Online Foot-Strike Detection using Inertial Measurements for Multi-Legged Walking Robots

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***Abstract*— Proprioceptive terrain sensing is essential for rough terrain traversal because it helps legged robots to negotiate individual steps by reacting to terrain irregularities. In this work, we propose to utilize inertial data in the detection of the contact between the leg and the terrain during the stride phase of the leg. We show that relatively cheap accelerometers can be utilized to reliably detect a foot-strike, and thus allow the robot to crawl irregular terrains. The continuous data processing is compared with the interrupt mode in which data are provided only around the foot-strike event. The interrupt mode exhibits significantly better performance, and it also supports generalization of the foot-strike event detector learned from data collected in slow locomotion to faster locomotion where the signals slightly change. The proposed solution is experimentally validated using a real hexapod walking robot for which the walking speed has been improved in comparison to the previous adaptive motion gait based on a force threshold-based position controller for the foot-strike detection.**

I. Introduction

Enhanced traversability capabilities are the main advantage of legged robots in traversing rough terrains. Different methods of locomotion control have been recently presented to control the robot attitude when crawling irregular terrains which all share a common property of utilizing sensory feedback to negotiate the traversed terrain and maintain the robot stability. However, for practical deployment of multi-legged robots in various missions, the efficiency of the rough terrain locomotion is studied to improve and speed up the robot locomotion, and thus more quickly accomplish the mission objectives. Hence the primary motivation for the proposed approach is to enable fast and reliable locomotion over rough terrains for affordable hexapod walking robot using as few sensors as possible.

The critical part of the locomotion control with robot stability is timely and reliable foot-strike detection, because, in a case of failure, the robot construction is put under stress, the stability can be lost, and high torque values in joints may damage the actuators. Although a direct drive [1] or highly compliant elastic actuators [2] may mitigate the stress on the robot construction, they are less energy efficient than the large-reduction gear actuators. Different approaches to delivering the tactile feedback for detecting the moment of the leg contact with the ground have been developed. A straightforward approach is to place contact sensors at the leg foot tips [3]. A more indirect method is to estimate or measure ground-reaction forces or joint torques. This can be achieved by measuring joint torques at each joint directly [4], estimate them using a linear model of the servomotor's position error [5], current [6], or utilizing strain-gauges [7], force-sensitive resistors [8] or expensive force-torque sensors [9] to measure the ground reaction force at the leg foot-tip.

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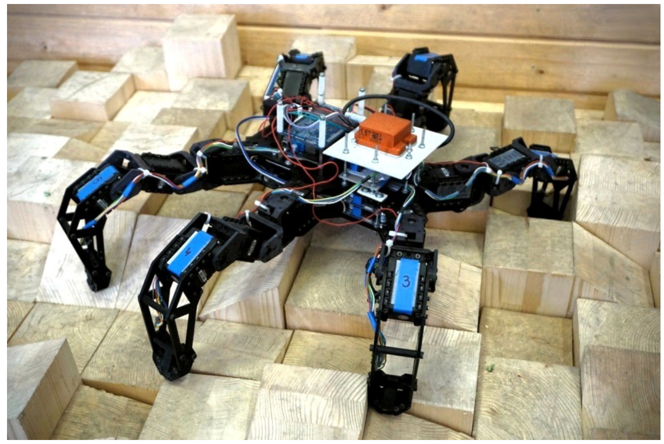


Fig. 1. Hexapod walking robot with ADXL-345 accelerometers mounted on each leg and wired to the custom designed multiplexing board connected to the Odroid XU-4 embedded computer. Notice the attached Xsense MTi-30 AHRS (the orange box) is not utilized in the proposed foot-strike detection.

In this work, we propose the foot-strike detection based on inertial measurements provided by the specific feature of the utilized accelerometers. The proposed approach is based on the previous adaptive motion gait [5] developed for a hexapod crawling robot shown in Fig. 1. In the previous approach, position feedback from the servomotors only is used to detect the contact point of the leg with the ground, which represents an affordable approach to crawl irregular terrains. However, due to the limited communication capabilities of the used servomotors, the approach provides relatively slow locomotion because of the minimum latency of 20 ms when reading position data out of 18 servomotors. Therefore we investigated the foot-strike detection using inertial data from cheap, 3-axis ADXL-345 accelerometers attached to the legs.

The challenge of the foot-strike detection from the inertial data is in the nature of the legged locomotion that induces vibrations into the robot body. Hence, an event detection mechanism is necessary to detect the foot-strike events correctly. Aside of the traditional event detection in the continuous operation mode, we exploit the property of the used accelerometers to event-filtering at the hardware level which can isolate the relevant data and improve the performance of the foot-strike detection.

For the foot-strike detection, we propose to employ a signal detector that is learned from the real data using the adaptive motion gait [5] which is capable of crawling irregular terrains, but it is relatively slow. In the presented results, we show that the learned detector of the inertial feedback is sufficient to allow the robot to traverse irregular terrains. Moreover, we show that the signal classifier learned using data from slow locomotion generalize to faster movement, and thus the proposed approach scales with increasing locomotion speed. The proposed approach provides up to 1.6 times speedup of the base approach [5] in irregular terrains mainly due to the event-filtering as a similar generalization is very challenging with continuous signal processing.

The remainder of the paper is organized as follows. Section II reviews related approaches to gait event detection and terrain sensing using inertial data. The addressed problemm, the necessary background of the employed robotic platform, and its locomotion [5] are provided in Section III. The proposed approach is presented in Section IV and experimental results are reported in Section V. Finally, concluding remarks are in Section VI.

II. Related work

Multi-legged locomotion over rough terrains is a largely studied topic for which numerous contributions have been proposed in the past years. In legged robotics, the foot-strike detection is usually done using contact sensors [3] or various setups with force/torque measurements. The inertial data are utilized primarily for the attitude control to determine a slope of the traversed terrain and adjust the robot pose accordingly [6], [10]. Another application is a terrain classification on both legged [11], [12] and wheeled platforms [13].

Most of the related work on the foot-strike detection and gait phase detection using the inertial data can be found in the field of medical applications and rehabilitation. In this field, inertial data, possibly combined with force sensitive resistors (FSR), are utilized to detect foot-strikes [14], gait phases [15], and stimulate muscle activity [16], and thus help to restore walking abilities [14]. Different setups using single [16] or multiple [17], [18] 2-axis or 3-axis accelerometers are used similarly to the setups utilizing the FSR on the foot for improving reliability and robustness [19] or training the gait event classifiers [16], [20].

The foot-strike or gait phase detections are achieved using rule-based detection with a given set of states and transitions between them [15] or by detecting extremes in inertial measurements [17]. Besides, methods utilizing detection based on feed-forward neural networks [20] and recurrent neural networks (RNN) [16] have been introduced. Last but not least, the support vector machine (SVM) has been used in [21] to distinguish five different gait phases from the inertial data. Stream-Based detection is used in approaches with classifiers that are usually trained by the FSR detection.

The herein proposed method uses only a single accelerometer per each leg, and for the foot-strike detection, the SVM based classifier and neural network based classifiers have been evaluated. The learning of the classifiers is based on collected data using the existing work on the adaptive motion gait [5] as it is suggested by multiple related work to use real data with successful ground detection [15]–[17], [19]–[21].

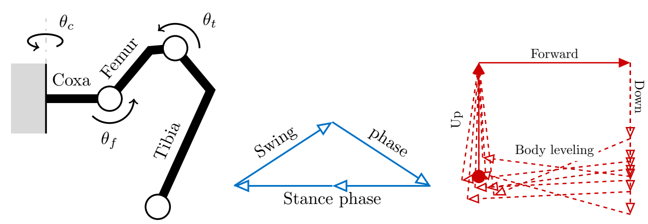
III. Problem Statement

The addressed problem is to provide fast and reliable detection of the leg foot strike using only inertial measurements provided by relatively cheap accelerometers. Moreover, we aim to speed up the locomotion over the irregular terrains concerning the previous work based only on the feedback from the Dynamixel AX-12 servomotors firstly introduced in [5]. In particular, the proposed approach is considered with the hexapod walking robot depicted in Fig. 1 with the single ADXL-345 accelerometer attached to each leg.

A locomotion controller capable of crawling irregular terrains is necessary to collect real data for learning classifiers of the inertial signals, and thus learning the detection of the leg contact with the ground. Since [5] already provides this capability, it is employed for the first initial data collection. Therefore, the used hexapod walking robot platform and a brief description of the operation modes of the employed ADXL-345 accelerometers are presented in the following section together with the groundwork [5] described in Section III-B.

A. Hexapod walking robot

The utilized hexapod robot has six legs attached to the trunk, each with three joints named coxa θ_c, femur θ_f, and tibia θ_t, respectively, as shown in Fig. 2a. The joints are actuated by the Dynamixel AX-12 servomotors that provide the position feedback utilized in the force threshold-based position (FTP) controller [5] further described in the following section. Each servomotor support reading and writing of the desired position every 1.2 ms, which represents a significant bottleneck concerning 18 active actuators.



(a) Leg schema (b) Regular gait (c) Adaptive gait

Fig. 2. (a) A schematic diagram of the leg. Each leg has three parts (links) – Coxa, Femur, and Tibia connected by three joints (θ_c, θ_f, and θ_t). The coxa joint is fixed to the body with a vertical rotation axis while the two other joints are oriented with respect to the horizontal axis. (b) The leg trajectory without feedback; and (c) the leg trajectory for the adaptive gait that combines the detection of the ground during the swing down phase of the leg motion with the follow-up robot body leveling.

In the proposed approach, the ADXL-345, a low-cost 3-axis digital accelerometer, is attached to each leg and connected to the main controller via the 400 kHz $\mathrm{I^2C}$ interface with the raw output data rate at 800 Hz. Besides, an interrupt pin is connected directly to the controller because the ADXL-345 can operate in two modes as follows.

The first mode is the traditional continuous mode when the data are fetched by the controller immediately as they

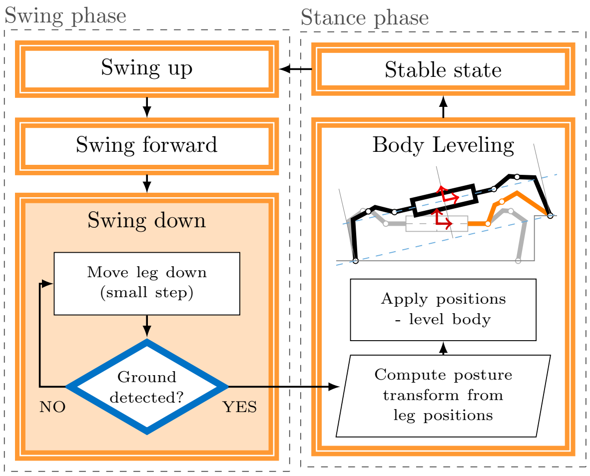


Fig. 3. An overall schema of the utilized adaptive locomotion control, together with visualization of the body leveling.

are available. The second mode is the interrupt mode that interrupts the controller if a predefined event occurs, e.g., *free fall*, *single tap* or *double tap*, that is a single acceleration event larger than a predefined threshold. In the interrupt mode, the ADXL-345 provides data within a pre-set time window directly preceding and following the event with the sampling rate up to 3200 Hz. The raw acceleration measurements in all three axes α_x, α_y, and α_z are stored in a 32-element deep buffer. The main controller is the Odroid XU-4 with 2 GHz ARM Cortex A7 octa-core processor (Samsung Exynos5422) and with 2 GB RAM.

B. Foot-Strike Detection in Adaptive Motion Gait

During the locomotion, the leg foot-tip follows a prescribed trajectory which defines whether the leg is in the swing phase, reaching a new foothold, or in the stance phase supporting the body. On flat surfaces, a simple feed-forward controller is sufficient for reliable locomotion as the leg follows the trajectory as shown in Fig. 2b. However, in rough terrains, proprioceptive feedback has to be incorporated in the locomotion control for adaptation to terrain irregularities. The adaptive motion gait [5] splits the robot motion into legs movement followed by the body movement. The ground detection is performed during the leg swing down phase (see Fig. 3) and the leg trajectories can look like in Fig. 2c.

The main idea of the ground detection [5] is to move the leg using the position control until a contact point of the leg with the ground is detected. The position feedback of the servomotors is used to estimate the ground reaction force and stop the leg motion when the servo position error between the desired and current position exceeds the predefined threshold.

During the swing down phase, the leg trajectory is interpolated into small steps, and the collision check of the leg with the ground is performed. Once the active leg reaches a new foothold position, its movement stops and the robot posture is adjusted to cope with the terrain irregularities using the body leveling. Although the adaptive locomotion control [5] enables the robot to crawl irregular terrains, it is relatively slow because of the limited communication of the servos. Therefore, the presented approach is to detect the ground during the leg swing down motion using independent inertial data provided by the ADXL-345 accelerometers, i.e., we aim to develop inertial based ground detection shown as a blue block in Fig. 3. Two different approaches based on two operational modes of the ADXL-345 have been investigated, and they are described in the following section.

IV. Proposed Foot-Strike Detection Method

The proposed foot-strike detection method relies on detection of the ground contact point from the inertial data provided by the accelerometers attached to each leg. The traditional approach based on the event detection in a stream of accelerometer measurements has been investigated together with the proposed exploitation of the *single tap* feature of the utilized ADXL-345 accelerometers, further referred as the *tap event mode*. The overall structure of these two methods is visualized in Fig. 4 and Fig. 5, respectively.

For the both approaches, the inertial data processing pipeline consists of three individual steps: 1) *data acquisition*, 2) *data preprocessing*, and 3) *detection*. The data acquisition and detection steps differ for each particular approaches, but both methods share the same data preprocessing step. The preprocessing step is to unify the data and simplify the event detection by compensating the effect of the robot posture and sensor mount. A detail description of individual steps together with the classifier training using the groundwork [5] is presented in the following parts.

A. Data Acquisition

The data acquisition differs for the continuous and the tap event modes. In the continuous mode visualized in Fig. 4, the controller continuously reads the available data that are preprocessed and then, the detection of the foot-strike events is performed. Multiple legs can be simultaneously in the swing phase, and therefore, the bandwidth of the `I²C` bus has to be divided equally between the individual accelerometers of the currently moving legs to read all the data.

On the other hand, the tap event mode (visualized in Fig. 5) relies on the ability of the ADXL-345 accelerometer to generate a hardware interrupt whenever the specified event occurs. The accelerometer features a buffer for 32 entries, which can be set up to hold the acceleration data for the specified time window around the event. The controller is triggered when the interrupt is generated and delivered via the dedicated `IRQ` signal. Afterward, the content of the buffer is read through the `I²C` bus and processed similarly to the continuous operation mode. The particular parameters for generating the tap event have been found experimentally as follows: the minimum tap duration is 6.9 ms, the tap threshold as 4.9 g, the sampling rate should be 800 Hz, and the window event index is set to 16.

B. Data Preprocessing

Before detecting the foot strike itself, the raw accelerometer measurements have to be preprocessed to compensate for the robot posture as the leg can hit the ground

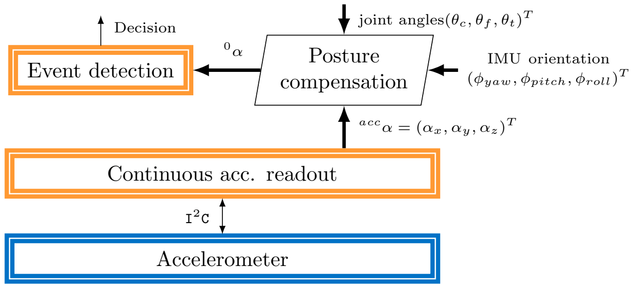


Fig. 4. Foot-strike detection in the continuous operation mode.

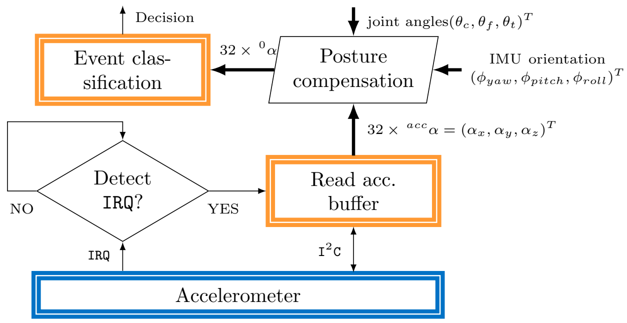


Fig. 5. Foot-strike detection in the tap even (interrupt) operation mode.

at different angles. Therefore, the acceleration readings $^{acc}\boldsymbol{\alpha} = (\alpha_x, \alpha_y, \alpha_z)$ expressed in the reference frame relative to the particular accelerometer (further denoted with the superscript acc) have to be transformed to the global coordinate frame denoted with the superscript 0, i.e., $^0\boldsymbol{\alpha}$.

Given the joint angles $(\theta_c, \theta_f, \theta_t)$ of the respective leg and the global orientation of the robot body $(\phi_{yaw}, \phi_{pitch}, \phi_{roll})$, the transformation compensating the body posture can be expressed as

$$
\begin{aligned}
^0\boldsymbol{\alpha} &= \boldsymbol{R}_{body}\boldsymbol{R}_{leg}\boldsymbol{R}_{acc}\,{}^{acc}\boldsymbol{\alpha}, && (1)\\
\boldsymbol{R}_{body} &= \boldsymbol{R}_y(\phi_{pitch})\boldsymbol{R}_x(\phi_{roll}), && (2)\\
\boldsymbol{R}_{leg} &= \boldsymbol{R}_z(\theta_c - \theta_c^{off})\boldsymbol{R}_y(-\theta_f - \theta_t), && (3)\\
\boldsymbol{R}_{acc} &= \boldsymbol{R}_y(\beta_{off}), && (4)
\end{aligned}
$$

where $\boldsymbol{R}_x$, $\boldsymbol{R}_y$, and $\boldsymbol{R}_z$ are the rotations around the respective axes, θ_c^{off} is the coxa angle mount offset, and β_{off} is the mount offset angle of the accelerometer w.r.t. the leg. The transformed data are then processed for the foot-strikes.

The global orientation of the robot can be provided by the AHRS unit attached to the robot trunk. However, to make the robot affordable, we rather propose to estimate the global orientation from the accelerometer measurements of the legs that are in the stance phase using

$$
\begin{aligned}
^{acc}\phi_{pitch} &= \arctan\left(\frac{\alpha_y}{\sqrt{\alpha_x^2 + \alpha_z^2}}\right),\\
^{acc}\phi_{roll} &= \arctan\left(\frac{-\alpha_x}{\alpha_z}\right).
\end{aligned} \qquad (5)
$$

The orientation of the accelerometers is transformed from the leg to the body coordinate frame $\boldsymbol{R}_{body}\boldsymbol{R}_{leg}$ to get the global orientation. Note, the legs in the stance phase do not move except small vibrations because of the split motion of the legs and the body. Hence, the estimation according to (5) is sufficient and has been used in preprocessing, albeit more elaborate methods might improve the performance [22].

C. Foot-Strike Event Detection

After the preprocessing, the data are fed into the event detector in the case of the continuous operation mode and to the event classifier in the case of the tap event mode. This difference is based on the fact that the former operates on a stream of continuous data, whereas the tap event mode only classifies discrete events which are not related in time. Besides, the discrete events consist always of 32 measurements because of the size of the ADXL-345 buffer.

In our experimental evaluation, we consider the SVM for both of the methods. However, a sliding window approach is used in the continuous operation mode, whereas in the tap event mode, the whole input vector of all 96 values is fed to the learned SVM. Besides, we consider the long-short term memory [23] (LSTM) recurrent neural network learning using the backpropagation through time [24] (BPTT) for the detection in the continuous mode. Finally, we also consider a simple multi-layer neural network (NN) for the event classification of the tap event mode.

The most important part of the foot-strike detection is the learning of the detector/classifier using real data. We employed a real working adaptive motion gait [5] capable of walking rough terrains. The robot has been guided through the rough terrain area, and both the data from the accelerometers and the detected events provided by the adaptive motion gait [5] have been recorded. Then, these labeled data have been used for training as follows.

In the continuous operation mode, the unbalanced nature of the data (one event per several hundreds of measurements) leads us to modify the labels to alternate between the zero and one in the case of the foot-strike event. Hence, it is possible to use the standard learning approaches with the root mean squared error minimization as the objective function.

For the tap event mode, the main challenge is to assign the event to the corresponding tap event produced by the accelerometer. Therefore, we consider k-nearest neighbors in a pre-defined time window around the labeled event for the selection of the corresponding tap event, which shows to be sufficient for a reliable foot-strike detection. The experimental results together with the visualization of the data are reported in the following section.

V. RESULTS

The proposed ground detection approach has been experimentally verified in two scenarios using the real data and hexapod walking robot. Besides, the performance of the proposed approach is compared with the groundwork method [5]. The first scenario evaluates the performance of the individual detection methods with datasets collected using the groundwork method. In the second scenario, the best performing method from the first scenario has been deployed on the real robot and tested in several experimental trials to

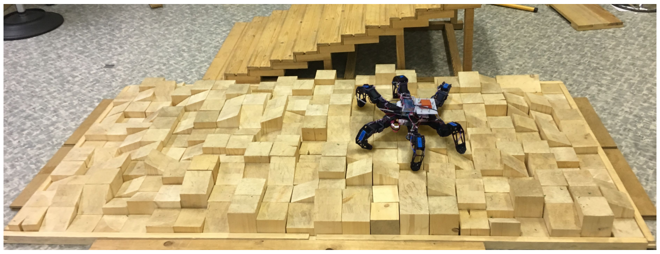


Fig. 6. Experimental rough terrain test-track.

compare its performance with the groundwork approach. The achieved results are reported as follows.

A. Performance Analysis of the Foot-Strike Detection

The performance of the learned foot-strike detection has been statistically evaluated on the dataset collected using the groundwork method [5] on a rough terrain laboratory test-track shown in Fig. 6. It has dimensions 2.5×1.2 m, and it consists of irregular height and sloped 10×10 cm wooden blocks. The robot has been guided by the operator across the experimental test-track and the acceleration data together with the ground-detections provided by the adaptive motion gait [5] have been recorded. Altogether, 1332 events for the continuous mode and 1401 events for the tap mode have been recorded and split into the training and testing data in the ratio 0.7:0.3. Each detection method has been trained on the collected data, and its parameters have been further experimentally tuned.

For the stream-based processing, the SVM classifier has been parametrized to detect events on the 32 elements wide window of ${}^{0}\boldsymbol{\alpha}$ values with the radial basis function (RBF) kernel, because the polynomial kernels perform poorly on the given data. Next, the LSTM [23] with 3 inputs, 32 hidden states, and a single output with the sigmoid activation function has been evaluated.

For the tap event mode, the individual events are represented as 32 vectors ${}^{0}\boldsymbol{\alpha}$ where each batch of vectors is processed at once. In addition to the SVM classifier with the RBF kernel, we also tested a feed-forward neural network (NN) with 32 inputs, two hidden layers, and a single output layer trained using the backpropagation, which provides competitive results to the SVM classification.

TABLE I
DETECTION RESULTS

	Stream processing		**Tap event processing**	
	SVM	LSTM	SVM	NN
Precision	0.63	0.57	0.81	0.78
Recall	0.31	0.15	0.85	0.60

Example waveforms of the collected data for the stream processing and tap event processing, together with the groundwork detections and the results of the best performing event detection using SVM are visualized in Fig. 7a and Fig. 7b, respectively. The statistical measures of the precision and recall of the individual detection approaches are listed in Table I. The results indicate that the processing of the stream data is more error prone as there is a huge number of miss detections, whereas the filtering using the *single tap* feature of the utilized accelerometers provides detection with the significantly improved precision. The major problem with both approaches is the false positive detections induced mainly due to the fast acceleration of the leg when transferring from the forward swing to the downswing phase. Nevertheless, the best performing method is the foot-strike detection in the tap event mode using the SVM classifiers that is further used in practical deployment with our real hexapod walking robot.

B. Deployment on the Real Hexapod Walking Robot

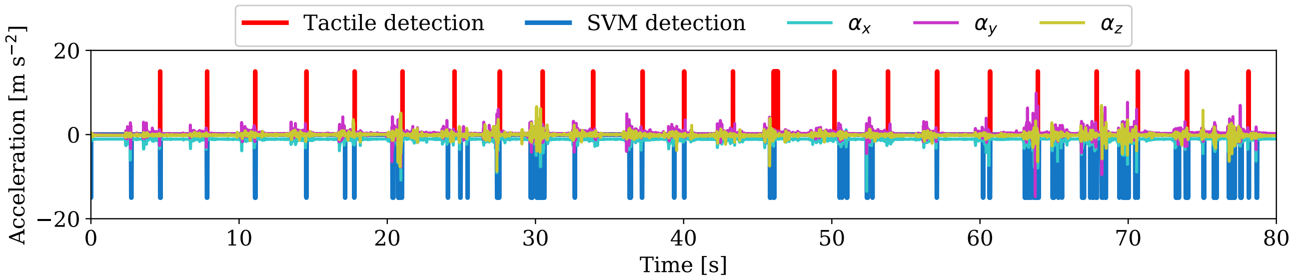
Feasibility of the proposed approach and its expected benefits have been verified by the deployment of the best performing method on the real hexapod walking robot, i.e., the tap event processing with the learned SVM classifier. The robot has been requested to traverse the rough terrain test-track using the feedback solely from the accelerometers. The robot has been able to traverse the test-track as expected, and therefore, we started to speed up its motion to verify the benefits of using the accelerometers in the foot-strike detection. Specifically, we focused on the generalization of the learned classifier for higher speeds of the locomotion.

We have gradually increased the forward speed of the robot by decreasing the swing time from 2.8 s, which is the default setting for the groundwork [5], down to 1.2 s, which has shown to be the limit for a reliable operation of the proposed ground detection, and measure the time it takes the robot to traverse the test-track in ten trials. The absolute value of the robot forward speed has been increased from 0.034 ± 0.006 ms^{-1} to 0.056 ± 0.007 ms^{-1}. Hence, about 1.6 speed-up in comparison to the groundwork [5] has been achieved while maintaining a similar velocity variance.

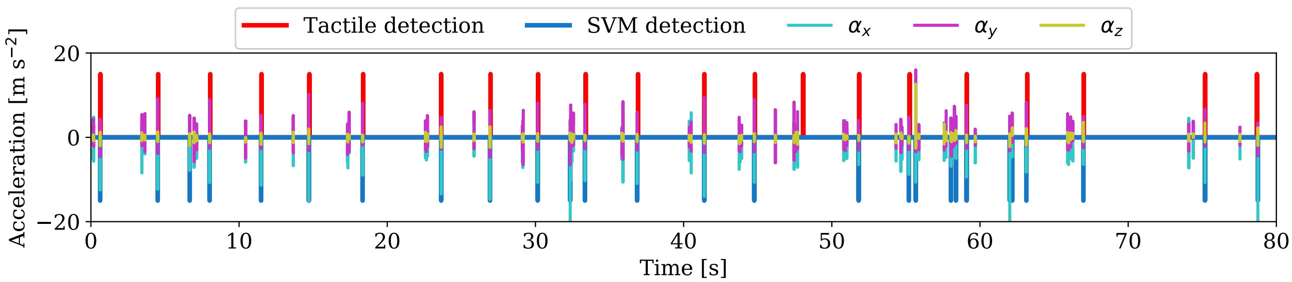
Beyond this speedup, the tap event detection method ceases to detect the foot-strikes correctly; however, we believe that by self-supervised learning of the event classifier for the increased speed, it would be possible to achieve a higher speedup, which is a subject of our future work.

VI. Conclusion

In this work, we propose a foot-strike detection method solely based on inertial measurements that enables a hexapod walking robot to traverse rough terrains. Besides, the proposed method speeds up the robot locomotion in comparison to the previous approach which uses only the position feedback from the servomotors. Two complementary approaches based on stream data event detection and *single tap* events classification have been presented and experimentally evaluated. In the made comparison, the former method needs to perform event detection on time series, whereas the later exploits the capability of the sensor itself to isolate the relevant data, and thus supports effective classification into two discrete classes over these data. The proposed tap event-based method achieves better results and delivers a competitive performance in comparison to the groundwork [5]. Moreover, an overall 1.6 speedup has been achieved for crawling the irregular terrain. For the future work, we aim to use the inertial readings from the body-attached inertial unit in self-supervised learning of the event



(a) Stream data from the ADXL-345 accelerometer



(b) *Single tap* event data from the ADXL-345 accelerometer

Fig. 7. Visualization of the raw data provided by the ADXL-345 accelerometer. The foot-strike events given by the groundwork approach used for detection learning are visualized in red, the events detected from the accelerometric data are visualized in blue.

classifier based on the evaluation of the locomotion stability, and thus further improve the performance of the ground detection and locomotion.

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