contained in data of the time step k. Therefore, the general form (1) is simplified to

$$\theta^i_{\text{pred}}(k+1) = f^i(k) + \mathcal{N}(0, \sigma^2), \tag{2}$$

where f^i is an unknown leg dynamics for the i-th servomotor with a specific trajectory and specific initial conditions, k is the current time step since the beginning of the contact segment (Segment 1 in Fig. 2), and $\mathcal{N}(0,\sigma^2)$ characterizes inherent inaccuracies and noise that can be observed in Fig. 3. The inaccuracies and noise are modeled as a normal distribution with the variance σ^2 that can be estimated empirically.

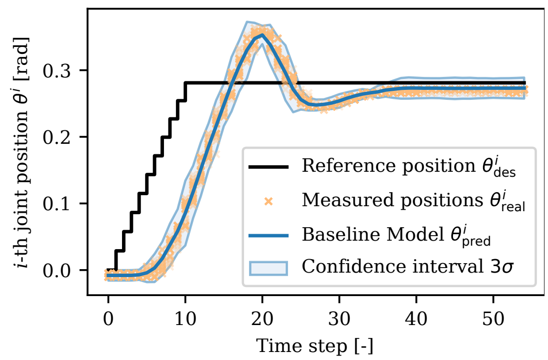

Fig. 3. Example of a femur servomotor response, where the real measured servomotor response θ^i_{real} (yellow) to the reference signal θ^i_{des} (black) varies because of inherent inaccuracies and noise that can be characterized by the standard deviation σ. The data mean data value is depicted in blue.

Having the learned model (function f^i), the foot contact is based on the adaptive thresholding as in the approach [1], where the interpolated trajectory consisting of $\theta^i_{\text{des}}(k)$ is executed step-wise, and at each step k, the real joint position $\theta^i_{\text{real}}(k)$ is measured. An example of collision-free trajectory for the second joint (femur servomotor) is depicted in Fig. 3. The leg is assumed to be in a collision with the surface if the Root Mean Squared Error (RMSE) for the N^i leg servomotors

$$\text{RMSE}(k) = \sqrt{\frac{1}{N^i}\sum_{i=1}^{N^i}(\theta^i_{\text{real}}(k) - \theta^i_{\text{pred}}(k))^2} \tag{3}$$

exceeds the leg-specific experimentally found safety margin ϵ, compensating for the joint discretization, mechanical inaccuracies, and noise characterized by σ^2 of the particular leg.

IV. Results

The proposed method has been evaluated in realistic deployments based on collected datasets with the real SCARAB hexapod walking robot. The leg dynamics f^i in (2) can be learned by various models, and we consider two lightweight learning approaches similarly to [8]. Both methods construct a model for a single leg, take the time step k as a single input, and produce three joint predictions $\theta^i_{\text{pred}}(k)$, one for each leg joint. The first method is an ordinary least squares regression with the n-th-order polynomial features denoted as *Polynomial regressor*. The second method, denoted as *ReLU regressor*, is a neural network with three fully-connected layers and h

neurons in the hidden layer. Among usual activation functions, Leaky Rectified Linear Unit (ReLU) activation function

$$f(x) = \begin{cases} ax & x < 0 \\ x & x \geq 0 \end{cases} \quad (4)$$

is used in all hidden layers to reduce overfitting and vanishing gradients.

Both methods are compared with the baseline model based on direct usage of the collected data, where for each time step k, an average value of all the measured values is used as the prediction for the particular k. Note that the average value is the best estimate for minimizing the RMSE error. The performance of the regressors has been studied for various settings for which regressors' hyperparameters have been learned using the collected datasets.

A. Datasets

Each of the five collected datasets consists of 200 collision-free gait cycles for the triangular-shaped leg trajectory with the circumference $d = 5\,\mathrm{cm}$ as depicted in Fig. 2. The datasets have been collected for the robot sufficiently above the terrain to ensure collision-free leg motion that would otherwise cause contact with the terrain surface. Individual trajectory segments have been executed with the interpolation step size $i_s = 0.5\,\mathrm{mm}$ at the control rate $f_s = 100\,\mathrm{Hz}$ and 111 samples are collected for each Segment 1, which is the only contact segment, resulting in the total segment duration $t_s = 1.11\,\mathrm{s}$. After execution of each segment, the robot leg has been stopped for an additional two seconds to ensure the same initial conditions for each run and reflect the real leg movement during the locomotion. If not stated otherwise, only the first 55 samples are used in the performance evaluation since the servomotor internal steady-state error is reached and the joint dynamics remain unchanged, see Fig. 3.

The datasets have been collected for the specific leg conditions mimicking real-life modification and they are named as *no-modes*, *no-link* (NL), *no-link-weight* (NLW), *weight-link* (WL), and *weight-servo* (WS). The first *no-modes* dataset represent a regular default configuration. The last link of the leg has been removed for the *no-link* dataset, and additional weight $m_m = 52\,\mathrm{g}$ has been added to the penultimate servomotor for the dataset *no-link-weight*. The same additional weight m_m has been added to the last leg link for the *weight-link* dataset. Finally, the same weight m_m has been added to the penultimate link for the *weight-servo* dataset. The collected segments are split in $0.75 : 0.25$ training-testing ratio if not stated otherwise.

B. Influence of the Model Parameters

The polynomial regressor can be parameterized by the degree p and the ReLU regressor by the size of the hidden layer h. For both parameters, we consider grid search where the training and evaluation using the cumulative RMSE have been repeated ten times for each configuration of the regressors.[1] The performance of the polynomial regressor is depicted as a bar plot and ReLU as the five-number summary in Fig. 4. Based on the presented results, we select $p = 18$ and $h = 60$ parametrization for the further evaluations.

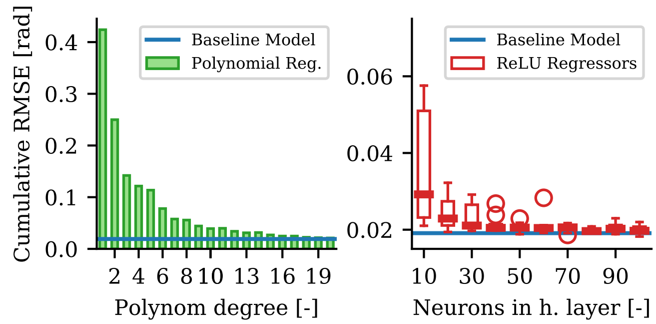

Fig. 4. Influence of regressors' parametrization: polynom degree p of the Polynomial regressor and size of the hidden layer h of the ReLU regressor.

C. Performance under Different Robot Setup

The generalizability of the learned predictors has been examined for regressors trained using a non-modified leg that has been utilized for the prediction in the datasets with the modified robot setup. The mean cumulative RMSE is used to measure accuracy over the results, where the RMSE is computed for each servomotor individually. Finally, the mean is computed, and the sum of mean values over all servomotor is used to examine the performance. Similarly, the regressors learned only for the particular dataset have been evaluated on the other datasets using the same measure. The results in Fig. 5 suggest that regressors can cope with leg modifications.

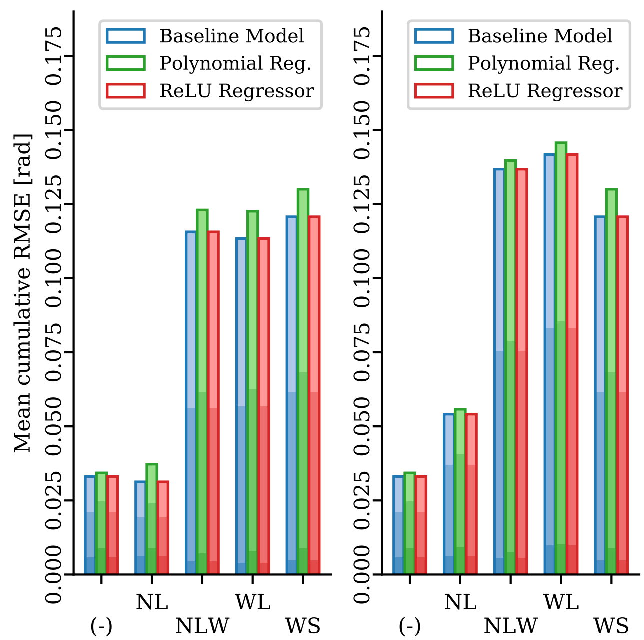

Fig. 5. Performance of regressors learned for the particular robot setup evaluated on the prediction for all other robot setups (left) and generalization of the learned regressor using the *no-mods* dataset (right).

[1]The evaluation using the R-squared measure provides identical qualitative comparison results.

The results indicate regressors' performance similar to the baseline model for arbitrary leg dynamics, albeit the generalization is limited and an error increase can be expected; therefore, the effect of the training data size has been studied.

D. Influence of the Training Data Size

The prediction performance has been studied for the regressors trained using the number of segments ranging from 1 to 100. For each size of the training set s, s unique segments have been selected from the whole dataset and used to train the regressors. The prediction error is computed as the mean cumulative RMSE using $200 - s$ segments not used for the training. The results are depicted in Fig. 6.

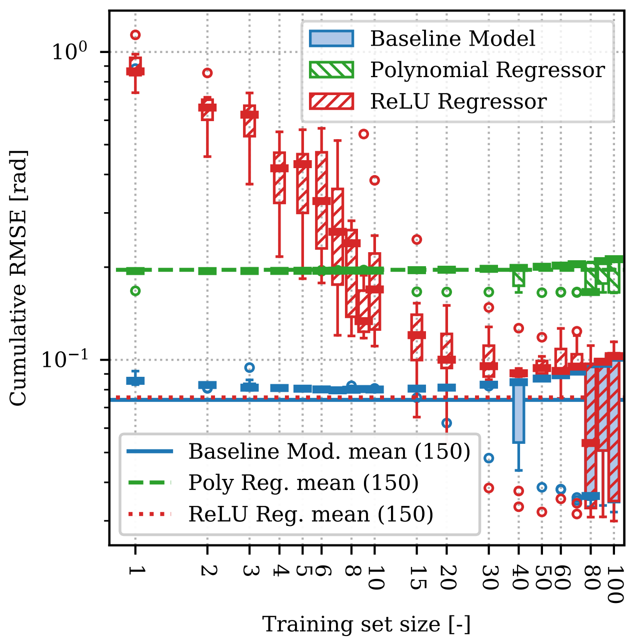

Fig. 6. Influence of the training data size on the prediction error.

The results suggest that 15 samples are sufficient for the ReLU regressor to learn the expected trajectory shape as the other two methods. The mean cumulative RMSE is about four times the error of those trained using 150 segments, and from this point on, the performance increases slowly. The baseline and polynomial regressors are not affected by the training size.

Based on the training times depicted in Fig. 7, the baseline regressor is about ten times less demanding than the polynomial regressor, which is still several orders of magnitude less demanding than the ReLU regressor. The baseline regressor has 330 parameters, the polynomial regressor 54 parameters, and the ReLU regressor 303 parameters. Therefore, the polynomial regressor with $p = 18$ seems to be a suitable choice for practical deployments.

V. Conclusion

We evaluated lightweight learning methods to detect the leg contact with a surface in locomotion control of a small hexapod walking robot with only position feedback. The polynomial and neural network regressors have been examined

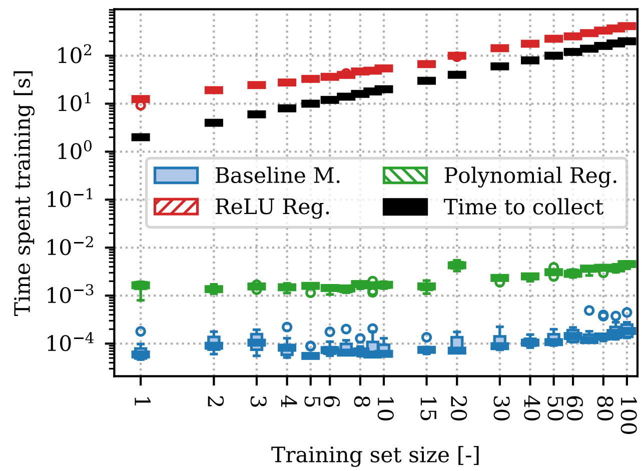

Fig. 7. Influence of the training data size to the training time.

using datasets collected by a real robot. The presented results suggest that the proposed regressors are competitive. The polynomial regressor is the most suitable predictor because it performs similarly to the baseline but has fewer parameters. It would thus scale better for different leg trajectories.

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