13th International Workshop on Innovative Simulation for Healthcare, 013
21st International Multidisciplinary Modeling & Simulation Multiconference

2724-0371 © 2024 The Authors.
doi: 10.46354/i3m.2024.iwish.013

Gait Evaluation for Prevention and Rehabilitation based on Dynamic-Time-Warping and Acceleration Measurement

Jan Beckmann[1] and Volkhard Klinger[1,*]

[1]Department of Embedded Systems, University of Applied Science Hannover (FHDW), D-30173 Hannover, LS, Germany

[*]Corresponding author. Email address: volkhard.klinger@fhdw.de

Abstract

Each person's gait pattern is individual and influenced by many factors. Maintaining safe mobility with the fullest possible functional capacity is an essential objective of rehabilitative and preventive approaches. An abnormal gait is a change in the gait pattern. Every person's natural walking style is unique. However, injuries and illnesses can affect your gait. Anything that affects your brain, spinal cord, legs or feet can alter your gait. The signs and symptoms of gait abnormalities depend on the type of abnormality you suffer from. Some of the most common symptoms are, for example: Dragging or shuffling of the feet, loosing balance, pain when walking, etc.. Gait analysis is the method that makes it possible to recognize problems when walking, identify the cause and initiate appropriate measures to rectify them (Kirtley, 2006; Richards et al., 2022).

This paper proposes a solution for a simple yet reliable evaluation of the individual's gait pattern in order to reduce asymmetries and to realize a phase of rehabilitation until full recovery by evaluating the gait as completely as possible. The objective is to record and document information on the gait pattern and the forces acting on each leg. The approach is based on micro-electro-mechanical systems (MEMS)-Acceleration sensors and the application of the Dynamic-Time-Warping (DTW)-algorithm, implemented on a mobile Internet of Things (IoT)-module, which is used on each leg. Thereby a mobile system is realized, providing the continuous data acquisition which makes long-term evaluation possible.

Keywords: model-based; IoT; platform; dynamic time-warping; gait evaluation

1. Introduction

Human gait is influenced by various factors, including poor fitness, neurological and musculoskeletal conditions and, of course, degenerative changes due to ageing or Injuries. Poor gait control is associated with disability, falls, increased morbidity and mortality and is therefore an important personal and public health issue. This project aims to lay the foundation for continuous monitoring of gait in order to achieve benefits for the user in both prevention and rehabilitation by evaluating the gait and the forces acting on the respective leg. The focus is on short, medium and long-term changes in both prevention and rehabilitation progress (Hartmann et al., 2013; Huang et al., 2017). Both domains have short-term as well as medium- and long-term objectives. The short-term objectives include recognizing an asymmetrical gait and analyzing the causes through posture exercises and analysis of footwear. This identification is the basis for an evaluation of the causes and subsequent correction of the gait in order to avoid the corresponding long-term consequences. The medium- and long-term objectives are an recognition of age, accident and health-related changes at an early stage in order to achieve a targeted improvement.

In the context of rehabilitation, for example in the case of a broken leg and the subsequent healing phase, it should also be possible to monitor the forces acting on the damaged leg so, that rehabilitation can be optimally supported by appropriate load specifications. Such force specifications exist, but it is almost impossible for the user to carry out such specifications, such as a maximum load of 30 %, in practice without system support. The system presented in this paper is an IoT-platform, based on (Klinger, 2019), that meets the requirements for mobility, Plug-and-Play (PnP) and can be used as wearable without any specific requirements like special shoes, etc..

In section 2 the IoT-system is introduced, based on our platform design. The following section 3 describes the application which is in focus in this paper and shows either the gait analysis and the corresponding results. In section 4 we conclude the paper and show aspects of further work.

2. Embedded Systems in the Focus of Biomedical Applications

There are a large number of biomedical applications that use different sensors to obtain information about the condition of the body or to obtain information about movement statics and dynamics. These sensors include force sensors, acceleration and gyro sensors and also sensors for the acquisition of electrocardiogram (ECG), electromyogram (EMG) electroneurogram (ENG), and electroencephalogram (EEG).

We describe some applications for prosthesis control, gait monitoring and and posture assessment, all of which are aligned with our system platform, including the use of Internet of Things (IoT) modules. The system architecture is a key factor in supporting stationary and mobile applications. and mobile applications. Mobile applications have special requirements, e.g. in terms of portability, energy consumption, computing power and integration into existing infrastructures. Therefore, the system architecture is based on the system we presented in (Klinger and Bohlmann, 2020). IoT-modules have been added to the original to expand the range of functions. These IoT-modules enable the wireless connection of the various system different system components to a central unit. Thanks to the platform architecture, the various modules span their own network (via Bluetooth Low Energy (BLE)) or wireless local network in accordance with IEEE 802.11 (wireless local area network according IEEE 802.11 (WiFi))) and connect to a gateway over a greater range. This gateway, i.e. a SmartDevice, enables the system to be integrated via WiFi or Global System for Mobile Communication (GSM), i.e. cellular-secured Internet. To realize a platform-based system architecture, which enables mobile operation that is only which is only person-bound and not location-bound, the following features are essential:

- C1 Independence from a specific environment environment.
- C2 Integration of all necessary sensors into the platform.

These properties make the platform universally adaptable. For example, the gait evaluation based on shoe-integrated pressure sensors described in (Klinger, 2016)

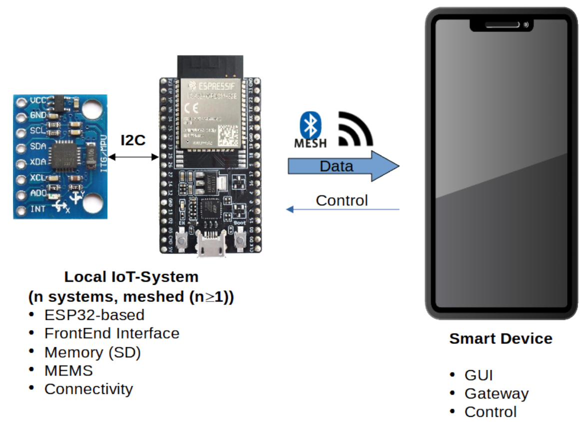

Figure 1. Low-level system architecture.

can be replaced by a different sensor configuration to meet these requirements. Other current solutions, described in (Matuska et al., 2020) and (Bourahmoune et al., 2022), take a different approach and shift the functionality to external, non-personal equipment (chairs, cushions). This allows application only in specific locations. The lowest level of the platform architecture used here is shown in Figure 1. The local IoT system, hereafter called SmartBox, consists of an ESP32 (Espressif, 2019) and application-specific sensors; here we have only one MEMSsensor with 6 axes (acceleration (x , y, z) and gyroscope (x , y, z)), an MPU6050. This ESP32 platform is the workhorse for all applications and can be adapted to the specific application using a variety of sensors.

The SmartDevice is connected for configuration and data modification, e.g. to download and display all the raw data stored on the ESP32 or to configure the platform. The other levels are not the focus here, a brief description will suffice: The cloud database is the sink for all data from all local IoT systems and the source for all data mining and data-based fusion and identification operations. This architecture integrates all IoT systems and supports various different modes and the corresponding scenarios (Klinger and Bohlmann, 2020). In all applications, we try to improve the PnP character by achieving as little system complexity as possible for the measurement and at the same time as much measurement and operating convenience as possible and a low cost approach. This means that the SmartDevice is only required for certain displays and events. A more advanced system mode, which allows the raw measurement data to be transferred at certain times from the local system to a cloud architecture and thus also to a server for evaluation, has already been presented in (Klinger and Bohlmann, 2020). In gait monitoring and posture assessment in particular, the main task is to compare trajectories or curves in order to identify specific movements. In the following subsections, we present this relationship in more detail.

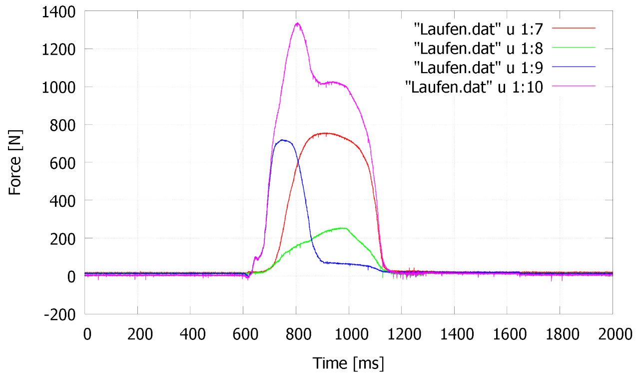

Figure 2. Normal gait, one step, right leg: Vertical Force plotted over time for 3 sensors (1 (red), 2 (green), 3 (blue), sum(1,2,3) (magenta), see Figure 3.

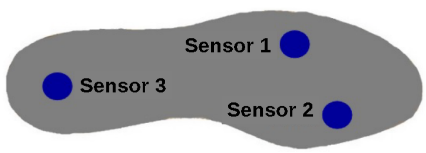

Figure 3. Positions of the force sensors in side the sole.

3. Applications

While the posture evaluation was in focus in (Beckmann and Klinger, 2023), here we concentrate on the gait evaluation. In this paper we are focusing on the gait evaluation to to enable prevention and rehabilitation in this context. According the simple PnP-approach, we are using only simple sensor and device configurations. Therefore, we are not using specific footwear for integrating force sensors but utilize acceleration sensors exclusively within MEMS-modules integrated in our IoT-platform. In (Donath et al., 2016b) it was shown that the reliability of such an approach is sufficient compared to more complex solutions. Therefore we have no detailed information regarding the force curves (see figure 2) using for example three force sensors in a specific sole (shown in figure 3).

3.1. Gait Analysis

Gait control, also known as gait modulation, refers to the techniques and mechanisms used to control and influence individual gait. This is particularly important in the fields of prevention and rehabilitation, but also in sports science, neurology and not least in robotics. Gait control is crucial for improving mobility, preventing and healing injuries and increasing performance. This involves a variety of areas that are not the focus here, such as bio-mechanics, neurological control, muscle function, sensory feedback, etc.. There are lots of basic spatiotemporal parameters, like gait cycle time, cadence, gait speed and stride length. There are various options to acquire data for gait analysis (Kirtley, 2006; Richards et al., 2022), for example:

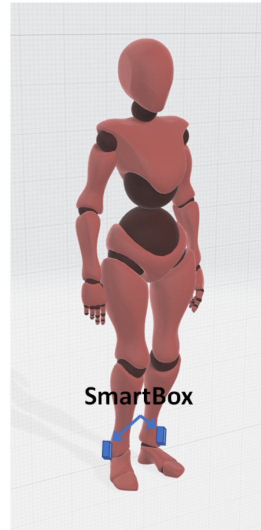

Figure 4. Position of the SmartBoxes for gait monitoring.

- Computerized video cameras to show movement in slow motion,
- Markers placed on the skin to monitor motion on camera,
- Sensors on a platform to measure footstep pressure and stride length,
- Electrodes placed on skin to monitor muscle movement,
- Infrared markers to measure joint movement in three dimensions.

In this paper the focus is the realisation of a simple and efficient method, based on a IoT-module without any identification capabilities and a corresponding server environment, the PnP-approach. Here, we are using only two SmartBoxes at the ankles, shown in figure 4.

As already described in the introduction, the focus here is primarily on prevention and rehabilitation, identifying the following tasks:

- Prevention
  - Analysis of the evenness of gait.
  - Offline Identification of various parameters, such as different leg lengths, etc..
- Rehabilitation:
  - Monitoring of the momentary and cumulative forces that occur.
  - Return to a evenness of gait to indicate the end of rehabilitation.

With regard to the PnP-constraint, the question remains as to which signals need to be recorded and evaluated in order to achieve these objectives. First we have used the trajectory of the feet to analyse the corresponding movement between left-right steps. But the later on

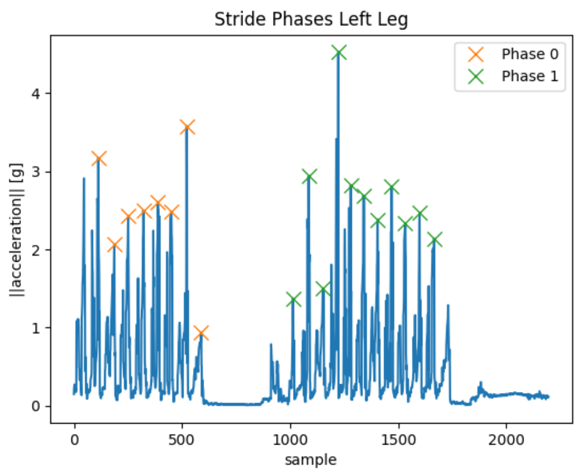

Figure 5. Stride phases for normal gait, left leg.

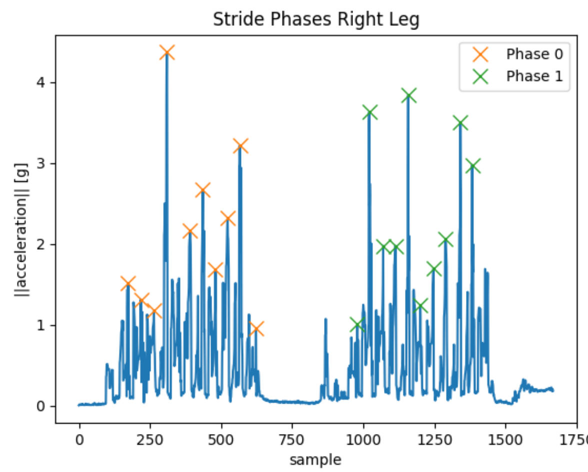

Figure 6. Stride phases for normal gait, right leg.

we have switched to the norm of the acceleration sensor (x, y, z) only to realize both, the gait monitoring and the force measurement based on one data stream per leg. We show in section 3.2 the results of different application tasks related to gait monitoring.

3.2. Results

First of all we have realized a step identification, this is important to find the maximal forces per gait. In addition there is a gait phase identification integrated, based on typical pauses between steps (Ullrich et al., 2020). When walking, each step is the result of a complex process in which current speed, position of the person's center of gravity, ground conditions and a variety of other parameters have to take into consideration. Therefore it is necessary to realize the DTW-based (Jablonski, 2012; Srivastava and Sinha, 2016) gait monitoring by mean values of gait phases (Barth et al., 2013). Not every pair of left-right steps are very similar due to the effect of the described influencing factors. So, compared to force measurement, the analysis of the gait evenness is based in the first order on average values.

In figure 5 and 6 a typical gait of some left-right steps is shown, the left steps in Figure 6, the right steps in Figure 6.

Each step is characterized by a maximum acceleration ($acc_{total} = \sqrt{acc_x{}^2 + acc_y{}^2 + acc_z{}^2}$. This maximum is created by the impact on the ground and shows the reaction forces of the footstep. The force maximum for every step is marked by a cross, different gait phases are identified by colors. Using the DTW-algorithm you can calculate a mean value between all consecutive steps of one gait phase. One example for one pair of steps is shown in figure 7; the similarity of the two steps left-right is clearly shown.

The data for DTW and the force equivalent $||acc||$ are shown in table 1.

Both, the force-difference and the DTW-distance are small, indicating a normal gait. Nevertheless, the gait is

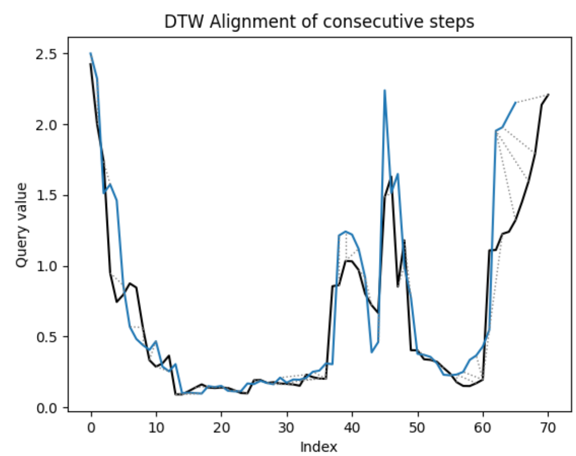

Figure 7. DTW-alignment of consecutive steps for the normal gait.

not perfect...

In figure 8 and 9 the gait of a person with a limp is shown. All information in the figures are to be understood as in the previous example.

Using the DTW-algorithm you can calculate a mean value between all consecutive steps of one gait phase. One example for one pair of steps for the gait with a limp is shown in figure 10. The similarity of the two steps left-right is clearly shown.

The data for DTW and the force measurement are shown in table 1.

Both, the force-difference and the DTW-distance are clearly visible, indicating a non normal gait.

The second project objective was to determine the forces, using only the acceleration sensor. The objective is to obtain information on the corresponding healing phase for the rehabilitation of a broken leg, for example, and to establish a correlation between healing success and the

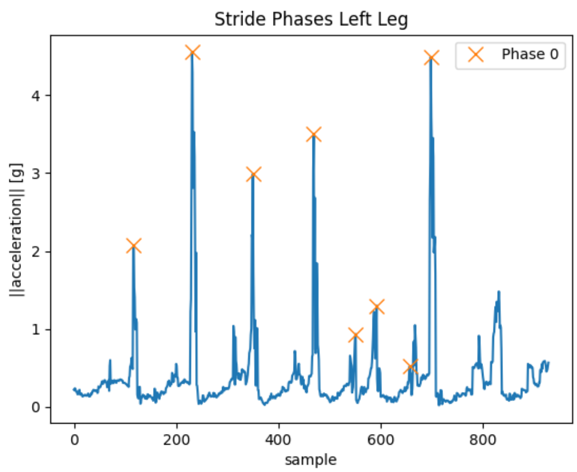

Figure 8. Stride phases for gait with a limb, left leg.

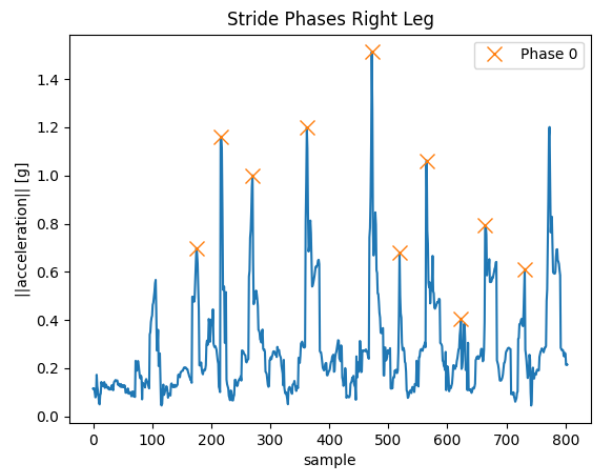

Figure 9. Stride phases for gait with a limb, left leg.

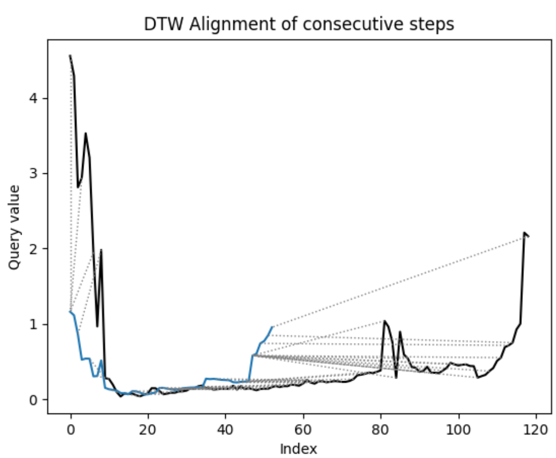

Figure 10. DTW-alignment of consecutive steps for the gait with a limb.

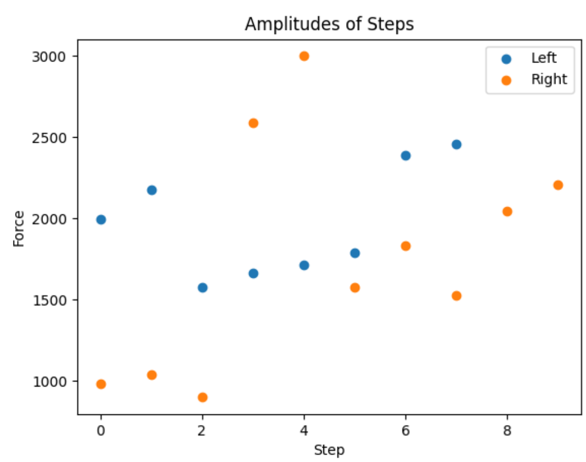

Figure 11. Maximum force per step (normal gait).

occurrence of load peaks and a total load with the help of the seamless data. According (Donath et al., 2016a,b), the force measurement based on acceleration sensors is reliable and can therefore in this application replaced the more complex measurement with force sensors. This certainly leads to more abstract statements, but is very likely sufficient for an initial correlation. The SmartBoxes, used for this project, are attached to the ankles with Velcro straps. This makes them easy to use and requires no special footwear. So, the force measurement is carried out exclusively with the acceleration sensor and the corresponding norm of the 3 dimensions. Calibration is necessary here in order to be able to take into account different shoes according to their damping behavior. The damping behavior changes the force peaks compared to the force curve.

In figure 11 the forces of the normal gait are depicted, shown in figures 5 and 6.

It is clear that there are differences in the normal gait, as each step has to balance the gait over the left and right foot.

In figure 12 the forces of the gait with a limp are depicted, shown in figures 8 and 9. Here it is clearly visible that one foot is less loaded. In addition, a limit is shown here, which allows the force assigned to the rehabilitation

Mean Diff $\|\|acc\|\|$ per Phase	Mean DTW-Distance per Phase	
	left	right
Normal Gait		
0.03	12.8	16.0
Normal Gait with a Limb		
1.29	18.3	11.1
Normal Gait (Zhou et al., 2023)		
0.14 ± 0.10	15.05 ± 2.14	14.55 ± 3.09

Table 1. Force equivalent and DTW-distance for normal gait and gait with a limb.

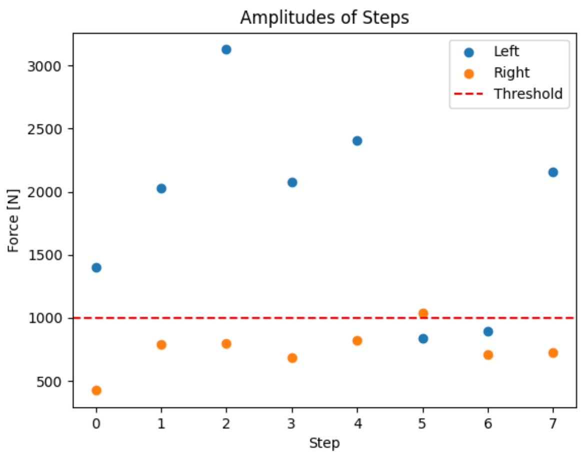

Figure 12. Maximum force per step including a limit (gait with a limp).

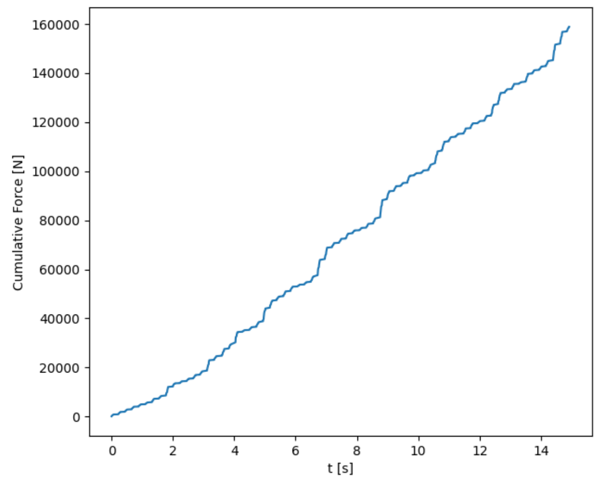

Figure 13. Cumulative force over time.

progress to be entered and the user to be informed, for example by a signal tone from the smart device, that the current limit has been exceeded. Without this help, it is hardly possible to estimate the specified maximum load accordingly. In figure 13 the cumulative force is shown, to get additional information on how much load has occurred in total over a period of time. This enables an additional correlation with the progress in healing.

3.3. Validation

To validate the soundness of our approach, we apply it to the DUO-Gait dataset presented in (Zhou et al., 2023). The dataset contains 6-minute walking sessions recorded for 16 participants under different conditions. As there is no comparable data available for the gait with a limp, we use the normal gait data for validation. The results are averaged across all subjects and presented in table 1 as well; clearly exhibiting the similarities to the results obtained in this paper. A subset of the forces from a normal gait in the DUO-Gait dataset (subject 1, first 17s) is depicted in figure 14, relating to the results shown in figure 11. The results are highly similar, indicating the reliability of our approach.

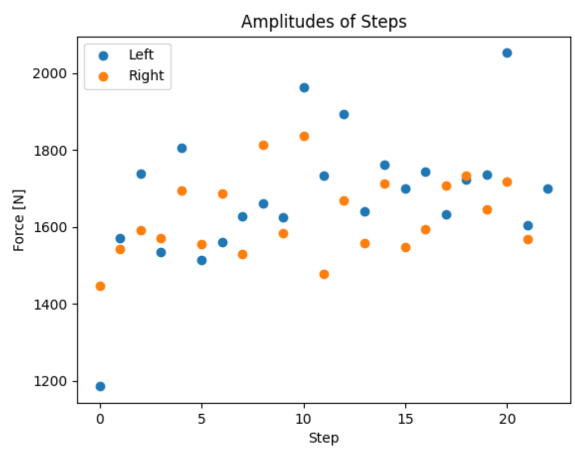

Figure 14. Maximum force per step (normal gait, validation).

4. Conclusions

The platform has also proven itself in this project for the integration of IoT-applications; the ESP32 workhorse offers sufficient flexibility to implement this application as well. The use of a platform for recording and processing data and statuses in biomedical applications therefore allows a high level of system complexity for different application scenarios and at the same time offers a high level of system flexibility. The integration of micro-controller-based IoT-modules into the platform enables decentralized intelligence, so that functions and evaluations can be executed locally and thus, for example, the identification of application-specific events can be realized at a low system level. In addition, corresponding trigger functions, such as the notification of an excessive load on a leg, can be implemented directly. All aspects also provide a very good opportunity to reduce the communication effort and thus improve subsequent data integration and data evaluation.

In this work, the objective was to perform a reliable and simple evaluation of gait movements already on the SmartBoxes (IoT-modules, ESP32) in order to have an easier application in mobile operation; in other words, to have a better PnPbehavior. Using the data for an evaluation of gaits and making rehabilitation scenarios more transparent especially by the mobile application represent an improvement in the prevention and rehabilitation of postural deformities when walking. Using the DTW-algorithm and accelerometer-based force measurement are the key factors to achieve the project goals. The disadvantage of a mandatory calibration procedure is outweighed by the advantage of simplicity; no special footwear is required. The number of users must be increased in order to ensure the reliability of the results and to recognize possible interindividual challenges in data acquisition and the corresponding identification. Furthermore, the following tasks and key aspects have to be in focus of future work:

- Working on a simple housing for the SmartBoxes with regard to robustness.
- Extension of verification patterns and procedures to optimize the reliability of gait evaluation.
- Optimization of calibration and initialization procedures.
- Establishing a better limit handling, using a table for the rehabilitation phase and generating an easy log-procedure.
- Work on a version for use in the sports sector for various running disciplines (Chambers et al., 2015).
- Testing the power consumption in different scenarios to get a reliable statement about the operating time in mobile operation.

References

Barth, J., Oberndorfer, C., Kugler, P., Schuldhaus, D., Winkler, J., Klucken, J., and Eskofier, B. (2013). Subsequence dynamic time warping as a method for robust step segmentation using gyroscope signals of daily life activities. In *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 6744–6747.

Beckmann, J. and Klinger, V. (2023). Performance-optimized Dynamic-Time-Warping Based Identification of Motion Trajectories. In Bruzzone, A. G., Frascio, M., Longo, F., and Novak, V., editors, *Proceedings of the 12th International Workshop on Innovative Simulation for Healthcare (IWISH 2023)*.

Bourahmoune, K., Ishac, K., and Amagasa, T. (2022). Intelligent posture training: Machine-learning-powered human sitting posture recognition based on a pressure-sensing iot cushion. *Sensors*, 22(14):5337.

Chambers, R., Gabbett, T. J., Cole, M. H., and Beard, A. (2015). The Use of Wearable Microsensors to Quantify Sport-Specific Movements. *Sports Medicine*, 45(7):1065–1081.

Donath, L., Faude, O., Lichtenstein, E., Nüesch, C., and Mündermann, A. (2016a). Validity and reliability of a portable gait analysis system for measuring spatiotemporal gait characteristics: Comparison to an instrumented treadmill. *Journal of NeuroEngineering and Rehabilitation*, 13.

Donath, L., Faude, O., Lichtenstein, E., Pagenstert, G., Nüesch, C., and Mündermann, A. (2016b). Mobile inertial sensor based gait analysis: Validity and reliability of spatiotemporal gait characteristics in healthy seniors. *Gait & posture*, 49:371–374. Copyright © 2016 Elsevier B.V. All rights reserved.

Espressif (2019). Esp32 series, datasheet. Technical report.

Hartmann, B., Spallek, M., and Ellegast, R. (2013). *Arbeitsbezogene Muskel-Skelett-Erkrankungen: Ursachen, Prävention, Ergonomie, Rehabilitation (mit CD-ROM)*. Handbuch der betriebsärztlichen Praxis. ecomed Verlagsgesellschaft in Hüthig Jehle Rehm.

Huang, P.-C., Liu, K.-C., Hsieh, C.-Y., and Chan, C.-T. (2017). Human motion identification for rehabilitation exercise assessment of knee osteoarthritis. In *2017 International Conference on Applied System Innovation (ICASI)*, pages 246–249.

Jablonski, B. (2012). Quaternion dynamic time warping. *IEEE Transactions on Signal Processing*, 60(3):1174–1183.

Kirtley, C. (2006). *Clinical Gait Analysis: Theory and Practice*. Elsevier.

Klinger, V. (2016). Rehabilitation Monitoring and Biosignal Identification using IoT-Modules. In Bruzzone, A., Frascio, M., Novak, V., Longo, F., Merkuryev, Y., and Novak, V., editors, *5n International Workshop on Innovative Simulation for Health Care (IWISH 2016)*.

Klinger, V. (2019). Smart Platform-based IoT-Modules for Applications in Health Care and Rehabilitation. In Bruzzone, A., Frascio, M., Novak, V., and Eds., F. L., editors, *8th International Workshop on Innovative Simulation for Health Care (IWISH 2019)*.

Klinger, V. and Bohlmann, S. (2020). Application-Based IoT-System for Pandemic Prevention Based on Platform-Approach. In Bruzzone, A., Frascio, M., Novak, V., and Eds., F. L., editors, *9th International Workshop on Innovative Simulation for Health Care (IWISH 2020)*.

Matuska, S., Paralic, M., and Hudec, R. (2020). A smart system for sitting posture detection based on force sensors and mobile application. *Mobile Information Systems*, 2020:1–13.

Richards, J., Levine, D., and Whittle, M. (2022). *Whittle's Gait Analysis - E-Book: Whittle's Gait Analysis - E-Book*. Elsevier Health Sciences.

Srivastava, R. and Sinha, P. (2016). Hand movements and gestures characterization using quaternion dynamic time warping technique. *IEEE Sensors Journal*, 16:1333–1341.

Ullrich, M., Küderle, A., Hannink, J., Din, S. D., Gaßner, H., Marxreiter, F., Klucken, J., Eskofier, B. M., and Kluge, F. (2020). Detection of gait from continuous inertial sensor data using harmonic frequencies. *IEEE Journal of Biomedical and Health Informatics*, 24(7):1869–1878.

Zhou, L., Fischer, E., Brahms, C., Granacher, U., and Arnrich, B. (2023). Duo-gait: A gait dataset for walking under dual-task and fatigue conditions with inertial measurement units. *Scientific Data*, 10.