TALLINN UNIVERSITY OF TECHNOLOGY
SCHOOL OF ENGINEERING
Department of Electrical Power Engineering and Mechatronics

THE CONTEXT SENSITIVE GAIT MONITORING FOR PATIENT SUPPORT

KONTEKSTITUNDLIK PATSIENDI KÕNNAKU JÄLGIMINE

MASTER THESIS

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Tallinn 2021

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Department of Electrical Power Engineering and Mechatronics

THESIS TASK

Student: Ulvi Ahmadov 194355MAHM

Study programme: MAHM02/18

main speciality: Mechatronics

Supervisor(s): Senior research scientist, Alar Kuusik, 620 2166;

Professor, Mart Tamre, 620 3202

Thesis topic:

(in English) *Context sensitive gait monitoring for the patient support*

(in Estonian) Kontekstitundlik patsiendi kõnnaku jälgimine

Thesis main objectives:

1. Collecting proper IMU data from different muscles with EMG for gait monitoring
2. Data comparison by applying MLA
3. Developing an assistive device to provide environmental information for mobile application

Thesis tasks and time schedule:

No	Task description	Deadline
1.	Literature review and analysis of the problem	30.10.2020
2.	Collecting IMU data using Shimmer sensor device	31.01.2020
3.	Testing MLA for classifying the collected data	26.03.2021
4.	Development of Bluetooth device like iBeacon	15.04.2021
5.	Thesis defence	01.06.2021

Language: English **Deadline for submission of thesis:** "18" May 2021

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PREFACE

This master thesis topic has been originated from the PRG424 Research and Development project called "Closed-loop communication system to support highly neuromuscular assistive stimulation" and proposed by the Tallinn University of Technology, project itself financed by the Estonian Research Council. The development procedure is conducted in the Thomas Johann Seebeck Department of Electronics and the thesis topic was offered by senior research scientist – Alar Kuusik.

The project aims to provide the personalized electrical neuromuscular stimulation and context awareness using a wireless real-time communication solution for the patients with the peripheral nerve damages causing gait impairments.

The thesis covers the data collection of human gait patterns with inertial motion sensors, developing the context information broadcasting Bluetooth beacon prototype, testing of the machine learning algorithms developed within PRG424 project to detect wrong step patterns on different floor surfaces.

Special thanks should be addressed to Alar Kuusik and Andrei Krivošei for their undeniable, constant support and guidance to the author beginning from the first day of the project till the graduation on my path. Big thanks to two valuable professors from Macedonia - Branislav Gerazov and Elena Hadzieva who always encouraged the author and assisted to conduct the project with their great support, contribution and unique feedback. The author much appreciated being aside in the same project with them and would be happy to collaborate again in the future.

This work has been dedicated to firstly, to millions of people who suffer from various gait abnormalities or have difficulties in their gait and secondly to my family and friends for their support.

List of abbreviations and symbols

AI – Artificial Intelligent

AT Command – Attention Command

BLE – Bluetooth Low Energy

CNS – Central Nervous System

COM port – Communication Port

ECG-to-HR – Electrocardiography to Heart Rate

EMG - Electromyography

FES – Functional Electrical Stimulation

FP – False Positive

GAP – Generic Access Profile

HAR – Human Activity Recognition

IDE – Integrated Development Environment

IMU – Inertial Measurement Unit

ML – Machine Learning

MLA – Machine Learning Algorithms

MLM – Machine Learning in Medicine

MSD – Mass Storage Device

NFC – Near-field Communication

OOB – Out-of Band

ROC – Receiver Operating Characteristics

sEMG – Surface Electromyography

SL – Supervised Learning

SoC – System on a Chip

UART – Universal Asynchronous Receiver/Transmitter

TP – True Positive

ULP – Ultra-Low-Power

6DoF – 6 Degrees of Freedom

9DoF – 9 Degrees of Freedom

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1. INTRODUCTION

Human walking is a standardized, repeatable, rhythmic locomotors act those involves the integrated efforts of the brain, nerves and muscles. Suffering from the gait abnormalities (uncontrollable walking patterns) for a short or long terms and getting older, makes the walking of people extremely problematic and increases falling risks while moving around the urban areas under different weather and road conditions.

The walking patterns of the patient demonstrate unnatural characteristics of walking under laboratory settings. The different walking patterns of the subject in real-world environment in comparison to the labs indicates the need to better understanding of the natural gait under ecologically valid circumstances before clinically relevant conclusions could be drawn on the test subjects. In order to address the more challenging environment issues and associated falling risks, performing of the gait monitoring outside of the laboratory settings can assist to predict fall risks better. The wearable sensor technologies have great impact on the recent advancement of gait monitoring, which provide a rich information source in different environment, low cost, portability and versatility, also ensure seamless gait analysis from lab settings to natural environments.

Falls is a major issue in older adults and its economic impact is the major concern for the health professionals. Although, different researches have been conducted to address fall risks with high accuracy up to day, fall occurrence is still challenging problem to take protection actions for falls prediction by means of long term data. Therefore, an advanced portable and affordable personalized monitoring device should be designed and developed for diagnostics and therapeutic interventions to the patient with the help of mobile application.

The expected result of the research is to develop a automatic personalized multi-sensor device which can predict falls with more than 90% accuracy in different environmental conditions and contexts for user mobile applications.

The thesis itself covers a part of the R&D project (PRG424) – "Closed-loop communication system to support highly neuromuscular assistive stimulation". Two million neural disease patients may benefit from FES in worldwide. Current wearable assistive stimulators do not provide context-awareness, thus directly affects patients' life quality by increasing safety risks. The proposed closed-loop wireless communication system ensures automated neuromuscular stimulation with intelligent monitoring and adds feedback from an actuator to coordinator for the decision-making and electrical stimulation tuning. Implementing, testing and validating of the developed solution on partially disabled neurodegenerative disease patients will be done in cooperation with practicing clinicians.

1.1 Problem statement

Even though various researches have been conducted and different solutions have been introduced, nevertheless there are some lacking points of gait monitoring accuracy related to fall predictions. Majority of implemented methods provide fall detection and cover only lab settings, however, fall prediction and the environmental context should be considered as well. In order to overcome the current limitations of gait analysis, this research will provide a contemporary approach to get high accuracy of gait monitoring by means of machine learning algorithms.

The main goals of the thesis are to collect and classify the human gait patterns in real-world environments such as different walking path surfaces (flat, polished, slippery), stair negotiation (up, down) and different weather conditions (rainy, snowy and icy) by using wearable sensors which includes IMUs and EMG and analyze the efficient placement of inertial measurement units for correct mapping of limb position with the lower limb muscular activity for the development of gait analysis technology and to develop a Bluetooth iBeacon-like prototype device to broadcast the environmental context information to people with special needs.

1.2 Research motivation

According to the demographic projections, the world's populations are ageing, which will cause the negative multi-ranging effects on social, economic and health systems [1]. The dramatic increase of gait disorders prevalence is highly dependent on age, especially while this rate can be observed at 10 % between adults the age of 60 and 70 years, it reaches above 60 % in people over 80 years [2]. Nearly 12 -15 % of the falls cause severe injuries like traumatic injuries on the brain or fractures on the hip, those are estimated as inadvertent damages which are considered the 5th most common reason for death in elderly people [3].
Increased probability of falls not only increases the risk of injury, but also affects an individual's independence and ability to interact within the community. Additionally, fear of falling has psychological consequences and can lead to self-isolation and depression [4].

Considering the increasing number of the people with gait abnormalities all over the world, developing of the assistive device with advanced FES control and context awareness is crucial and in demand for them.

1.3 Research objectives

To conduct the research, following steps will be taken:

- Collecting IMU motion data from different parts of lower extremities with muscles EMG signals by Shimmer wearable sensor device in different environmental conditions.
- Discovering and analysing differences in gait monitoring and mapping IMU with EMG for different surfaces
- Testing MLA to classify collected walking patterns giving by the prepared algorithms developed by the other project participants.
- Developing iBeacon/Eddystone like Bluetooth beaconing prototype device to provide environmental context information for gait assistive device. The beacon functioning to be tested with an off-the-self Bluetooth receiver.

1.4 Thesis structure

The content of thesis's chapters is provided in this section.

Chapter 1 - The introduction describes the aims, motivation and objectives of the thesis. It also included the problems to be solved.

Chapter 2 conducts a literature review about the gait disorders and current methods for gait analysis using wearable sensors and implementing ML algorithms.

Chapter 3 contains the methodology of research, authenticates the hardware and software selection.

Chapter 4 provides an explanation about the generated approach. In this chapter, the integration of IMUs with EMG sensors for performing instrumented gait analysis and development of beaconing device

Chapter 5 describes the testing of short frame tracking anomaly detection MLA and explains the master metrics and demonstrates the acquired results for the importance of context-awareness

Chapter 6 includes the discussion of research, limitations also possible future improvements respectively.

The completed work and some notes about achieved goals are concluded in the summary.

2. LITERATURE REVIEW AND BACKGROUND

This chapter introduces the gait disorders, the current situation of gait analyzing approaches, wearable sensor devices and implementation of machine learning algorithms as contemporary methods instead of traditional gait monitoring techniques.

2.1 Gait disorders

In [5], gait disorders are common both with aging and in the setting of specific neurological disorders and are a risk factor for dependence, cognitive decline, falls and death. After age 70 years, 35% of people have abnormal gait; after the age 85 years gait changes are found in the majority of people. While gait changes, specifically slowing and decreased stride length are common occurrence in older people, the presence of gait abnormalities suggests overt or covert pathologies. Both nervous system and non-nervous system changes contribute to age-related changes in gait. Table I demonstrates the classification of the gait disorders in [6]:

Table 1. Classification of clinical gait disorders [6]

The Gait Disorders	*The Gait Conditions*	*Typical Characteristics of Gait*
Peripheral Sensory	Visual	Uncertain and tentative
	Peripheral nerves	Stomping gait
	Vestibular	Unstable, drunken, weaving
Peripheral Motor	Arthritis	Antalgic gait
	Muscular or myopathy dystrophy	Trendelenburg gait
	Neuropathy	Foot drop, Steppage gait
Spasticity	Paraplegia or hemiplegia	Excessive plantar-flexion in ankle
	Quadriplegia or diplegia	Scissor gait, foot drop, circumduction on both sides
Cerebellar (Ataxic)	Seen in cerebellar diseases	Resembling acute alcohol intoxication gait
Parkinsonian	Especially observing in Parkinson disease	Destination, retropulsion, absence of arm swing
Choreiform (Hyperkinetic)	Dystonia, athetosis	Uncontrolled movements in all extremities, irregular

2.2 Common age-related gait changes

A normal cycle of each gait begins with the initial contact of a foot and finishes with the new initial contact of that foot (Figure 1). The stance and the swing phases generate a single cycle. The period of the foot contact with a surface is "the stance phase", and the period, while that foot stays in the air for the next cycle preparation of the gait is defined as the "swing phase". The legs can be placed either individually or simultaneously on the ground during the cycle of gait, thus assists to define the support stage of a single limb (the phase while one foot is on the ground) also the support stage of the double limbs while both of the legs are on the supportive surface during the one-step cycle in [7].

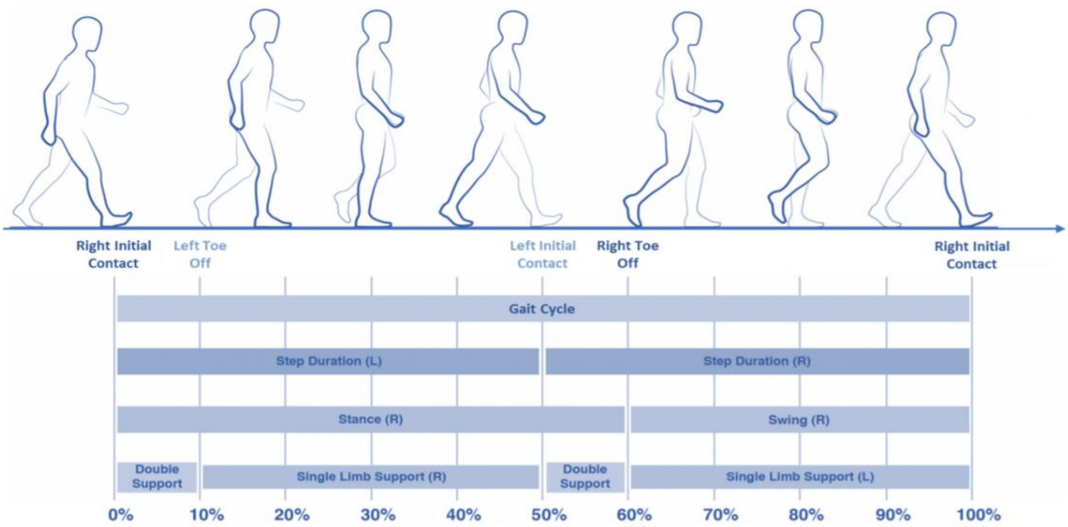

Figure 1. Normal gait cycle of the human [7]

In [8], some gait elements can typically change by aging:

The velocity of gait (walking speed) remains stable by the age of 70 and then the usual walking might decline around 15 % decade, also 20 % for the fast walking. The velocity of gait plays the predictor of mortality as well, which is extremely powerful as the number of chronic medical conditions and hospitalizations of the elder people. The slow walkers can die more than 6 years earlier rather than ordinary velocity walkers after the age of 75 and more than 10 years earlier in comparison to the fast walkers. With aging, the taken steps of elder people shorten at the same cadence and this slows the gait velocity. The calf muscles' weakness is one of the main issues that cause the shortened step length; the strength of the calf muscle is considerably decreased in elder adults. Nonetheless, it is observed that in comparison to young people, elder adults can compensate for the weakened lower calf power by means of extensor muscles and hip flexors as well.

Double stance time which is the period during ambulation when both feet on the surface, increases with age. The percentages of double stance time are changing from 18 % to more than 26 % in aging (from young people to healthy elder people). Increased time decreases the time the swing leg must move forward and shortens the stride length, in the double stance. The double stance time can be increased by elder adults when walking on slippery surfaces or uneven ground and if there is a risk of falling or impaired balance.

Walking posture slightly changes with age. Elder people walk upright with the greater anterior pelvic rotation and with no forward lean. A combination of different reasons such as increased abdominal fat, weak abdominal muscles, and rigid hip flexor muscles can change the described posture. Either hip internal rotation loss or the increase of lateral stability makes older adults walk with their legs turned sideways around 5 degrees. The swing's foot clearance remains stable with aging.

Joint motion is slightly changing with advanced aging. Typically, the overall knee motion, hip flexion, and extension remain unchanged but plantar flexion of the ankle is curtailed meanwhile the late stance stage. Pelvic motion is gradually decreased in all planes.

Figure 2. The changes in the gait and balance in time [10]

In [9], it has been suggested by the researchers that the main reason for the increased falls in patients with neurological problems is gait disorders. In order to allow prevention and getting better comprehension, gait disorders must be identified and observed.

To address the fall risks in the older population, it has been suggested by the authors [11] to get better insights into the mobility behavior and its possible effects by various underlying and superficial contexts. In [12], participants used accelerometers for step count recordings, also the travel diary was prepared to write down the aim of the trips. The study suggests that "highly walkable neighborhoods" can assist mobility and health of elderly population, nevertheless, this does not address the potential falling risks and various concerns of more challenging surroundings. Although the improvement of the fall risk-identification equipment had been led in the previous research, a better accuracy rate in the fall prediction was acquired in the clinical observation, in [13]. Recently, the wearable and ambient sensor-based approaches [14] have expedited the improvements of protocols used for testing which is determined to perform the environmental experiments regarding the gait analysis [15] and made possible to do experiments outside of the laboratories. This provides a possibility to observe the natural movement of the patient rather than to show the patients' best efforts of gait in the laboratory settings to the clinicians.

2.3 Abnormal gait changes

In [9], walking is a lasting decision-making process, which can be changed in various neurological pathologies. Any disorder of gait may cause different falls, disabilities, and impaired mobility, which ends up with reduced life quality, and increased death risks. Assessment of walking disorders assists to prevent and do adequate measures by predicting the falls.

In [10], Anwary has been suggested that the gait patterns of each person are presumed to be symmetrical in which each leg can perform the same locomotion. However, interestingly each person has a particular pattern of gait and one side's limb movement is not repeated as same as by the other side, which can lead to high differences in the legs' bilateral behavior while walking and indicate abnormalities of human gait. In addition to this, several disorders also can lead to dysfunctional gait that especially include:

- Musculoskeletal,
- Neurologic disorders.

Symmetry loss of motion and timing between sides commonly leads to a disorder. When the body is healthy, it moves symmetrically; cadence, step length, ankle, torso movement, hip, knee, and pelvis motion are balanced on the left and right sides. The typical asymmetry can occur with unilateral above-mentioned disorders. The considerably variable cadence of gait, stride width, or step length can indicate the motor control breakdown of gait because of cerebellar syndrome or the utilization of numerous psychoactive medications.

Gait initiating and maintaining difficulties can happen. Especially, in frontal, subcortical, or Parkinson diseases, there are several isolated initiation failures of gait such as when starting to walk the patients can feel the feet stuck to the floor and they cannot shift their body weight from one foot to another while moving forward. After gait is started, steps must be continuous with a few variabilities in the timing of the steps. Some concerns like freezing or stopping commonly associate with a cautious gait and suggest a falling fear, or frontal lobe disorders of gait, also scuffing of the feet is a high-risk factor for tripping.

Footdrop leads to the steppage gait or toe dragging and can also be secondary to the weakness of anterior tibialis (peroneal nerve trauma at the knee's lateral aspect or the peroneal mononeuropathy related to diabetes), calf muscle spasticity (soleus or gastrocnemius muscles), and lowering of the pelvis because of the proximal muscle weakness on the stance side (especially in the gluteus medius muscle). On account of the knee flexion reduction, the low swing of the foot can resemble foot-drop as well.

Retropulsion is the falling backward while initiating gait or walking and can happen with Parkinsonism, frontal gait disorder, supranuclear palsy, and central nervous system syphilis

Wide-based gait is specified by monitoring the gait of patients on the floor with around 30 cm tiles. Wide-based gait is only acknowledged in case of the outside of the feet cannot stay within the tile width. if the speed of gait decreases, in this case, the step width slightly increases. Various diseases or disorders such as cerebellar, hip, bilateral can lead to this type of gait problems. On account of the frontal and subcortical gait issues, low motor control can be indicated by the variable step-width.

Short step length can symbolize the falling fear or musculoskeletal and neurologic issues. The healthy side is a side with a short length of the step and the short step is generally due to the issue during the opposite leg's stance phase. Patients who suffer from weak and painful right leg do not spend more time in the single stance of the right leg and use less power to carry the body advance, which ends up with less swing time and shorter step for the left leg. The healthy left leg has a typical duration of the single stance and this results in the typical swing time and longer step length for the abnormal right leg.

Festination appears in patients with Parkinson and occasionally occurs as a side effect of atypical or typical antipsychotics drugs. Festination is the gradual acceleration of steps therefore patients can prevent forward falling.

Circumduction can be encountered if patients suffer from the weakness of pelvic muscle or have difficulties related to the knee bending. The spasticity of the extensor muscles of the knee is a typical reason [8].

Forward lean can happen to patients with Parkinson, kyphosis disorders, or parkinsonian features related to dementia.

2.4 Gait analysis approaches and implemented methods

Gait is the periodic movement of hands and feet [16]. Different gait patterns are distinguished by differences in velocity, limb movements, force, and ground contact duration. Gait analysis is the study of gait using visual assessment, and instruments such as cameras and sensors, in [17]. Gait analysis supports numerous applications in healthcare, security, sports and fitness domains in [18].

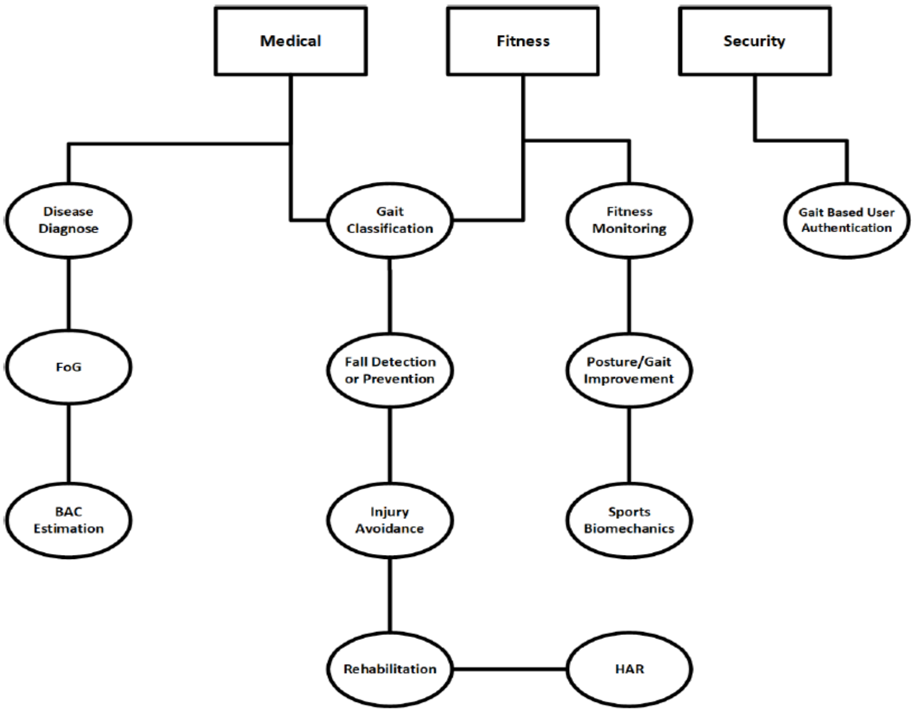

Figure 3. Most common applications of gait analysis [18]

2.5 Wearable sensor devices

In gait analysis, accelerometers, gyroscopes, IMUs and force sensors are widely used to measure gait characteristics.

In this paper [6], the purpose is to review current quantitative techniques of gait monitoring and suggest key metrics of the existing methods for evaluating the features of gait extracted from numerous wearable sensors. The paper also targets to highlight all key signs of progress in this quickly developing research field and shows potential future aspects for not only the research field but also the clinical applications. It should be noted that nowadays, more reasonable solutions can be found because of the decreasing instrumentation costs.

Table 2. The prevailing quantitative measuring equipment of the gait analysis [6]

	Kinematic Data		Kinetic Data		Acivitiy of the muscle
	Typical	Wearable	Typical	Wearable	Portative
Type of instrument	Motion capture system (optical)	Inertial Sensors	Force Plates	Pressure sensors	EMG sensors
Practicality	Pre-installation and expert operation	Compatible to wear	Pre-installation	Compatible to wear	Invasive to wear
Expenditure	More than $30000	Less than $2000	Between $200 and $30000	More than $3000	Around $10000
Regular Monitoring	Up to 10 minutes	More than 2 hours	Up to 10 minutes	More than 2 hours	In or out of lab settings
Accuracy & Precision	Very high	Algorithm or sensor dependent	High	Algorithm or sensor dependent	
Measures	Kinematic measures	Able of emulating optical motion capture	Kinetic measures	Able of emulating force plates	Kinetic measure s and muscle activities
Cost of computation	Very high	Less	Less	Less	Less
Real-time Potential	Very limited	Used in research	Very limited	Possible	Possible

In [19], two main approaches have recently matured for capturing a subject's walking patterns objectively and accurately in non-clinical settings: (1) Non-wearable systems, such as camera-based optical motion capture, or ground reaction force plates, and (2) wearable inertial measurement unit (IMU) sensor systems. The former requires considerable set-up time and equipment, and is generally restricted to lab environments or specialized centers. On the other hand, IMU sensors require less effort to set up for data collection outside the lab, and studies can be run without the need for direct observation of the test subject, thus enabling various real-world investigations to be undertaken.

IMU is a combined sensor device that outputs the linear acceleration, angular speed, gravitational force direction, and (absolute) orientation of the device using the combination of linear accelerometer, gyroscope, and magnetometer. Typically, Mahony filter with a supplemental Kalman filter is used for physical sensor fusion of triaxial IMU devices [19-20].

In this study [21] has described that the recent developments in inertial sensors made them promising candidates for monitoring motor symptoms and assessing gait dysfunctions. The decreases in their costs and sizes have made them more pervasive and attractive than ever. Attachable to almost any body part via straps, they have become viable, non-obtrusive alternatives for analyzing gait. Enhanced with wireless communication capabilities, multiple IMUs can gather real-time, synchronized data from multiple parts of the body that are active in gait.

In [22], using IMUs for the purposes of gait analysis also attracts the attention of the academic community, as there are numerous studies in the literature that employ IMUs. Especially for lower-body gait analysis with foot-located IMUs (either via straps or insoles), an accurate methodology that combines zero-velocity updates combined with Kalman filtering has been established and well tested in [23]. The ultimate aim of a gait analysis system is to extract a variety of standardized gait metrics to be easily interpreted by a clinician. However, a system solely consisting of wearable sensors, without the aid of infrastructural system elements, rarely achieves completeness in terms of gait metrics. The literature still lacks a complete system that can be easily used by non-professionals in a non-hospital setting [21-23].

In [24], with precisely accurate IMUs a double integration of the acceleration data yields accurate 3D position however, IMUs have small errors in acceleration and thus the position estimates based upon a double integration technique can only be valid for a short period of time as these small errors are accumulative and lead to 3D position drift.

This paper [25] suggests the importance of inertial measurement systems in gait monitoring and the control of the lower limb exoskeleton. In addition to this, contemporary control strategies are evaluated that demonstrate the human motion-sensing applications for the lower limb exoskeleton in the following parts of the paper.

In [26], Electromyography is a commonly used technique to record myoelectric signals, i.e., motor neuron signals that originate from the CNS and synergistically activate groups of muscles resulting in movement. EMG patterns underlying movement, recorded using surface or needle electrodes, can be used to detect muscle activation and gait abnormalities. In this review article, EMG signal processing techniques is examined which have been applied for diagnosing gait disorders. The aim in this article is to review EMG signal processing techniques that facilitate detection of gait and movement disorders. The researchers have discussed techniques from simple enveloping to complex computational machine learning algorithms that may help detect alterations in EMG patterns while performing daily life activities.

In [27], Surface electromyography is the main non-invasive tool used to record the electrical activity of muscles during dynamic tasks. In clinical gait analysis, a number of techniques have been developed to obtain and interpret the muscle activation patterns of patients showing altered locomotion. However, the body of knowledge described in these studies is very seldom translated into routine clinical practice. The aim of this work is to analyze critically the key factors limiting the extensive use of these powerful techniques among clinicians.

This study [28] describes the data quality and reliability of forearm electromyography and inertial measurement unit of armband sensors for construction activity classification. To achieve the proposed objective, the forearm EMG and IMU data collected from eight participants while performing construction activities such as screwing, wrenching, lifting, and carrying on two different days were used to analyze the data quality and reliability for activity recognition through seven different experiments. The results of these experiments show that the armband sensor data quality is comparable to the conventional EMG and IMU sensors with excellent relative and absolute reliability between trials for all the five activities.

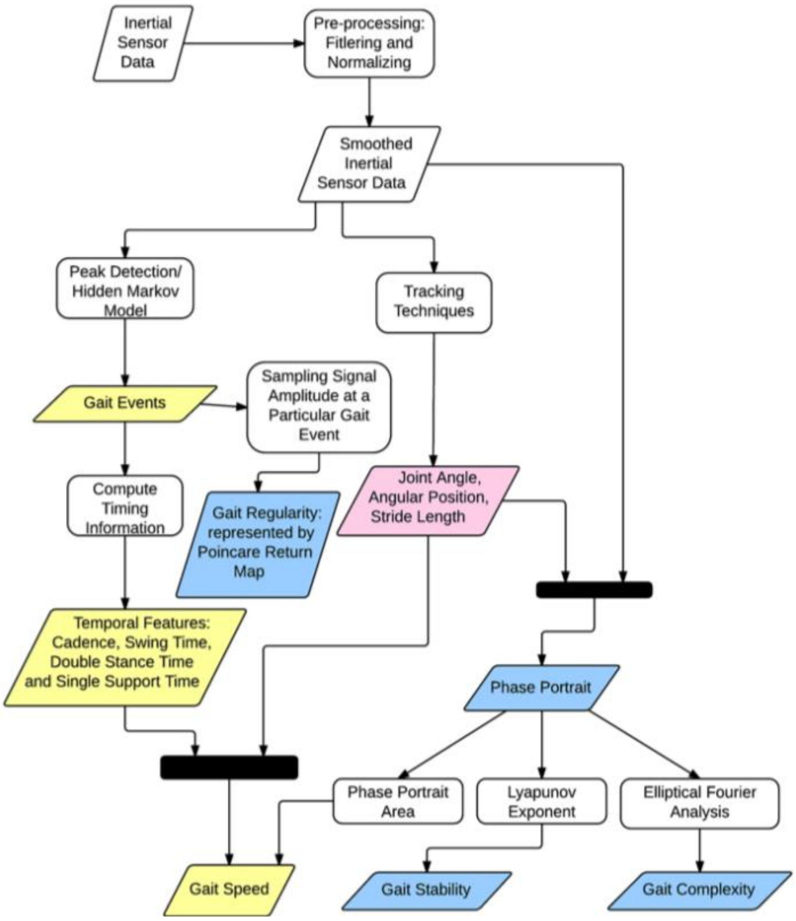

Figure 4. The extraction process of the gait features from the inertial sensors [6]

In Fig.4 and Fig 5, the sensor data transformation process to proper gait measures has been described [6]. These figures show that gait measures have been extracted from even wearable sensors. Inertial sensor data may be filtered and can be changed into different kinematic products for inertial sensors by implementing tracking techniques. Either hidden Markov model or event detection can assist to extract the crucial temporal features of human gait from data of inertial sensors. The detected events can be implemented in regularity analysis of gait as well. Gait speed can be determined through kinematic information and temporal features. Whereby sensor data and kinematic information, the non-linear analysis may be implemented to extract different measures such as gait complexity and stability. The insole position might be calibrated initially by the optical motion capture systems with markers and through mapping techniques to extract general GRF. The joint moment may be computed by applying generalized kinematics with the link segment model via optimized forward dynamics. Muscle force and moment can be extracted by using a combination of anatomical, activation and contraction dynamics models of muscles over EMG data. And lastly, the mechanical gait energy can be acquired with known muscle and joint moment.

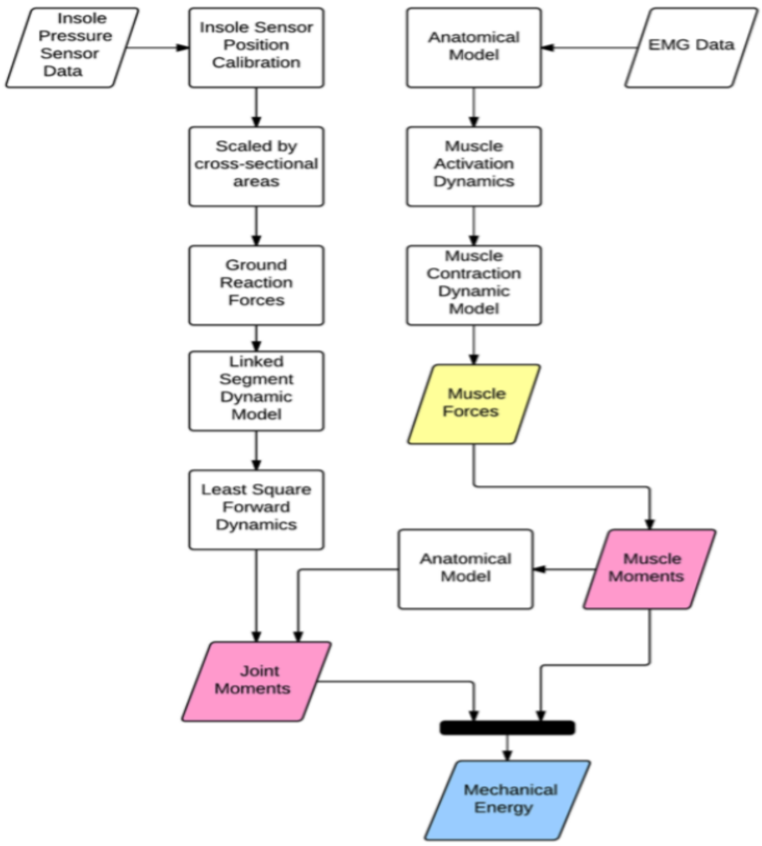

Figure 5. The extraction process of the gait features from both pressure and EMG sensors [6]

FES which was developed in the 1960s in the USA is a treatment and electrical charges have been applied to a patient's muscles that are weakened or paralyzed because of the spinal cord or brain damages. The usual movement can be stimulated through this small electrical charge to muscles. Due to some disruptions between the nerve pathways of the brain and legs, the patient cannot lift their foot to the usual angle while walking and this motivates to commonly use FES for the treatment of foot-drop in MS. FES provides stimulation that stops when the contact between foot and ground happened [29]. It is implemented to bring novelty and intelligence into FES that can react according to the context changes for the controlled stimulation in the PRG424 project.

2.6 Machine learning algorithms

The performance of gait analysis is highly dependent on the underlying algorithms for the analysis. Generally, different gait-based human activities such as lying down, falling, jogging, and running are closely related. In [30-32], it has been argued that traditional analysis of gait requires expensive technologies that are labor and time-intensive, particularly while analysis contains hand-crafted feature extraction. The statistical approaches and it is hard to classify such activities accurately, especially noisy, nonlinear, and complex data. The MLM proves to be an excellent alternative to provide high classification accuracy of gait parameters [18].

MLA gets data from past experiences by determining underlying, hidden patterns or relationships. ML field may be classified as unsupervised, supervised, and reinforcement learning, in [33-34]. SL starts with the aim of estimating a known target or output. Actually, supervised learning algorithms take a known group of input data (the training set) and known data responses (output) and can train the model to compose moderate predictions for the new input data response. The AI is capable to estimate tasks with high accuracy such as a trained physician in such algorithms. This shows that the algorithm generalized the training data to formerly unobserved situations in a "moderate" approach. All kinds of SL algorithms may be categorized as both classification and regression. While techniques for classification predict "discrete" responses, continuous responses can be predicted by regression techniques. They can be implemented for the risk modeling, which means the computer is performing more than reproducing the physician skills. The above-mentioned algorithms are able to discover new features that still not appear to the preliminary interpretation of humans.

The outlier detection has a significant role in data processing that includes a wide range of application scope from data security to gait analysis. Its duty becomes more challenging comparing with the techniques of traditional outlier detection due to the increasing demand to analyse rapid data streaming and assuming of not all data can be stored for processing [35]. Techniques of outlier detection mainly focused on investigating data samples that were generated by a particular mechanism and this paper introduce the algorithm by combining HAR and outlier detection, which provides detecting information and extracting data segments of different activities. However, the implementation of some activities shows the detection degradation with the increasing number of false positives (for climbing up includes 14 false positives) [36]. In addition to this, the outlier detection cannot provide desirable results independently of the defined similarity threshold in this paper [37]. So, during this research outlier detection will be tested to get better results for the context-awareness-based concept.

2.7 Conclusion

The literature review shows that there is quite less researches considering environmental context, which is directly related to the patients' daily life. The conducted researches mainly concentrated to lab-based methods and techniques that limit the person life quality in real-world environment. Also, these cause the other kind of mental illnesses. By means of recent advancement, different solutions have been introduced and they contributed to the people with gait abnormalities, but some limitations are still on-going.

The development of different multi-sensor wearable devices has played an important role in the gait analysis and nowadays, it is difficult to imagine the gait monitoring without them. The review also gives an overview about IMU and EMG and it should be acknowledged that the correct mapping of limb position is missing in most of the researches. Usage of EMG and IMU data for gait cycle analysis can be used with the same protocol when compared to in different context still not popular in use as well.

All of them are discussed in the literature review and their data acquisitions also explained according to the given references. The main point is to get data from sensors using contemporary methods which can be completed by means of MLA. So, various methods also explained in the review. While typical MLA needs more training data and provides correct results after the activity, a small training data has to be used and divided each activity into smaller portions to get pattern deviation feedback immediately in real-time for this research. Although, nowadays there are different assistive devices for patient support in the market, all have pros and cons. The analyzed literature review assists to design and develop an advanced assistive device for patients with mobile application by considering missing points and real-world environment. According to the analyzed literature survey, the following points will be the main objectives of this research:

- Usage of IMU motion data for gait cycle analysis with the same protocol when compared to in different contexts
- Obtaining the classification of the gait patterns of healthy subjects in real-world environments instead of lab settings
- Testing a short frame tracking anomaly detection method MLA developed within the project

3. RESEARCH METHODOLOGY

This chapter especially focused on the research methodology that contains 4 sections; The first section is about the suggested solution for the current project. The hardware and software selections have been explained in the second and third chapters respectively. The last chapter includes the analysis of the methodology part.

3.1 Proposal for solution

Fall prediction is a complicated challenge that should be addressed with the highest accuracy rate by using ordinary human gait data. In order to solve this problem, the measurement procedures of human gait have been conducted with healthy subjects in different surfaces and collected data is controlled by the physiotherapists for implementing further steps of the research.

Data collection needs to be divided into procedures of different gait abnormalities, and all anomalies must be applied according to the clinically approved ways. Experimental results of this project showed that using 2 multi-sensor devices was enough to conduct the procedures by attaching to the knee and top of the feet and according to the Shimmer guidelines, these sensors must be attached to the right leg of the subject [38]. The adjustments (the sampling rate, calibrations) of sensor devices should be evaluated depending on the data gaps during gait analysis and synchronization of IMU and EMG must be implemented in the relevant software for getting better performance. In addition to this, the correct lower limb position of the sensor attachment will be explained according to the selected surface.

Generally, MLA (Anomaly Detection) has to identify the different surfaces by using gait analysis results. Thereby, the trained data (annotated data) is a must-have stage for the implementation of the project's algorithm (Short frame tracking anomaly detection). In this project, implementation of several algorithms is planned to analyze which provides the best accuracy and that will be an executive MLA for the following procedures of the research. MLA will be quite deterministic for further development that assists to use the results for different IoT applications.

The development of a BLE device prototype, which broadcasts the sensor data is determined as the final stage of this research. This will assist to the relevant application by proving environmental context information for the user's awareness. The project will be executed by software development of the above-mentioned processses. It is aimed to develop an automated multi-sensor device for users who can control it by using the appropriate software application.

3.2 Hardware selection

Hardware selections are significant for accurate collection of human gait by the sensor device and context-aware implementation of this data using the context information from the energy and cost-efficient beaconing device.

3.2.1 Sensor device selection

The fundamental and also initial part of this project is related to data collection with a sensor device that includes IMU and EMG sensor. In addition to this, it is also known that there is literally no sensor introducing zero error accuracy. But selection of the multi-sensor device with better performance is quite crucial in this step. According to the below-mentioned features, "Shimmer wearable sensor device" (Figure 6) has been selected for this research:

- Robust and also wireless body worn sensors,
- Clear indication about the status,
- Time synchronization between the sensors,
- Clinically appropriate output of simultaneous biophysical and inertial data.

Figure 6. Shimmer wearable sensor device and embedded sensor dock [38]

The sensor device introduces the usage of different sensors simultaneously. It includes the measurement of accelerometer, magnetometer, gyroscope, electromyography, electrocardiogram, temperature and humidity. The simultaneous management of Shimmer sensors has been provided by the base component (sensor dock) that makes some features possible like sensor configurations, updates of the firmware, logging or processing data and charging of the sensor device. Shimmer 3 IMU development kit has been used in this research.

3.2.2 Bluetooth Low Energy Module

BLE is a type of wireless communication that is designed and commonly used in short range communication, and significantly important for the contemporary IoT. In comparison with classic Bluetooth, BLE provides desirable solutions such as the effective energy saving, better data transfer speed and so on. Most of the smart devices especially built since 2012, support the BLE technology. All these can be summarized in the below-given table (Table 3). It is known that widely used beaconing devices usually use BLE communication, so therefore, “Fanstel” certified module has been used in this project.

Table 3. Comparison of Bluetooth technologies

	BLE	Classic Bluetooth
Data transfer latency	Generally 3ms	Generally 100ms
Rate of data transfer	Up to 1.5Mbps	2-3Mps
Typical battery current consumption	Lower than 15mA	Around 30mA
Suitable application	Continuous data streaming is not required for use-cases	In which continuous data streaming is needed

According to the task description, it is necessary to advertise the sensor data with BLE device by implementing a beaconing mode in which the data is transmitted to the peripheral over the particular interval. nRF52 series evaluation board from Nordic Semiconductor family is used to execute the assignment in this project. nRF52 series Bluetooth controllers have been used at Taltech Electronics Department before that was the main reason for selecting this particular family. These SoC series provide ULP wireless and supporting Bluetooth5 to Zigbee, ANT, Thread, and so on wireless technologies. Its mesh topologies allow provision, configuration, and controlling of the mesh nodes. In order to wake up the device from the sleep mode and keep securely pair OOB, NFC is provided.

The nRF52 series development kit introduces the following features to the user applications:

- NFC-A listen mode is supported
- Drag and drop MSD programming
- I/O interface have been provided for Arduino form plug in modules
- Mbed Enabled
- SEGGER debugger with the functionality of debug out
- Multiprotocol radios can be supported by SoC microcontroller

The nRF52 series (with nRF52832 SoC) development board has been presented in the following figure (Figure 7):

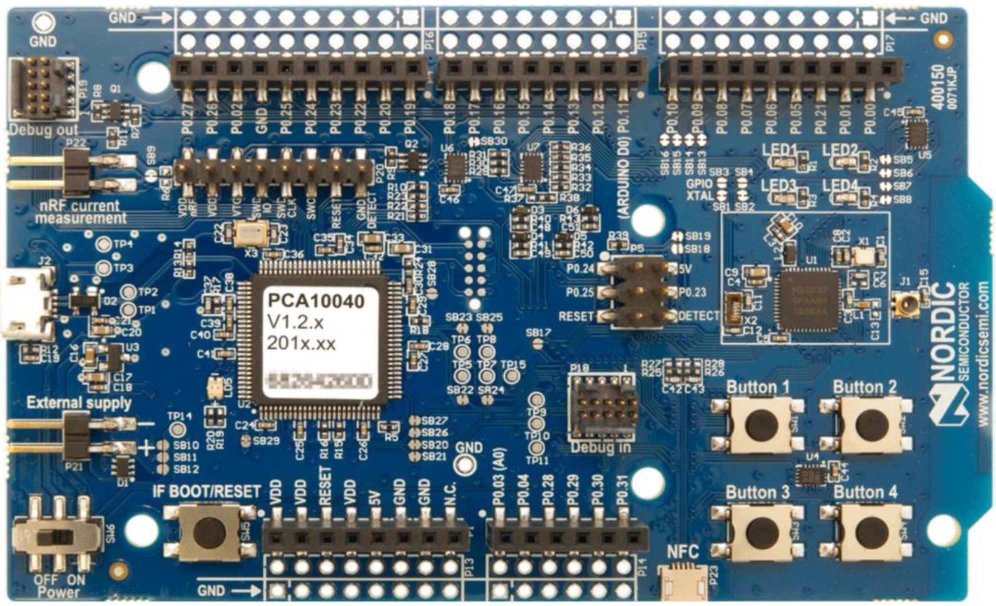

Figure 7. nRF52 series development board

The development board can be used for prototyping of required environmental context information beacon [39].

3.3 Software selection

This section mainly focused on the management of sensor components using its own-dedicated software and the special development environment for hardware devices.

3.3.1 Multi-sensor management

"Consensys"– a dedicated special software environment developed by the "Shimmer Technology includes the visualization of available sensors and hardware in the "Manage Devices" window. The more detailed information also can be acquired by this section that contains BT Radio identification, used firmware, relevant expansions, the capacity of SD card, current battery level, and real-time synchronization of the docked sensor devices. Firmware adjustment is a must-have setting while doing the sensor configuration according to the intended purpose. The two options are demonstrated by the firmware bootstraps for the users:

- Direct logging of data to SD card,
- Indirect logging of data to SD card (Live data streaming over Bluetooth and capturing data for SD card).

While looking through these options, the second one can seem desirable to the user for live visualization pros, but significant data gaps issues are appeared due to the Bluetooth streaming, so thus, the first option - direct logging is the final decision about firmware configuration in this project (Figure 8).

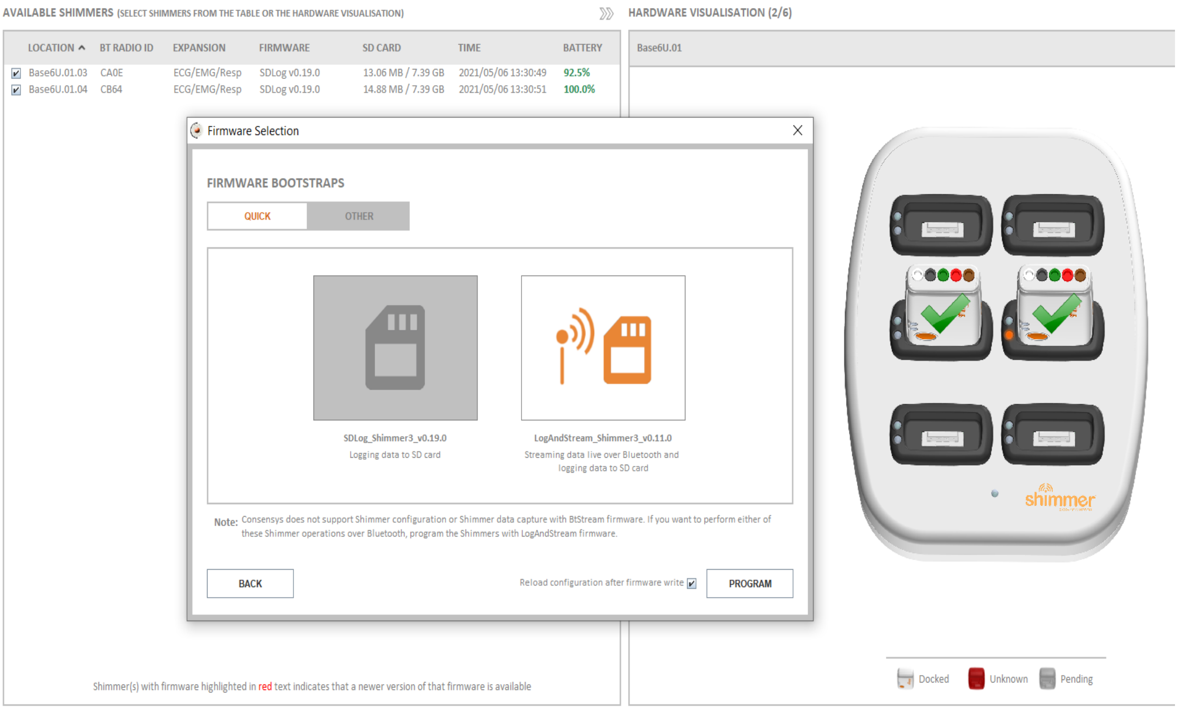

Figure 8. Firmware selection screenshot

The configuration will only be executed right after the completed firmware programming. This stage also requires sensor selections according to the project content, and labeling of them either using their default names (given on the backside of each multi-sensor component) or the relevant names (foot or knee sensors). Figure 9 shows that only required sensors - "Low-Noise Accelerometer", "Wide-Range

Accelerometer", "Gyroscope" and "EMG" have been selected by the author to perform the data collection procedures. "Consensys" software also provides the users with some additional built-in algorithms under the "Algorithms" section which includes "Gyro-on-the-fly-Calibration", "9DoF", "6DoF", "ECG-to-HR" and Activity" options for more sophisticated uses. However, none of the above-mentioned algorithms were applied for this task. The default calibration settings are enough for short-range measurements, but if the procedure is getting longer, the calibration has to be defined manually for decreasing the data gaps to the minimum level. The Bluetooth bandwidth range highly depends on the sampling rate adjustments, so if the rate increase this can cause specific issues. These will be explained in the further chapters.

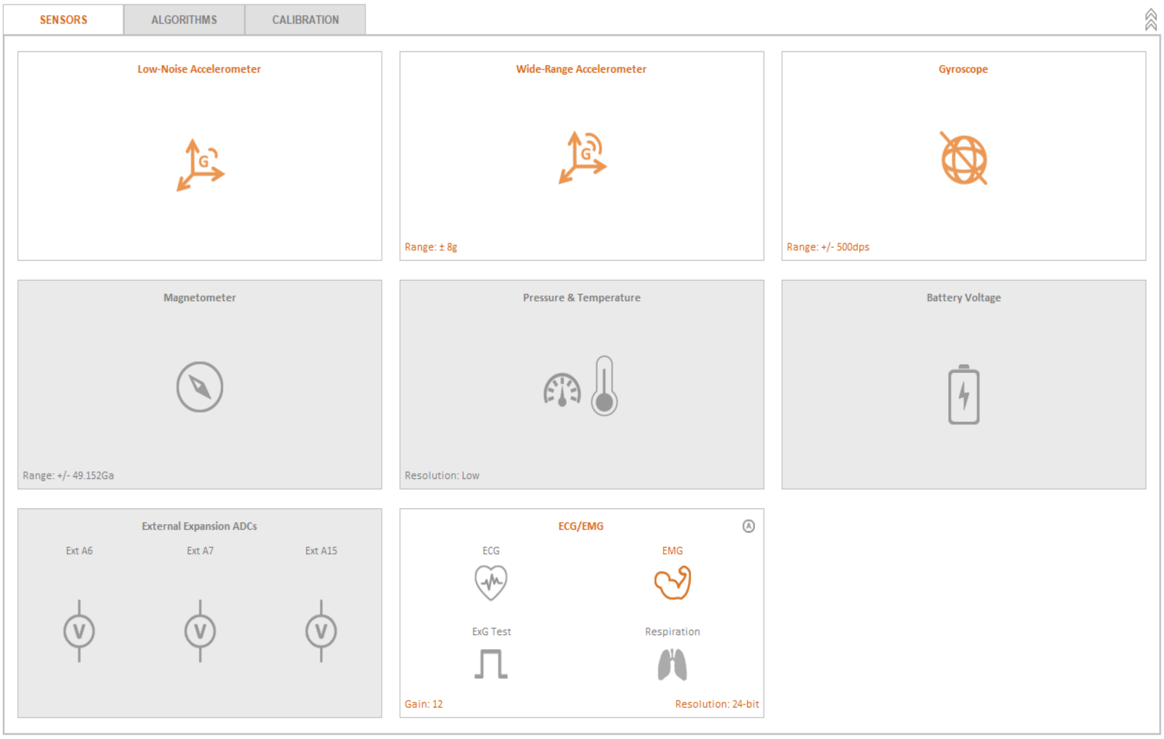

Figure 9. Sensor and algorithm configurations

Data capturing can be executed either by undocking the sensor device from the sensor board (dock) or by pressing the button on it. The captures dataset will be stored in the "Manage Data" section and they can be exported in 4 different data formats (Figure 10).

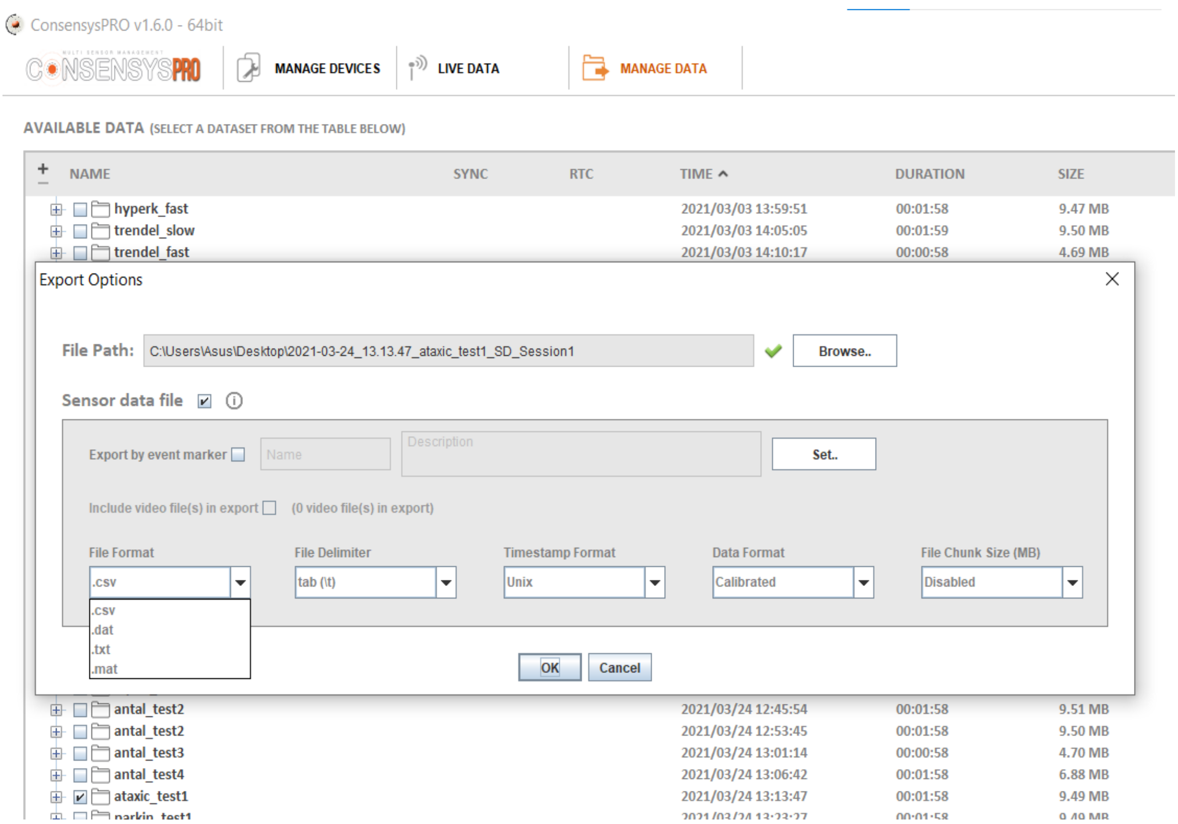

Figure 10. Multi-sensor data management

3.3.2 Integrated development environment

There are high enough IDE opportunities in this market to develop the software for nRF52 series hardware. SEGGER IDE is compatible with Nordic Semiconductor products and do not have any limitation for code size in comparison with Keil IDE. In order to develop the script for this development board, SEGGER Embedded Studio has been used in this project due to above mentioned reasons. This integrated and advanced development environment supports ARM Cortex devices with its project management equipment. Although it is also possible to work with other relevant software environments, SEGGER has better features and especially upgraded for nRF52 series Nordic devices by Nordic Semiconductor engineers.

Below-given key features assist to select this embedded studio for the hardware development:

- Runs on different platforms: Linux, macOS, Windows
- Embedded C or C++ programming IDE solution
- The advanced run-time library

- Projects can be generated depending on the microcontrollers packages
- No limitation to educational usage purposes

In this project, SEGGER Embedded Studio allows to test the written script with its advanced features. In addition to this, it should be noted that SEGGER introduce some prepared script examples which are quite straight-forward for the hardware development [40].

3.4 Selected methodology analysis

The proposed solution has been described; software and hardware selections are explained in this chapter. According to the suggested solution, sensor devices and development board must be used to conduct the experiments and relevant software environments installed depending on the purpose of management and testing processes.

The appropriate software licenses were purchased for the multi-sensor management and the hardware development environment is free to use for educational purposes. The selection criteria of the software environments are especially based on the performance, accuracy and advanced features.

Selection of the hardware devices is completed according to the performance and of course, accuracy rates. The main reason of selecting the introduced sensor device is its multi-sensor features and working quality with different sensor devices in real-time.

4. PROJECT IMPLEMENTATION BASED ON THE PROPOSED METHODOLOGY

This chapter includes the general implementation of the project by containing 3 main parts: conducting gait analysis, executing machine learning algorithms with collected data and development of hardware device for the beacon advertising.

4.1 Instrumented gait analysis

The data collection is the initial stage of each gait analysis, however, it also needs to correctly mapping of sensor devices and finding optimal position of body for attachment. In addition to this, encountered challanges and data annotations have been explained in this part.

4.1.1 Correct mapping of IMU and EMG sensors

According to "the wearability map" in most of the researches, the sensors have been attached to different places of the human body for analyzing the walking patterns. This research is mainly focusing on the highest accuracy rate of collected data, therefore the correct mapping of relevant sensors must be executed in a way that can provide better results while performing various abnormalities. In order to collect data, it has been identified that 2 different body locations will be necessary for sensor attachment in this research:

- Lower knee position,
- Top of the foot.

Gait abnormalities are quite different and there are some anomalies in which not only the foot, but the whole body is also predisposed to preternatural movements or shakes, thus it is needed to at least get data from upper body changes. The attached sensor on the lower knee position provides comprehensive and relevant data about the upper side shakes while performing the anomalies.

The second sensor device placement should be a position where the changes of movements can be detected with the highest acceleration. According to the 7 steps of the normal human gait cycle, it is determined that while walking, foot sensors collect the most dynamic data, therefore considering the sensor device sizes and mobility, the top of the foot is the correct position for the sensor.

The next step is to find a relevant position to EMG electrodes that can provide accurate electromyographic data. The motor and insertion points, tendon positions, the shape of muscle and fiber directionality assist to get high-quality readings of EMG signals. 3 different muscles are selected to proceed with the measurement in this research and the electrode insertion will be as following:

- gastrocnemius muscle,
- peroneus longus muscle,
- tibialis anterior muscle.

Beside these, two reference electrodes should be attached the right leg according to the Shimmer wearable sensor guidance. Therefore, knee and ankle are defined as a reference placement for the electrodes. In Figure 11, attached sensors and all their electrodes have been described.

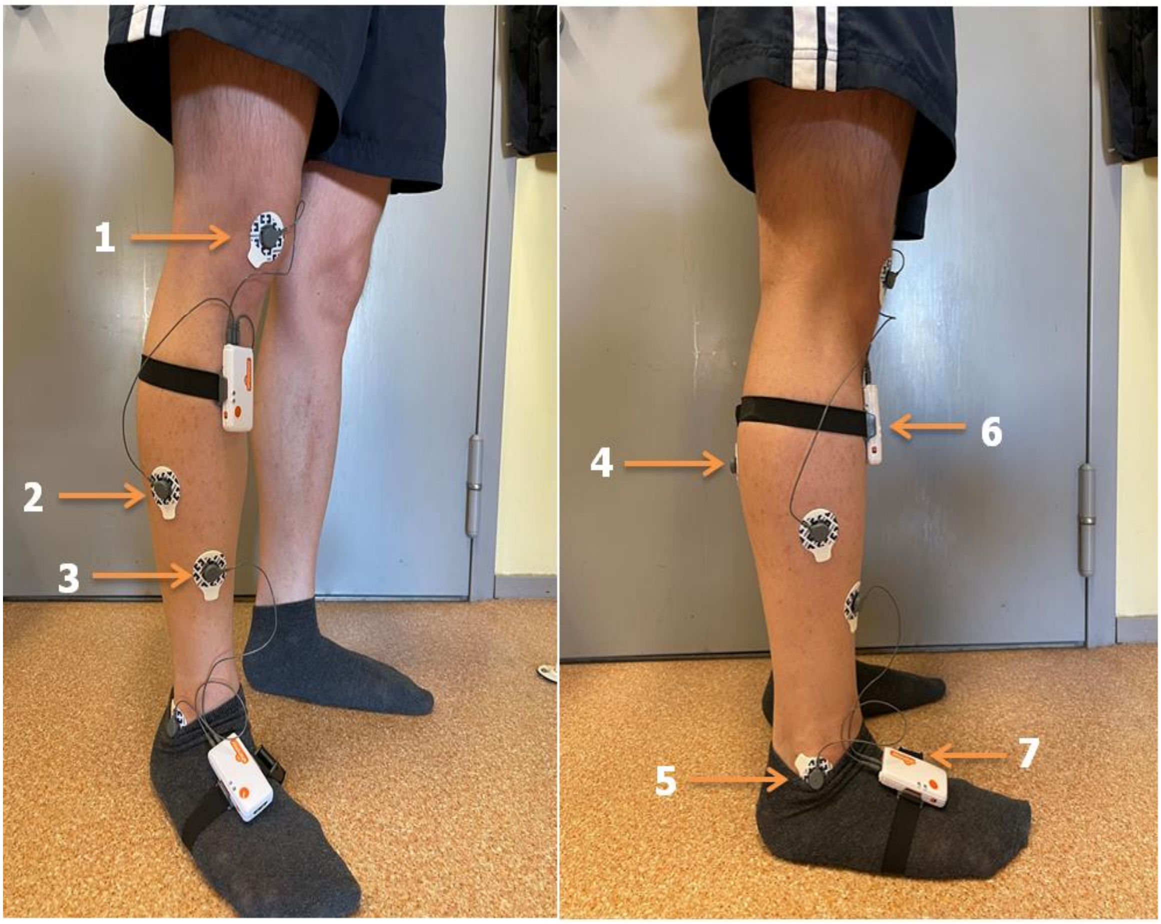

Figure 11. The attachment of electrodes on knee (1), peroneus longus (2), tibialis anterior (3), gastrocnemius (4) muscles, ankle (5) as a reference, and sensors placement in lower knee (6) and top of the foot (7) positions

4.1.2 Data gaps identification

The effective trained data for the further processes are important and some data gaps must be addressed before executing annotations. In these experiments, the gaps had been observed in different circumstances that are quite problematic for correct data collection. According to the Shimmer default settings, the range of "wide-range accelerometer" have to be ±2g and it should be ±500dps for "gyroscope". While configuring the settings to default properties, the software also prefer to use "gyro-on-the-fly" calibration algorithm, however above mentioned settings do not provide the desired results and includes many data gaps. During the measurement period, the possible reasons have been researched and some adjustments have been completed to get the relevant data for implementing them in MLA. The gaps can be clearly seen in the below given figure (Figure 12), and this means around 11% of lost packets.

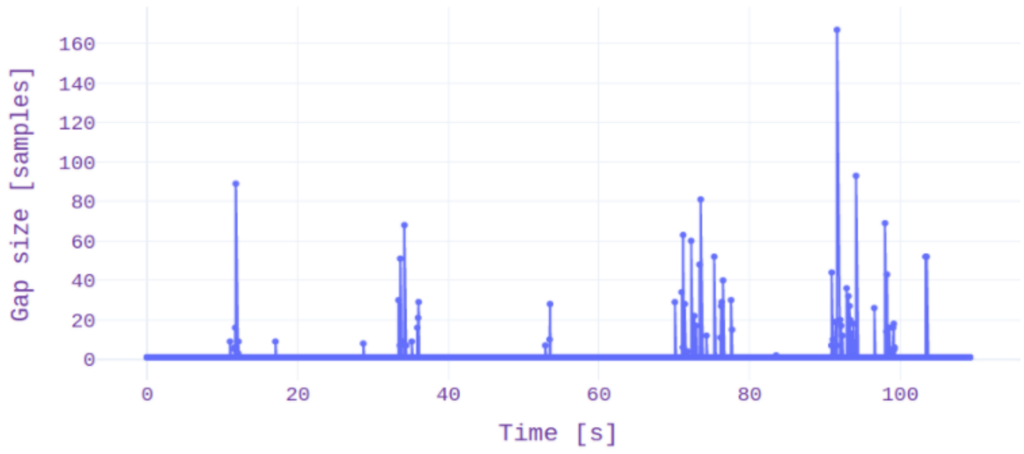

Figure 12. Unacceptable data gaps

This figure allows to say that the gaps are excessively abundant in real-time, so therefore the same procedure with the preplanned gait abnormality must be re-performed for better data collection. In order to achieve this, related adjustments have been tested and described as following:

- While the firmware part was explaining, it has been noted that the data can be either directly logging or can be logged by using Bluetooth streaming. At first, the author used to check the data by configuring the firmware with Bluetooth. It makes to follow the signals simultaneously by created plots. So, this was an excellent option for short measurement procedures (less than 10 meters). However, when the distance was getting longer, the data exposed making gaps because of the poor Bluetooth connection. Therefore, it was identified that using only logging data in the firmware configuration was the best priority for longer and various kind of procedures.

- According to the Shimmer sensor guidelines [38], it is desirable to conduct with the measurement procedures with the sampling rate in 512 Hz. However, some tests are enough to say that this sampling rate is one of the main reasons of data gaps. Thus, it has been agreed to decrease the sampling rate from 512 Hz to 256 Hz and increase the measurement limits both for gyroscope and acceleration signals.

- Default axis directions must be determined by using Shimmer wearable sensor user guidelines [41]. It is important to conduct the measurements according to those directions, otherwise synchronization and data gaps issues will be occurred. Figure 13 demonstrates how the sensor device should be attached to the right leg:

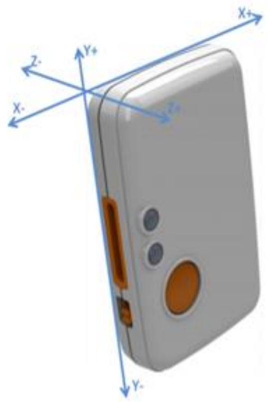

Figure 13. The correct axis directions for the Shimmer sensor [41]

- As it is mentioned before, it should be noted that some range adjustments must be tested for the best datasets. Therefore, the range is calibrated to ±8g and ±1000dps for accelerometer and gyroscope respectively, instead of the default settings which is proposed by Shimmer Technology (Figure 14). In addition to this, "gyro-on-the-fly" algorithm must not applied in this configuration.

Figure 14. The correct adjustments of range calibration

All these corrections assist to solve the huge gap issues. In the below given figure (Figure 15) provide a better understanding about the encountered challenge. Some gaps in the first 20 seconds are completely normal, because sensor device needs time for real-time synchronization. Four or five gaps in 14000 samples which are less than 0.02 out of 100 percent are not making any problem for the further steps of the data processing, so, data is ready to annotate and be conducted in MLA.

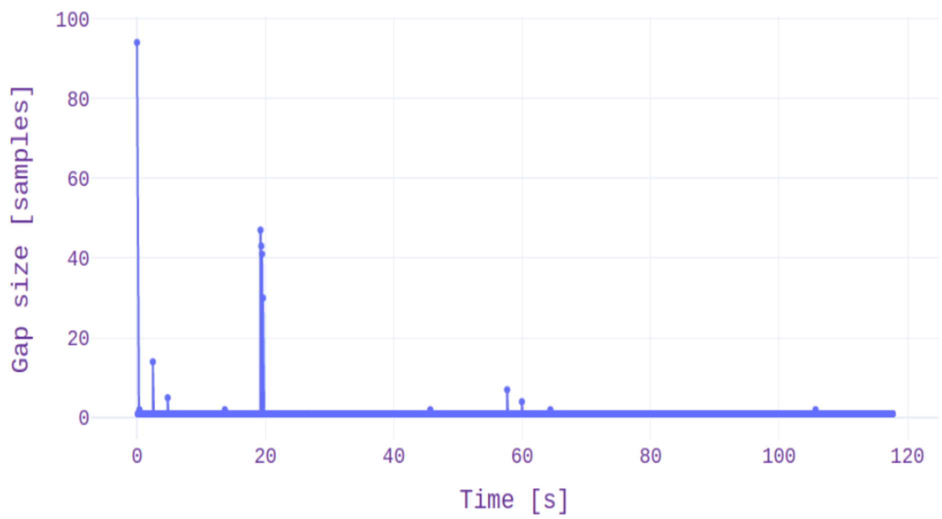

Figure 15. Corrected data gaps

4.1.3 Data collection

The sensor data play a fundamental role in this project in which all processes depend on correctly performed procedures. According to the clinically approved results, all measurement procedures of gait should be completed by healthy subjects in different contexts. This will allow understanding differences of the patterns in various contexts and provide to develop a system for improving the environmental awareness. Initial data plots with offsets for accelerometer have been provided in the following figures (Figure 16-19):

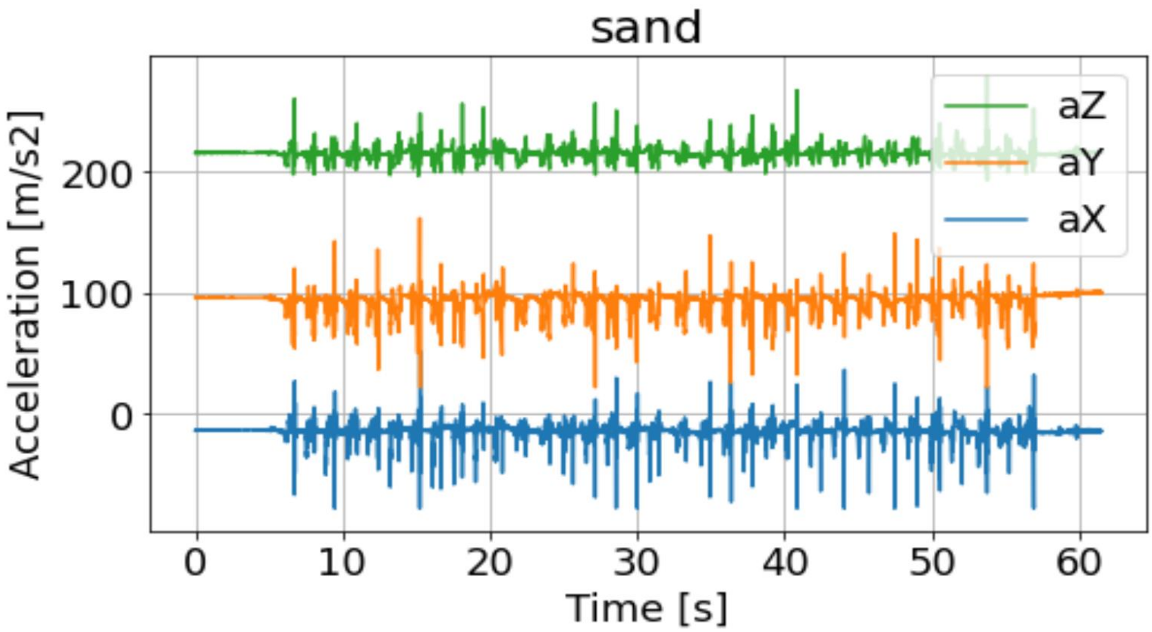

Figure 16. Accelerometer signal plot for X, Y and Z axis on sand surface

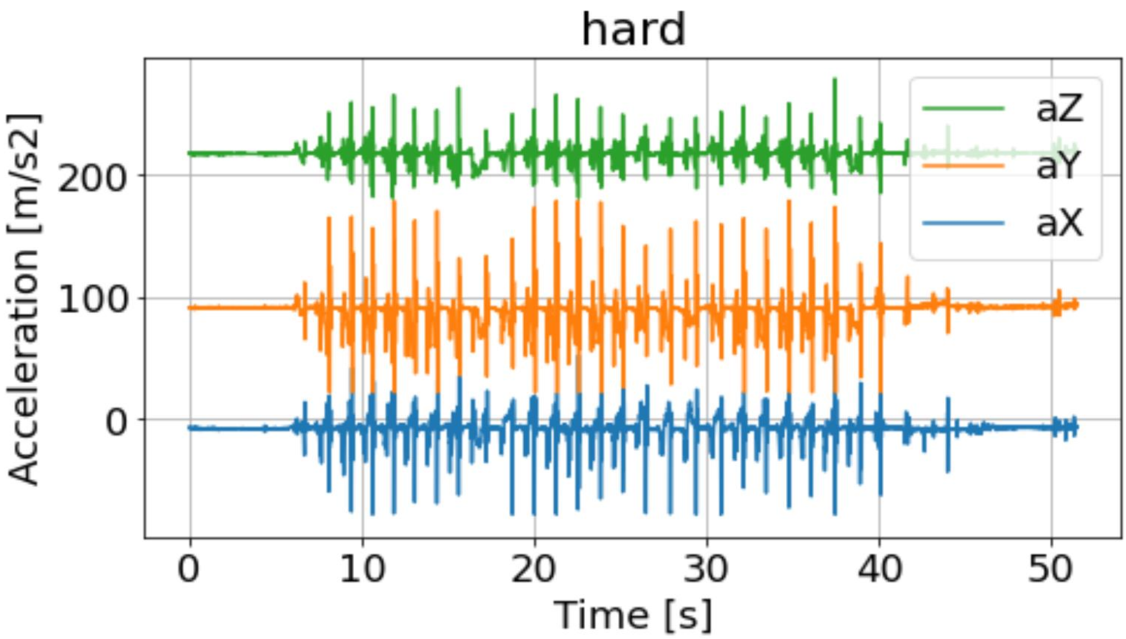

Figure 17. Accelerometer signal plot for X, Y and Z axis on hard surface

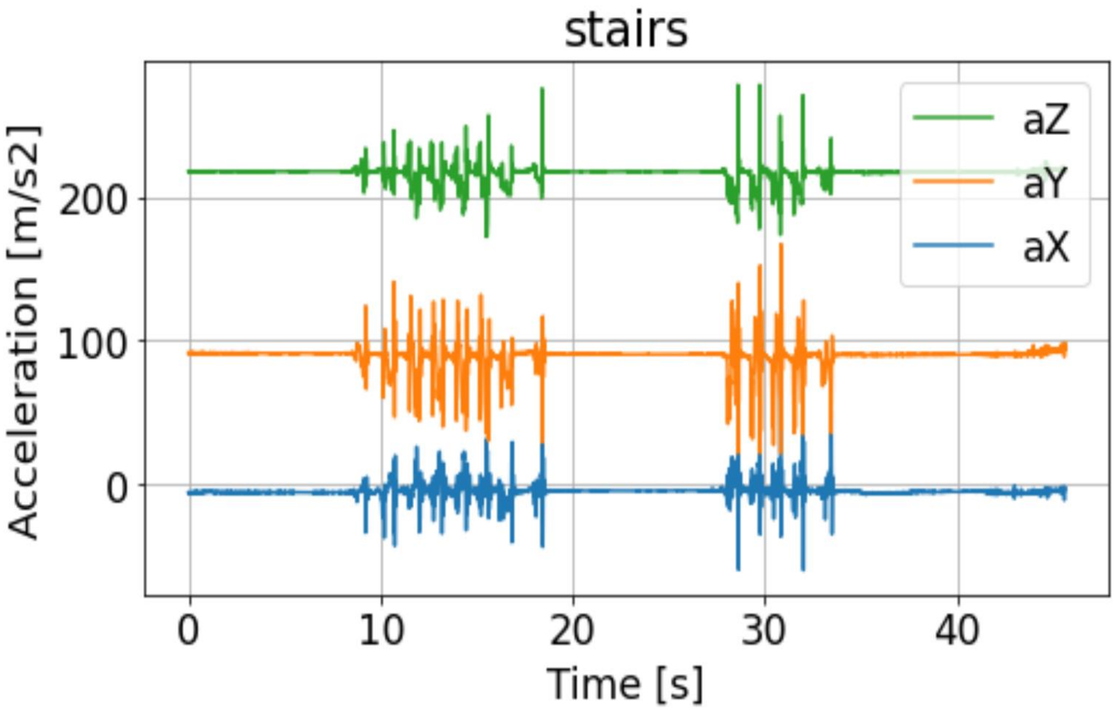

Figure 18. Accelerometer signal on stairs for X, Y and Z axis

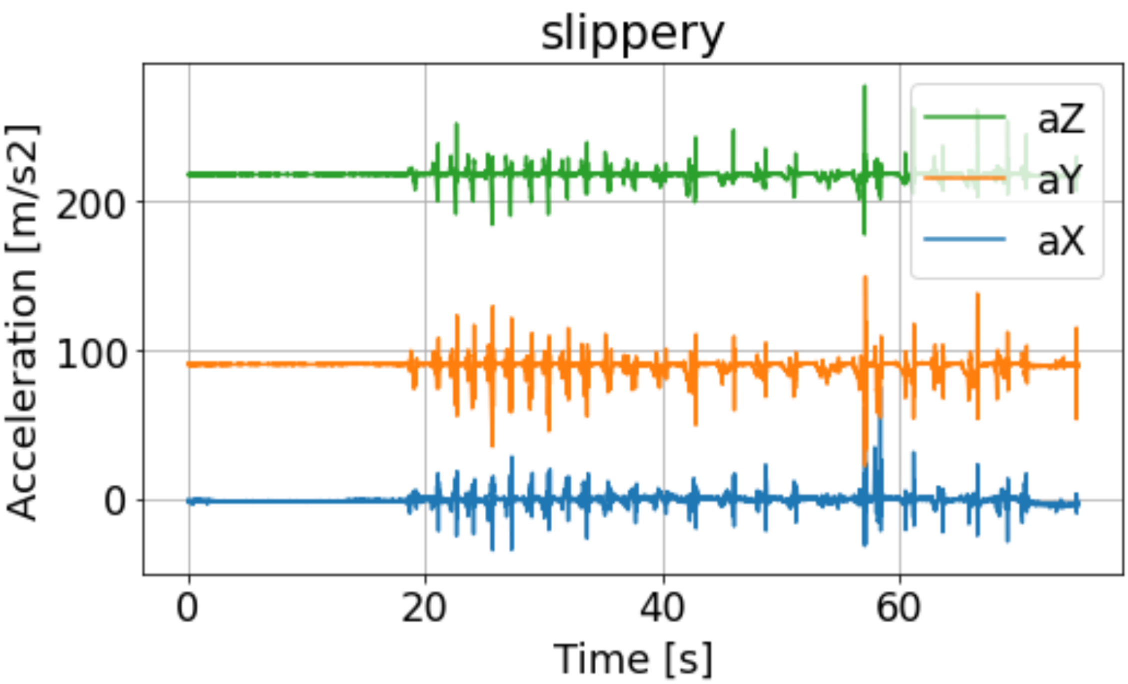

Figure 19. Accelerometer signal on slippery surface for X, Y and Z axis

The same data are also given for gyroscope signal in Figure 20-23:

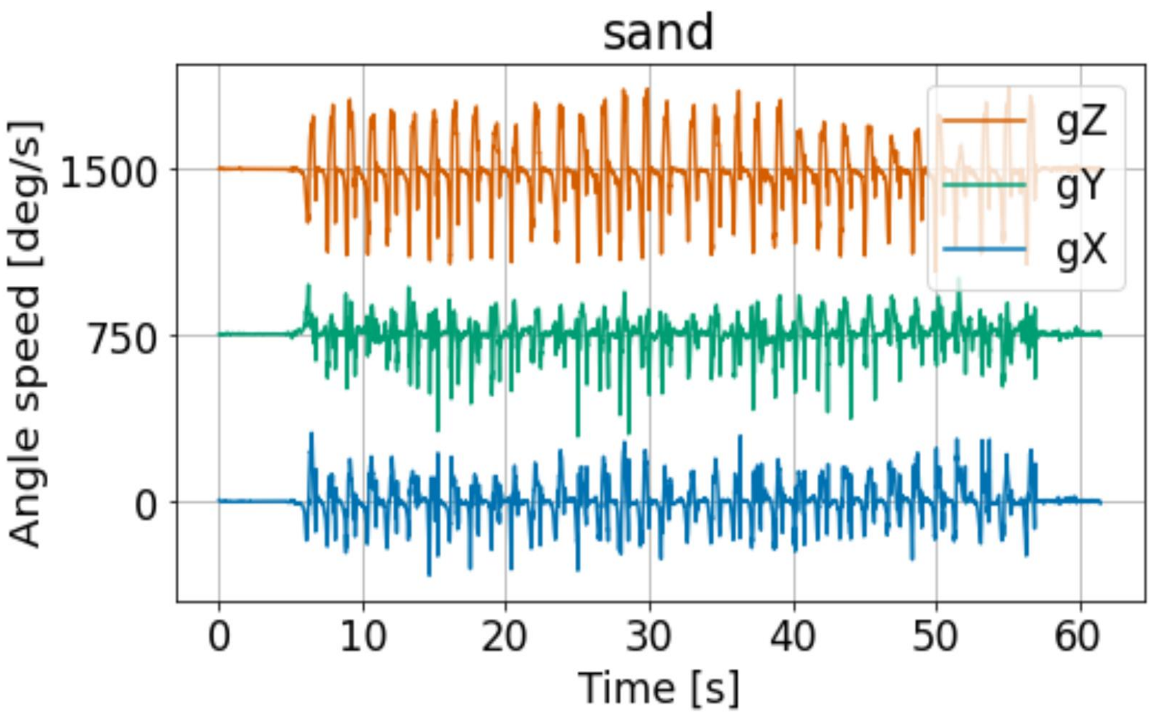

Figure 20. Gyroscope signal on sand surface

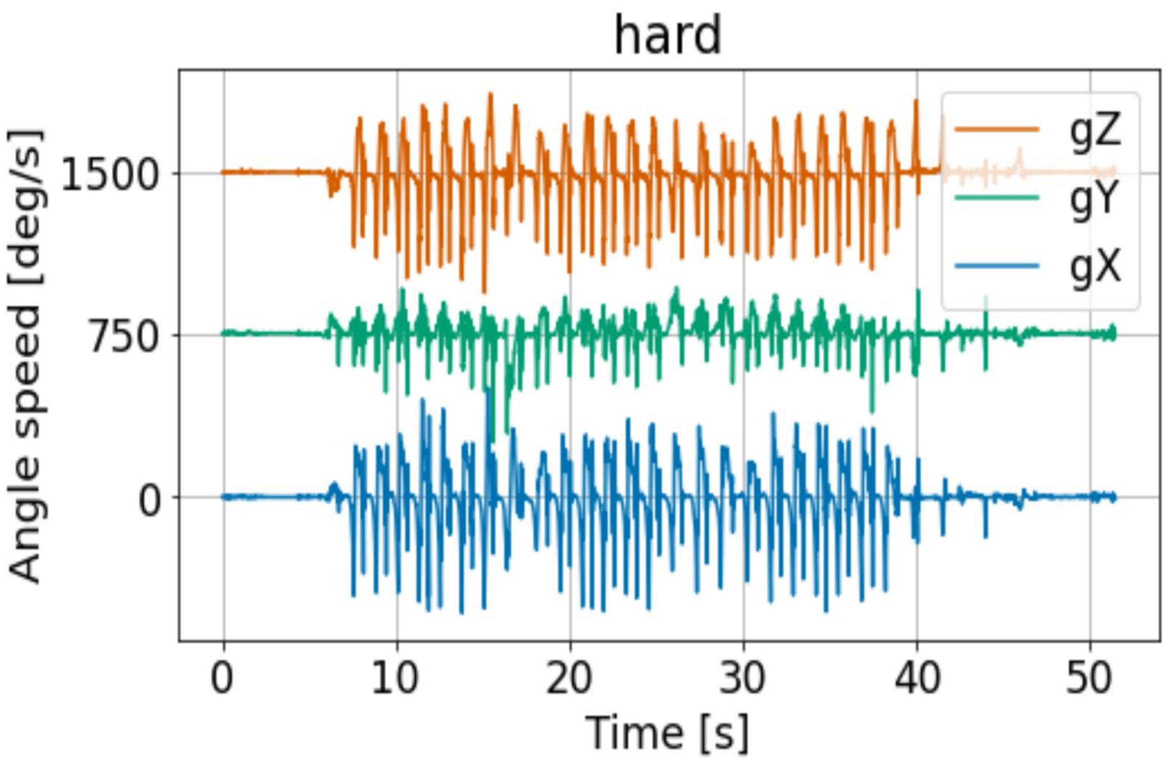

Figure 21. Gyroscope signal on hard surface

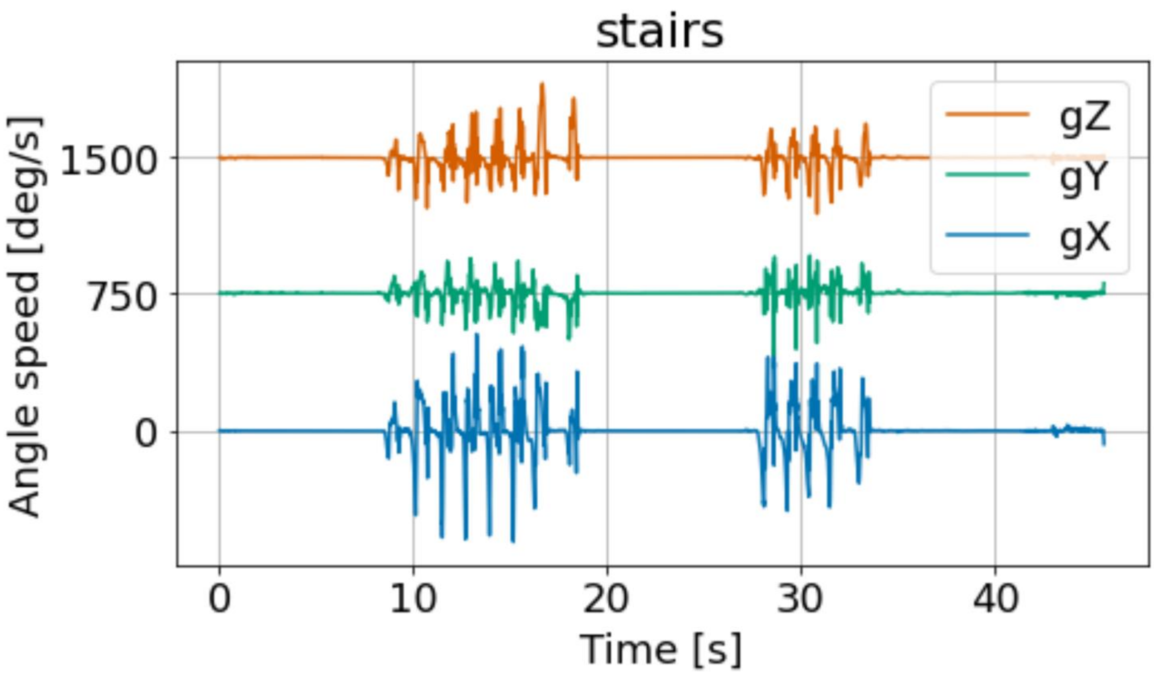

Figure 22. Gyroscope signal on stairs

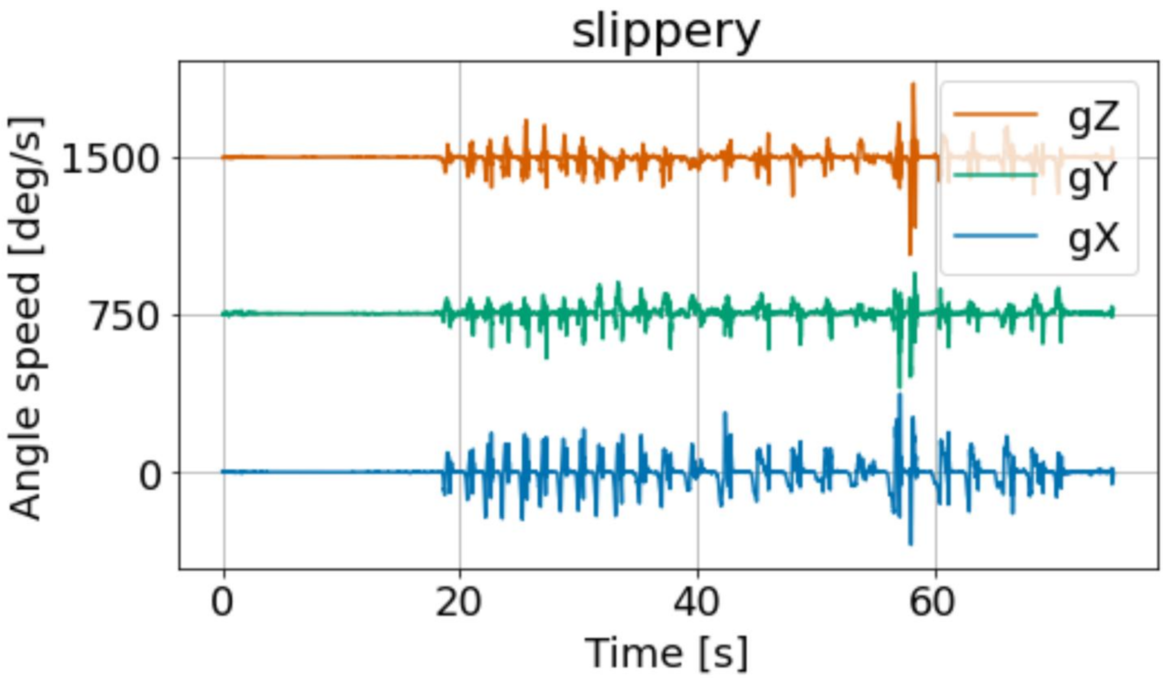

Figure 23. Gyroscope signal on slippery

As it can be seen from the above-mentioned plots, X and Y axes show rather smaller negative offsets and Z-axis creates bigger offsets, but it should be noted that these cases can be changed depending on the different kind of context scenarios. Even if only Z-axis is plotted, the signal changes (Figure 24-27) related to the surface will be clearly visible.

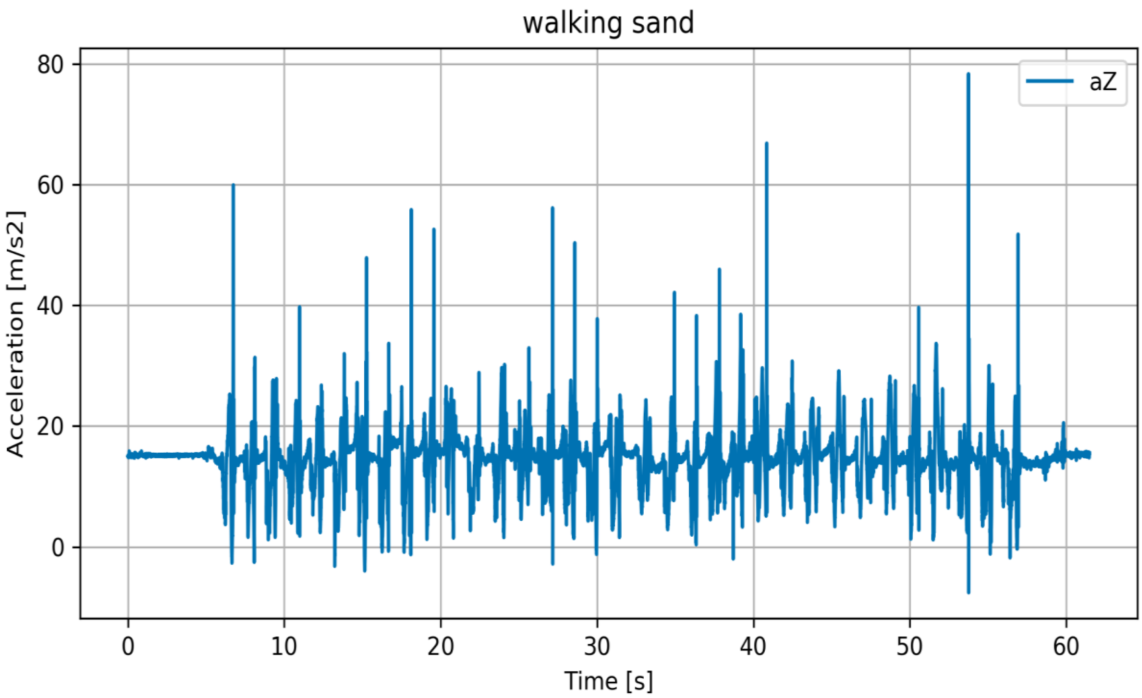

Figure 24. Accelerometer signal for Z-axis on sand surface

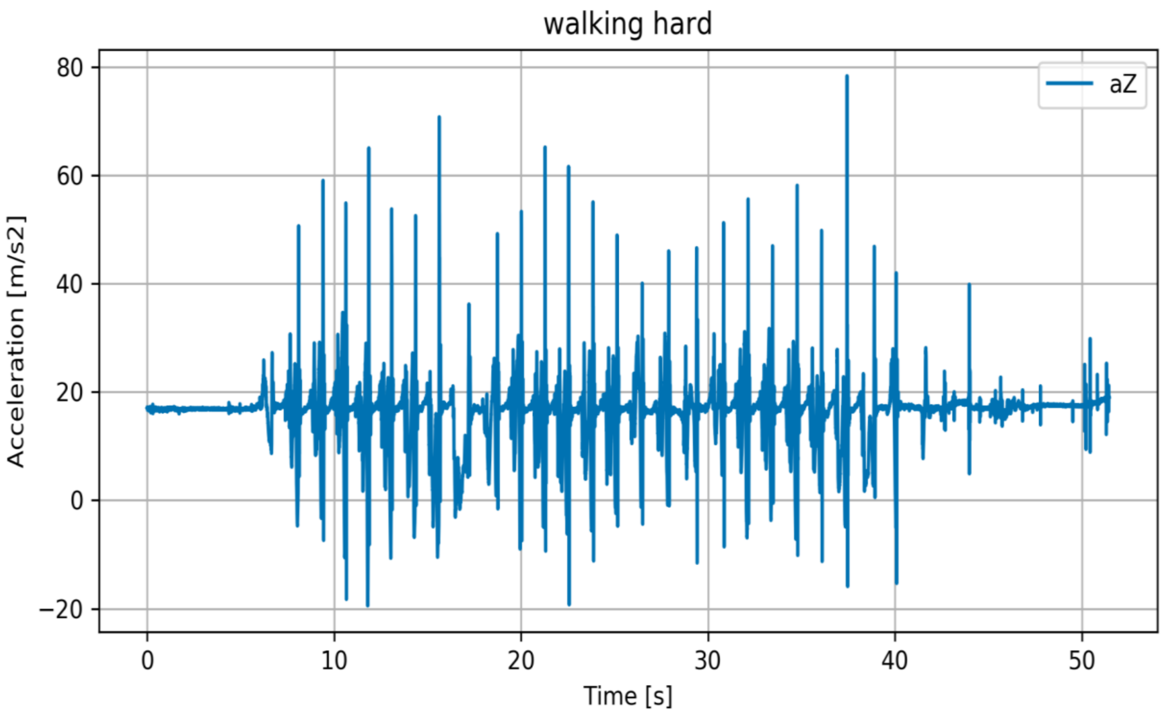

Figure 25. Accelerometer signal for Z-axis on hard surface

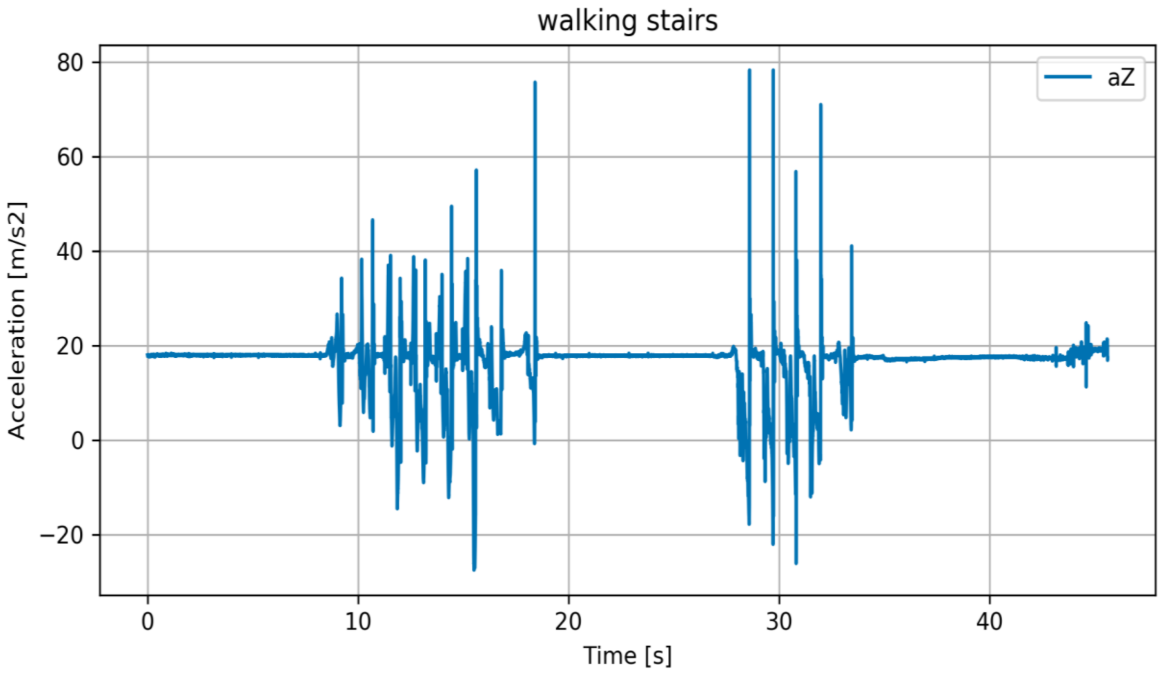

Figure 26. Accelerometer signal for Z-axis while walking on the stairs

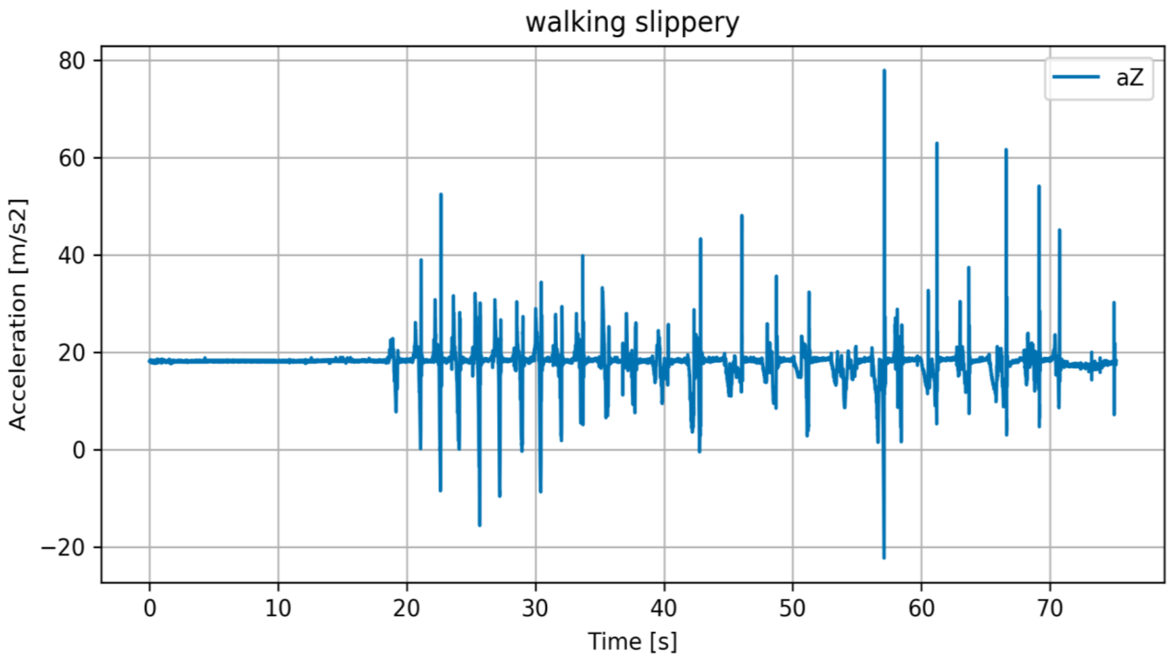

Figure 27. Accelerometer signal for Z-axis while walking on the slippery surface

These plots demonstrate that different surfaces must be considered in the gait analysis and various abnormalities should be performed in these contexts to get the higher accuracy for gait analysis. In this research, male and female subjects selected from the same age group (23 years old) have performed 9 different gait abnormalities that have been divided into following groups of datasets:

1. Normal gait + one abnormal step
2. Normal gait + one abnormal step + normal gait
3. Normal gait + N x abnormal step + normal gait + N x abnormal step, where N=0,1,2,3,4...
4. Random regular and abnormal steps mixture

There are some crucial reasons to create these datasets for data collection procedures. First of all, it should be acknowledged that MLA always depends on data and if there is various and ample database, the implemented algorithm will be more sophisticated and accurate as well. In addition to this, the gait abnormalities show different patterns in various environmental conditions and contexts and at least these changes must be observed and investigated for medical purposes.

4.1.4 Data annotations

Data annotations are the process of labeling data for the further uses of a machine and with the reliable labeled information can result in the desired output for the execution. As it is known that more trained data let to develop a more accurate and comprehensive algorithm for fall prediction. Annotations have been completed in the Linux environment with the prepared Python scripts and Audacity software. The performed and checked data are annotated both for knee and foot sensors, and the comparison is conducted in an applied algorithm to select which sensor is most appropriate and detects falls on time.

In order to start annotations, the Linux environment should be installed for utilizing its advanced features. Firstly, the relevant multi-track audio converter or editor software - Audacity should be installed. This software allows the user to navigate, edit and label tracks. Of course, it should be noted that set upping "Anaconda Navigator" is also necessary to launch "Spyder" for running the prepared Python script.

The Python script is developed to annotate the sensor data by adjusting the threshold value and adding the default label boundaries. If the starting and ending points are correctly labeled by changing the threshold value, then the script will generate the relevant audio and text files. The next step will be conducted the annotation labeling in "Audacity" environment. The appropriate audio file which is automatically converted by the Python script must be dragged to this audio editor software, firstly. And the text file should be imported as well, which contains the default label limits.

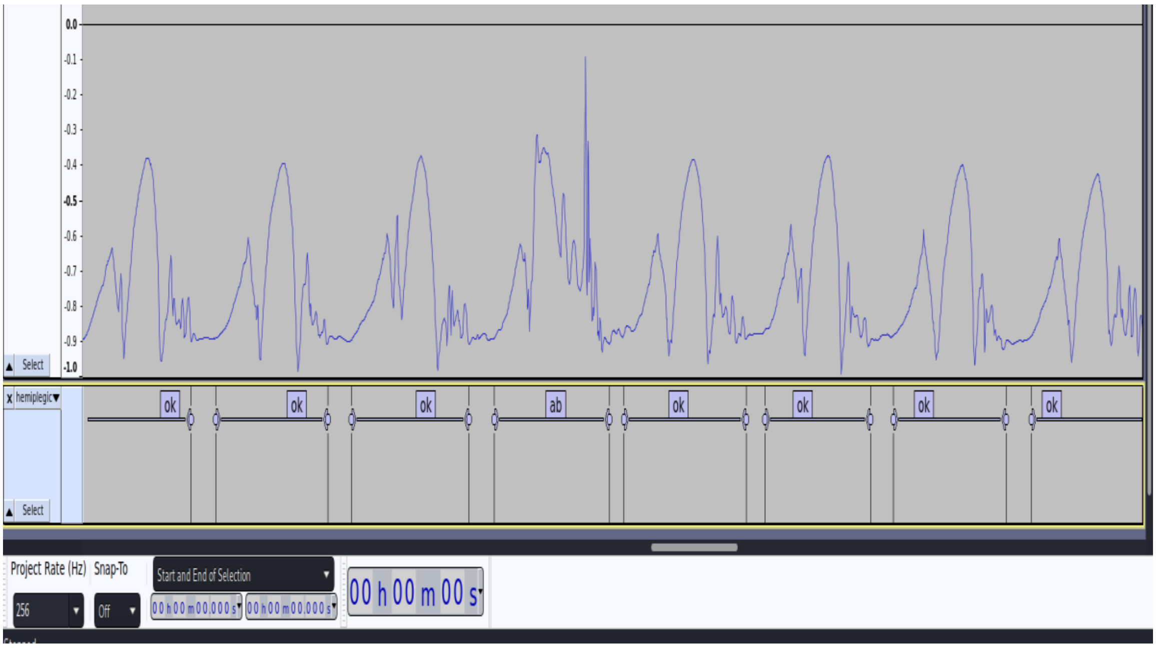

Figure 28. The annotated knee sensor data in "Audacity" environment

Figure 28 demonstrates an annotated knee sensor data (in this example, hemiplegic abnormality has been completed) which is already labeled by the author and is ready for the MLA executions. After importing the text file, the labels only show "OK" signals as the default value. The most important thing here is to adjust the beginning and end of all step cycles and label them according to the relevant type (normal or abnormal) of gait. According to the measurement procedure, the subject can walk a couple of seconds after the slap. As it can be seen from the above-mentioned figure, the first step is not considered a normal signal just because of the short gait cycle. After 4 normal gait cycles, one abnormal step has been performed by the subject and it is labeled as "ab" in Figure 28. While doing the experiment, it has been agreed to take turns to determine whether the prepared MLA can detect the turns or not. Therefore, all turns also labeled in the software, and the boundaries of the steps are limited. All the labeling processes for annotation must be conducted in this way and after finishing them, another Python script will allow checking the annotation if a few data gaps affect the signal.

Figure 29 illustrates the foot sensor data for hemiplegic gait in the Audacity environment. As it is known, the foot sensor must collect more detailed data because of being the most moving part of the gait. If all of these are completed, the algorithm or several algorithms can be tested with the trained data.

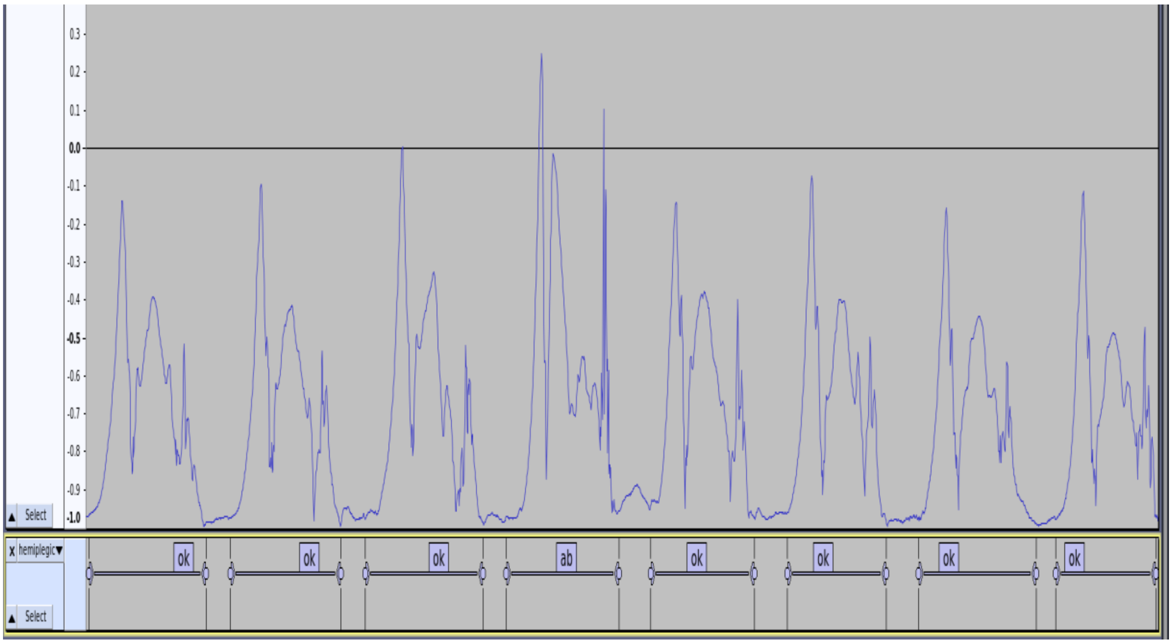

Figure 29. The annotated foot sensor data in Audacity

4.2 BLE beacon prototype development

The chapter mainly focused on the developing hardware device that can broadcast sensor data in beacon mode and the script has been written to provide the environmental information to the user for notifying about the context awereness.

4.2.1 System prototype

This section is mainly focused to explain the general implementation of proposed system prototype that has been demonstrated in the below given figure (Figure 30). As it is explained before, the multi sensor device collects data for the MLA, and the developed algorithm allows getting both context awareness and fall prevention. The Nordic Semiconductor introduces to the users its features for broadcasting data with the relevant purposes. The system prototype can be achieved by using MLA and by modifying broadcasting data script in beacon mode that assists to advertise sensor data for mobile applications on smart devices. In order to implement this system, hardware components integration must be provided which will be explained in the following sections. The written script will allow the connection through GAP service and get sensor information and execute a switch role according to the surface. The relevant surface name will be generated and a user can observe the environmental context information by using the proper application on their smart phones or other devices.

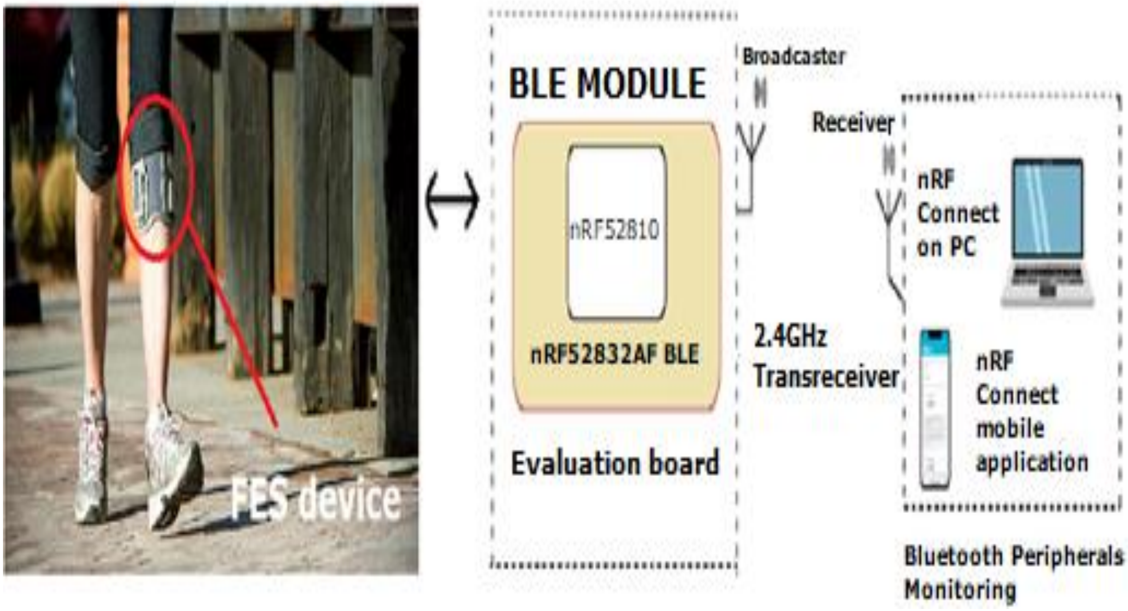

Figure 30. Block diagram of proposed prototype system

4.2.2 Hardware components integration

This part focuses on the hardware integration of nRF52 series development board and Fanstel evaluation board (EV-BT840 (832)-V4). The correct attachment of these boards allow the author to complete the uploading the written script from the nRF52 board to Fanstel evaluation board. The 5th generation of Nordic Semiconductor family – nRF52832 has been provided with a PCA10040 processor that plays a host processor role and takes debugging on. Fanstel evaluation board (EV-BT840 (832)-V4) includes BLE Module itself that assist to get available communication for advertising data in beacon mode. The debugging cable must be attached to the JS1 (Debug-In) and P19 (Debug-Out) ports of the Fanstel and nRF52832 boards, respectively (Figure 31). The sensors will later be attached to the relevant pins depending on their type. If this attachment is successfully established, the firmware can be debugged and uploaded to the evaluation board as a next step that will be explained in the following parts.

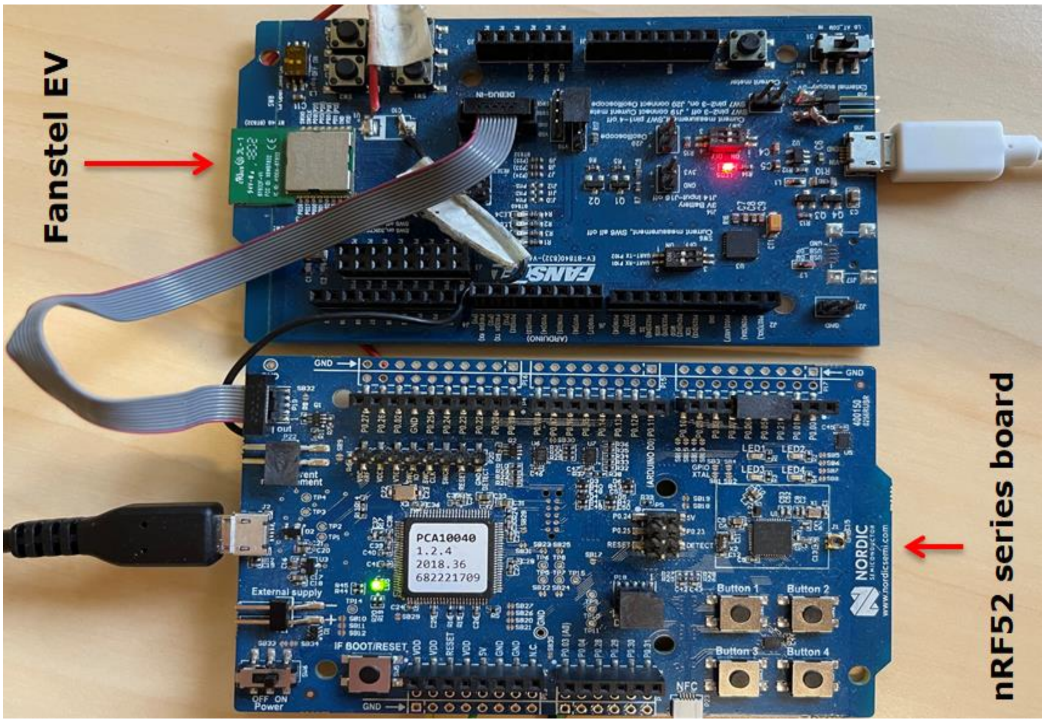

Figure 31. Attachment of hardware devices

4.2.3 Firmware development

Well-established connection let the author to modify the script [42] on Segger Embedded Studio that provides the advertising of the context information in beacon mode. The script will be run in nRF52832 board, if it works correctly, then this will be uploaded to the Fanstel evaluation board for testing. The generic access profile has been used in this script, the GAP service makes the broadcasting possible, and determines how BLE devices can show them available. After defining the service type it is time to define some parameters that is significant for the data broadcasting. It is needed to include the SoftDevice BLE tag for configuration. And as it is known, non-connectable advertising interval must be given according to the purpose, therefore this interval is 100 ms in the provided script. The most important points of developing a script for broadcasting are to correctly define the type of advertising, data length, major and minor values.

In order to advertise data in the relevant mode, 0x02 must be included that refers to the beacon. To add this, the total length of advertised information can be included, minor and major values that identify beacon can be modified depending on the purpose. The script is written according to the switching device name while the data acquired from the sensor shows that the environment is changed. So, therefore, it does not need so many modifcation about major and minor values.

```
// Build and set advertising data.
memset(&advdata, 0, sizeof(advdata));

advdata.name_type              = BLE_ADVDATA_NO_NAME;
advdata.flags                  = flags;
advdata.p_manuf_specific_data = &manuf_specific_data;

// Build and set scan response data.
memset(&srdata, 0, sizeof(srdata));
srdata.name_type              = BLE_ADVDATA_FULL_NAME;

// Initialize advertising parameters .
memset(&m_adv_params, 0, sizeof(m_adv_params));

m_adv_params.properties.type = BLE_GAP_ADV_TYPE_NONCONNECTABLE_SCANNABLE_UNDIRECTED;
m_adv_params.p_peer_addr     = NULL;
m_adv_params.filter_policy   = BLE_GAP_ADV_FP_ANY;
m_adv_params.interval        = NON_CONNECTABLE_ADV_INTERVAL;
m_adv_params.duration        = 0;
```

Figure 32. Setting parameters of BLE advertising and scanning

In Figure 32, some parameters related to the advertising and scanning must be arranged to get the desired results. In this project, there is a need to show the full name of advertised data, but this is not same for setting data for advertising. Even, if only a short name is enough for future purposes, the command will be updated as BLE_ADVDATA_SHORT_NAME, so this will use less byte while scanning data.

The initialization parameters are necessary that used when starting the advertising, thus, they should be implemented correctly. After the third comment in Figure 32, you can observe the defined parameters. As it is known the beaconing devices use only one-way communication that means they can be scanned but it is not possible to connect them. These devices only send data to the smart devices, in particular case FES prototype device to be developed within PRG424. In addition to this, the undirected advertisement, the duration and interval of the non-connectable BLE communication must be arranged. The duration should be never timed out, therefore, the value of duration is defined as 0 in this script. Several loops under functions will let the user to create a switch to change the device name depending on the environmental context information.

The screenshot of "nRF Connect" application has been demonstrated in Figure 33, and this shows that the script is completed successfully and the context name can be broadcasted according to the acquired data. The firmware uploading will assist to add the written script to the beacon device.

Figure 33. Scan response of the device in nRF Connect mobile application

4.2.4 Firmware testing

Bluetooth connectivity and proper response has been observed using AT commands on Fanstel evaluation board. In order to get connection several steps must be followed. Firstly, the nRF52 series board which is used for debugging and for programming, should be programmed to SoftDevice. The relevant hex files that contain SoftDevice, Application and BootLoader for nRF52832 board must be uploaded on "nRF Go Studio". After getting appropriate connection between nRF52 and Fanstel boards, nRF52 must be plugged in the COM port on PC, Segger should be selected under nRF52 development boards in the "Device Manager" section on the nRF Go Studio. Then, the hex files provided by the manufacturer must be programmed.

Next step is to check connectivity and relevant response by means of AT commands in DockLight application. In order to implement this, the nRF52 development board must be disconnected from both PC and Fanstel EV board and Fanstel will be connected to the device for testing. AT commands is provided for each Fanstel EV boards in manufacturer's web address, so the user must upload that AT commands file and select the relevant COM port from "Project Settings". Then, it is needed to set the evaluation board to AT command mode by scrolling the button up, and the Bluetooth connection can be seen after pressing "AT" from the command list.

The device will immediately reply with "OK" command and message from android is automatically generated in the screen. Android device can send the message to PC through the board, thus "Bluenor nRF5x" application must be installed and available "Bluenor device" should be selected and the command on third line must be given. Generally, "AT +NAME = <param>" command is defining the advertising beacon name in this mode, and standard name of advertising can be shortened depending on the purpose as well. Figure 34 shows the communication process sequence according to the sent and response format of the AT commands [43].

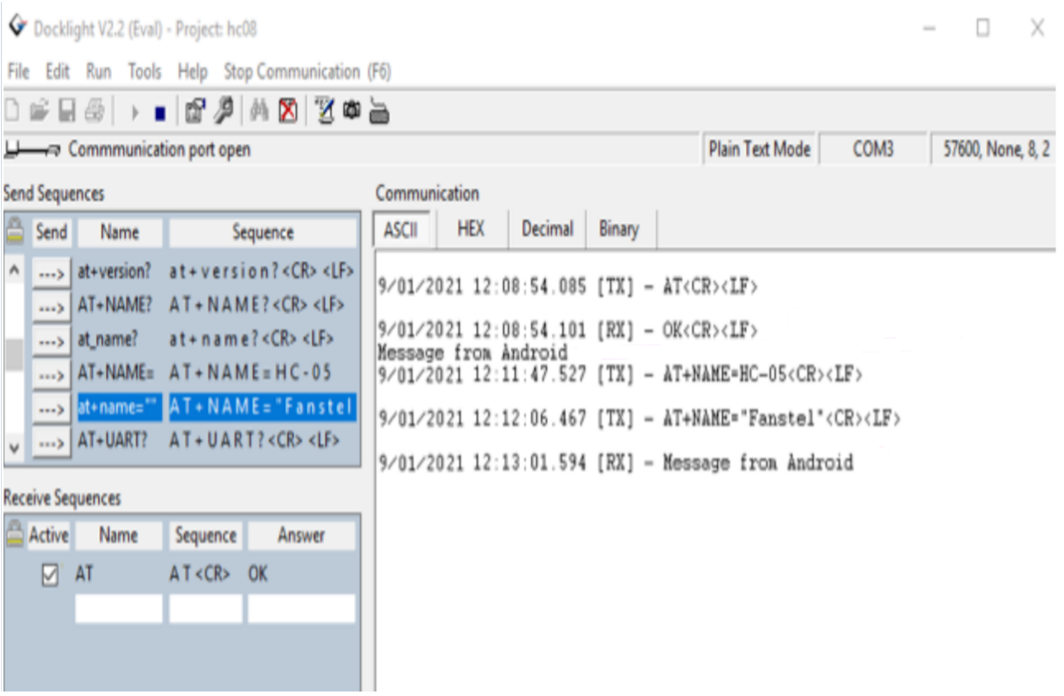

Figure 34. Given AT commands in DockLight

The fourth command line is sending the request which can be seen in the Android application, and contains only two possible response: either command accepted (COK) or command is not accepted (not recognized (CFAIL)). If the command accepted, the message from Android will appear in the Docklight which can be seen in the Figure 34.

Whenever the command sent, the Bluenor nRF5x application will show the full sent format that is demosntrated in the below given figure (Figure 35):

Figure 35. Bluenor application

4.2.5 Range measurements

Received signal strength highly depends on the distance from the device, therefore the possible range tests should be realized. When the distance is getting long, the sensitivity level of the signal diminishes. In order to measure the possible signal strength, some range measurements must be conducted using the evaluation board. Typically, BLE receivers have ca -96..-100 dBm sensitivity level that allows to communicate from the longer distance. The following table (Table 4) shows the test results of experimented range measurements by the author indoor environment. In order to do this experiment, RSSI levels should be observed in the application on smart FES devices to avoid improper context execution from a too long distance. "nRF Connect" application has been used for this measurement. The surface context execution should be done at signal strengths of ca -70..-60dBm.

Table 4. Range measurement results

Distance from the device	Received signal strength levels
1 m	-39 dBm
5 m	-50 dBm
10 m	-61 dBm
25 m	-76 dBm
50 m	-82 dBm
70 m	-87 dBm
80 m	-91 dBm
90 m	-94 dBm
100 m	-97 dBm

The value of signal which is close to zero is considered as the strongest one, and the table is a better example to demonstrate that the longer distances make the signal level decrease and it is getting weaker, the experiment showed that this BLE receiver level is nearly the same with the acquired signal level in 100 meters.

5. TESTING MACHINE LEARNING ALGORITHM FOR CONTEXT-AWARENESS

Short frame tracking anomaly detection MLA which is developed by the PRG424 member – Andrei Krivošei, has been tested by the author to observe the comparable differences for the context changes and fall prediction. The chapter includes a short description of proposed anomaly detection, presents the base and master metrics, and also compares the numeric results to prove the importance of context-awareness in gait analysis by providing proper histogram, ROC curves, and a metric table.

5.1 Short frame tracking anomaly detection

"Anomaly Detection" allows finding unusual situations or patterns in data. These unusual situations or patterns are that do not conform to the expected behavior of data. These unexpected patterns are simply called outliers, exceptions, or anomalies in the literature. This algorithm mainly provides the fall prediction and demonstrates the significance of context changes depending on the adaptive (updateable) and fixed reference in this research. The tested algorithm outputs the plots which can be better to understand the fall prediction depending on the threshold changes. Figure 36 shows the steppage gait plot with lower threshold value. As it can be seen from the plot, 2 abnormalities have been correctly detected that called TP, however, the plot contains 2 FP that have been detected the normal steps as abnormal because of the defined threshold as well. In addition to this, the red lines represent the alarm which shows the earliness of detection.

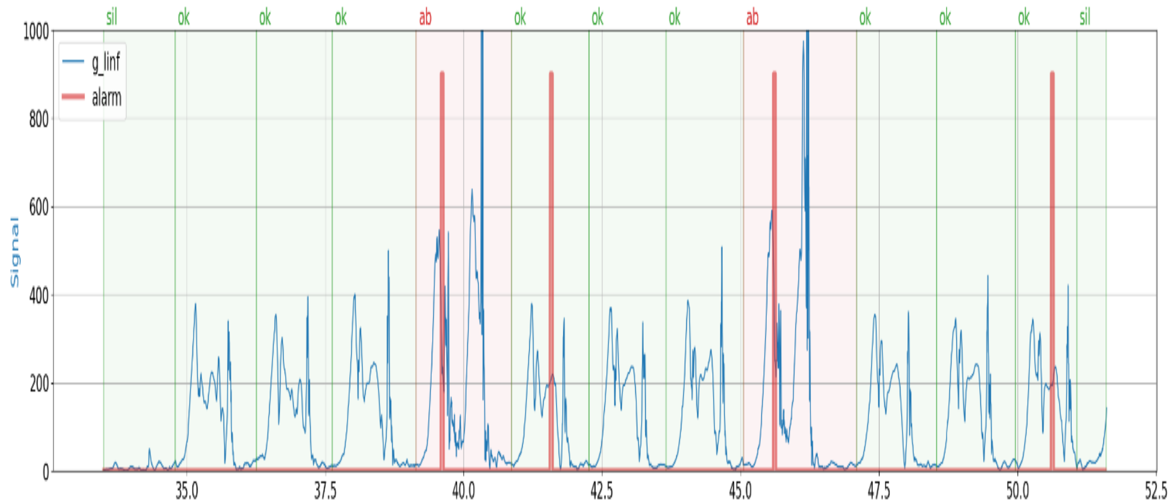

Figure 36. Short frame tracking anomaly detection with lower threshold on steppage gait

The increased threshold value needs to be tested for looking through the detection accuracy and observe if the plots include FP. The below given figure (Figure 37) demonstrates the same gait with higher threshold. The labeled abnormalities have been detected correctly without including FP and the earliness is desirable in this threshold level as well. True and false positives are the main terms in MLA, so more detailed figures and tables will be provided in the further sections to explain them comprehensively. Shortly, it should be noted that these are necessary to define base and master metrics.

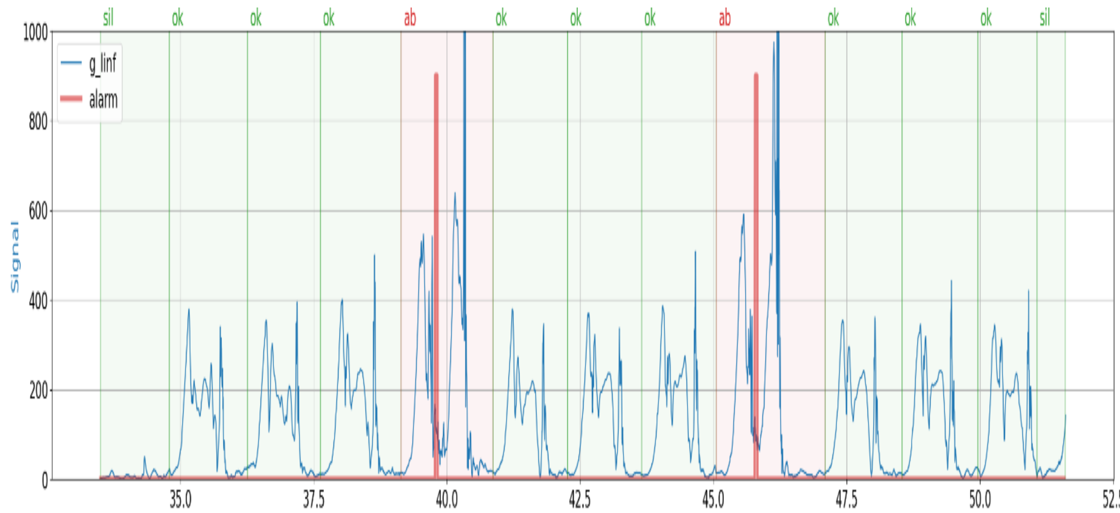

Figure 37. Short frame tracking anomaly detection with higher threshold on steppage gait

5.2 Evaluation of master metrics

The short frame tracking algorithm also calculates the base and master metrics. True positives, true negatives, false positives, false negatives and earliness –defines the base metrics those assist to generate certain calculation for the master metrics for more detailed analysis of the result. In Table 5, the adaptive reference pattern on the hard surface has been evaluated for the master metrics. According to the threshold changes, the numbers of the given values vary as well. The calculation of these parameters will be provided in this section.

True Positive Ratio is defined as the division of the number of true positives to the number of positives:

$$TPR = \frac{TP}{P}$$

True Negative Ratio is the fraction of true negatives to negatives:

$$\text{TNR} = \frac{\text{TN}}{\text{N}}$$

Table 5. Master metrics result for adaptive reference pattern on hard surface

Anomaly	**Thres hold**	**posit ive**	**negati ve**	**TPR**	**TNR**	**PPV**	**FPR**	**ACC**	**BA**	**F1**	**earli ness**
diplegic	3	10	67	0.5	0.537	0.138	0.462	0.532	0.518	0.217	0.471
hemiplegic	3	3	21	0.666	0.380	0.133	0.619	0.416	0.523	0.222	0.498
slap	3	8	29	0.5	0.620	0.266	0.379	0.594	0.560	0.347	0.812
steppage	3	13	50	1	0.88	0.684	0.12	0.904	0.94	0.812	0.492
diplegic	4	10	67	0.3	0.895	0.3	0.104	0.818	0.597	0.3	0.570
hemiplegic	4	3	21	0.333	0.952	0.5	0.047	0.875	0.642	0.4	0.611
slap	4	8	29	0	0.965	0	0.034	0.756	0.482	0	0
steppage	4	13	50	1	1	1	0	1	1	1	0.557
diplegic	5	10	67	0.2	0.865	0.181	0.134	0.779	0.532	0.190	0.702
hemiplegic	5	3	21	0.333	0.952	0.5	0.047	0.875	0.642	0.4	0.658
slap	5	8	29	0	1	0	0	0.783	0.5	0	0
steppage	5	13	50	1	1	1	0	1	1	1	0.622
diplegic	6	10	67	0.1	0.955	0.25	0.044	0.844	0.527	0.142	0.614
hemiplegic	6	3	21	0.333	1	1	0	0.916	0.666	0.5	0.658
slap	6	8	29	0	1	0	0	0.783	0.5	0	0
steppage	6	13	50	0.769	1	1	0	0.952	0.884	0.869	0.654
diplegic	7	10	67	0.1	1	1	0	0.883	0.55	0.181	0.661
hemiplegic	7	3	21	0	1	0	0	0.875	0.5	0	0
slap	7	8	29	0	1	0	0	0.783	0.5	0	0

False Positive Ratio (1) is also called fall-out can be calculated with the fraction of false positives to negatives:

$$\text{FPR} = \frac{\text{FP}}{\text{N}} \tag{1}$$

Accuracy (2) is a metric that can be defined as the fraction of true positives and true negatives to the base metrics:

$$\text{ACC} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{2}$$

When there is a need to correctly estimate the positive and negative classes, the most common master metric for preventing misleading accuracy – balanced accuracy (3) is used. Sensitivity and specificity are the basis of this metric, which means TPR and TNR respectively:

$$\text{BA} = \frac{\text{TPR+TNR}}{2} \tag{3}$$

F1 score is a harmonic mean of recall and precision. It is a harmonic mean instead of a simple average is that extreme cases have to be ignored. If there was a simple average calculation, the F1 Score of a model with an Absolute value of 1 and a Recall value of 0 would come as 0.5 and this would result with misleading. The main reason for using the F1 Score value instead of accuracy is not to make an incorrect model selection in non-uniform data sets. In addition, the F1 Score (4) is significant that includes not only FN or FP, but also all error costs. F1 score is defined as the below given equation [44]:

$$\text{F1} = \frac{\text{2TP}}{\text{2TP+FP+FN}} \tag{4}$$

These are the main metrics which always allow classifying them and explaining the Table 5.

5.3 Context based comparison of acquired results

Context-awareness is the most important part of this research, therefore different case scenarios have been tested to get comparable results that are enough to acknowledge if the proper surface reference can improve the detection accuracy. Adaptive and fixed reference patterns have been tested with the relevant measurement files on different surfaces. The testing procedures are listed with the structure of reference patterns and the incoming real-time streaming data in the following lines:

- Adaptive reference pattern on hard surface,
- Adaptive reference pattern on sand surface,
- Fixed hard reference pattern on hard surface,
- Fixed sand reference pattern on sand surface,

- Fixed hard reference pattern on sand surface,
- Fixed sand reference pattern on hard surface.

The adaptive pattern means the reference is updating during the working process of the algorithm, simply, it can be called an "updateable reference pattern" as well. All steps are continuously collecting and participate in module reference construction. Using anomaly detection, the bad steps (outliers) are filtered out and the remaining steps are averaged that construct the reference pattern in this algorithm.

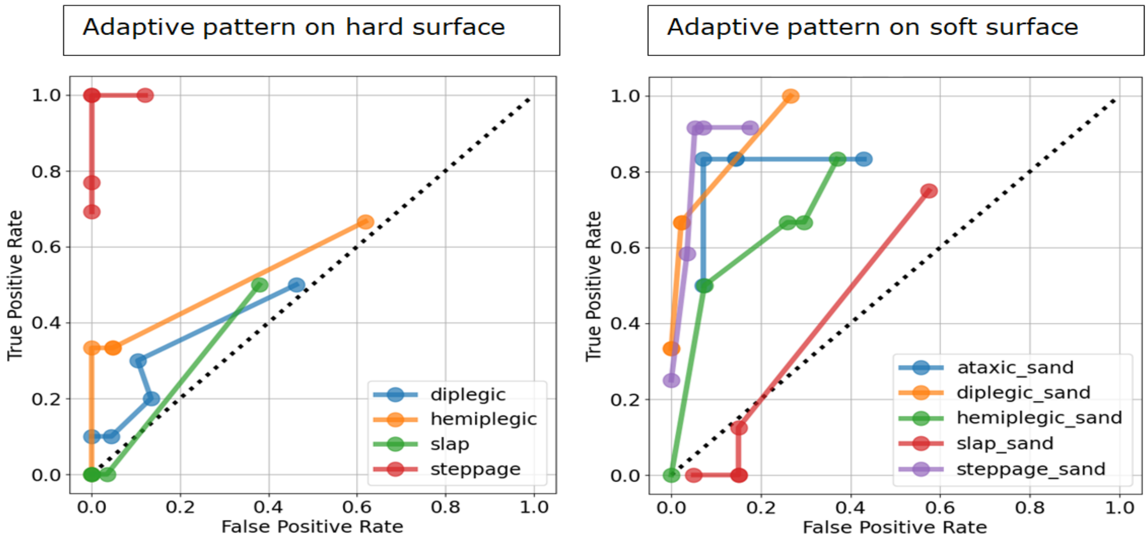

Figure 38. The comparison of ROC curves using the adaptive reference pattern

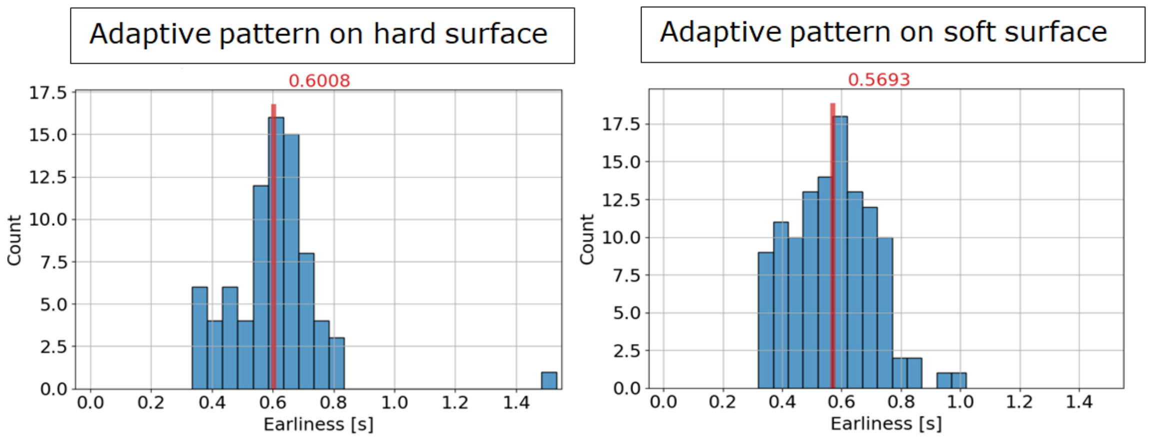

Figure 39. The comparison of averaged earliness histograms using the adaptive reference pattern

Figure 38 shows the adaptive reference pattern on two different surfaces, and differences can be clearly seen. While the steppage gait demonstrates the best result on the hard surface with the highest TP rate and lowest FP rate, however, this gait presents a slightly lower TP rate with an increased FP rate on the soft surface in comparison to the hard surface. While the other gait anomalies show undesirable results with more FP rates on the hard surface, these are interestingly better on the soft surface with higher TP rates. On account of resembling foot drop, the steppage gait will be the most focused gait abnormality while deciding if the context-awareness improves the detection accuracy. Thus, it can be concluded that the adaptive reference pattern on hard surface plays an important role (for foot-drop) to show the significance of the context with its good earliness (Gait pattern deviation detection time from the beginning of step) time (Figure 39), but the context-awareness cannot help for the other gait abnormalities at all. In addition to this, Adaptive reference pattern on sand surface is useful for only steppage and diglegic gaits, which can be assisted by the context.

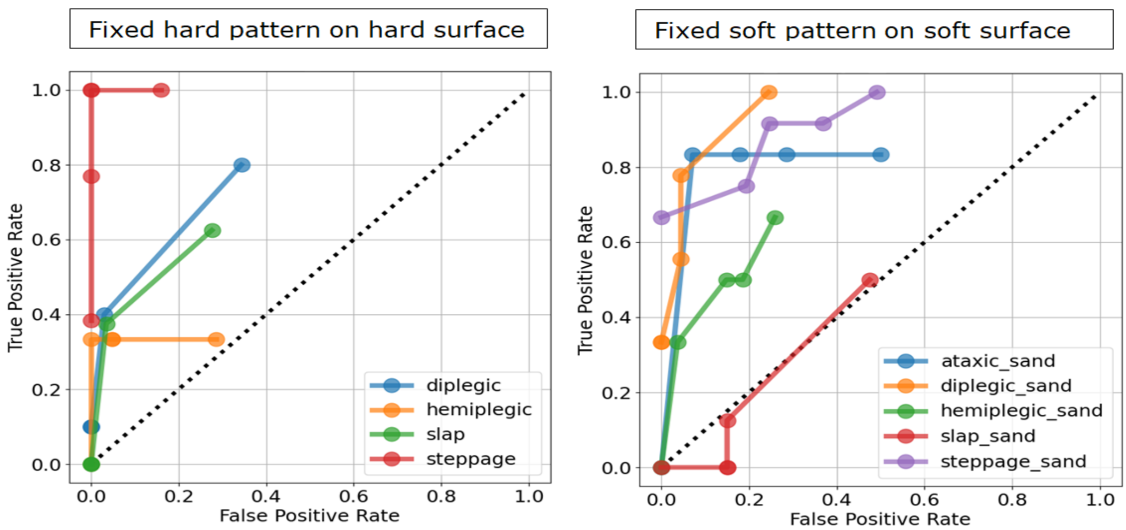

Figure 40. The comparison of ROC curves using the fixed hard and soft reference patterns

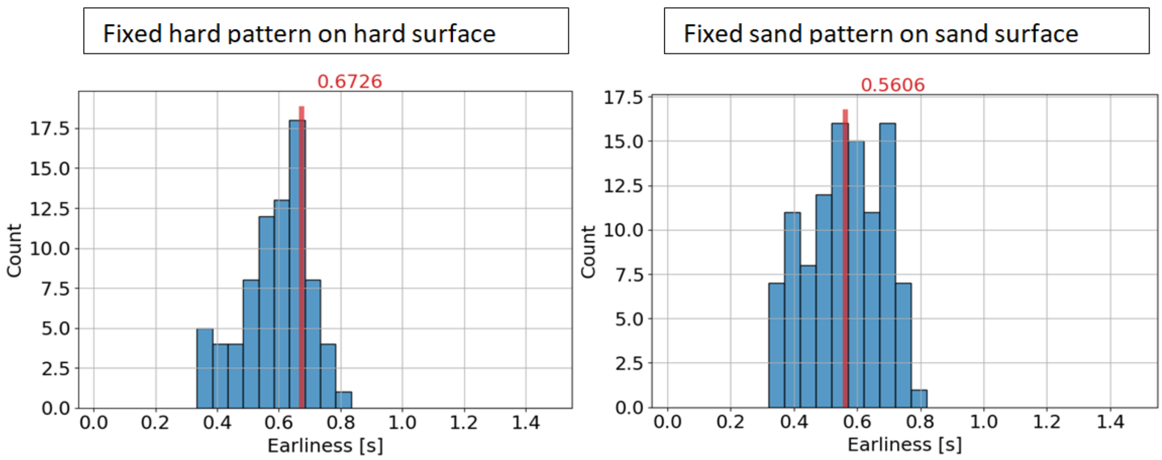

Figure 41. The comparison of averaged earliness histograms using the fixed hard and sand reference patterns

The next step is to analyze the necessity of the fixed reference patterns with the provided visual examples. In Figure 40, the ROC curves show the same reference and surface combinations. The steppage gait (foot-drop) presents the best result for hard surface, which dramatically changes with increased FP rates on the sand surface although it has a perfect TP rate. Diplegic gait is slightly better on the sand surface with the soft reference pattern, but the rest of the abnormalities are not in the expected points, so this means that this context reference scenario only helps the diplegic gait. Although the earliness is a bit later than the soft reference pattern (Figure 41), the hard reference pattern on a hard surface is in the desired point for the steppage gait and can be considered helpful for the diplegic gait as well.

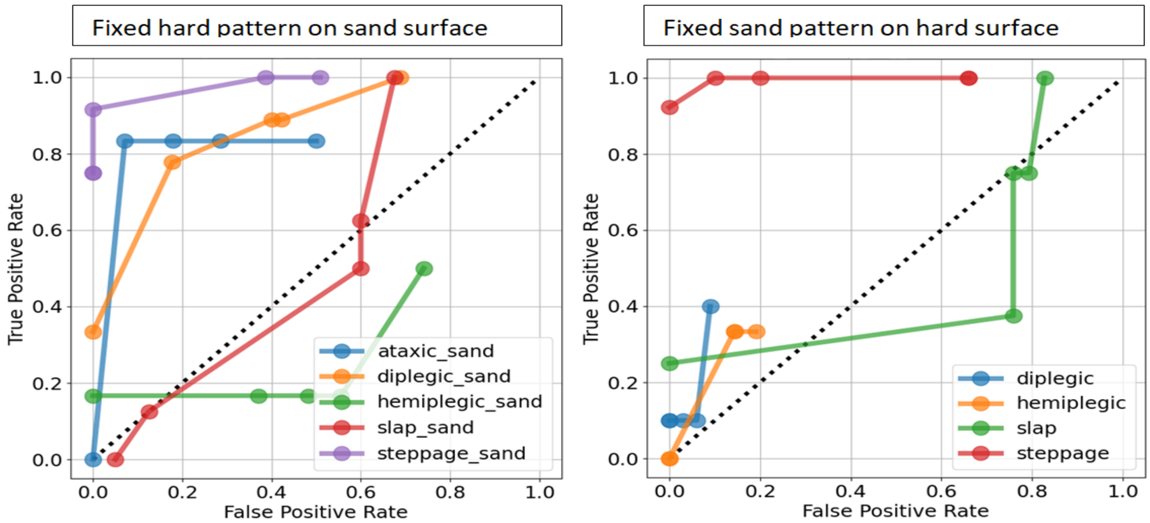

Figure 42. ROC curves comparison

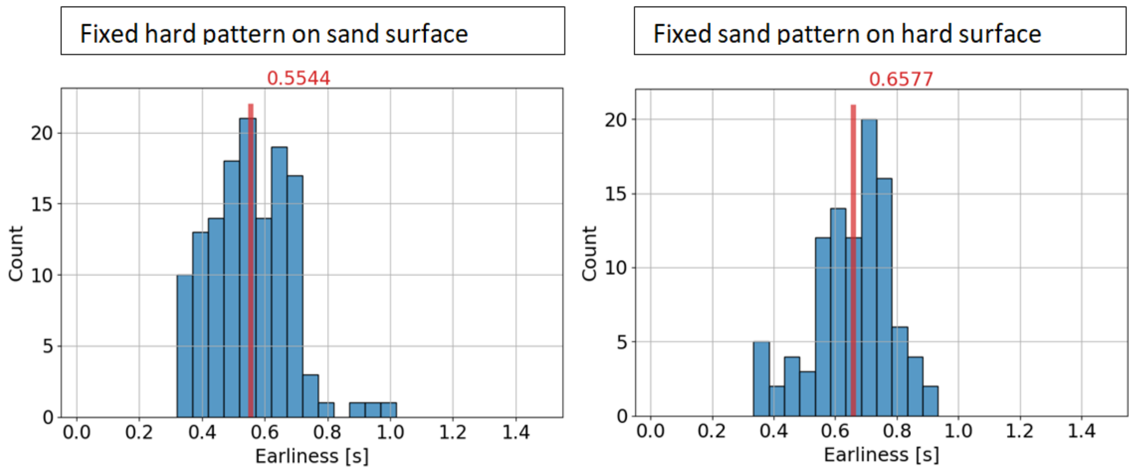

Figure 43. Earliness histograms with the different references

The last comparison will be explained on opposite reference and surface results. Figure 42 demonstrates that using different surface and reference examples do not provide decent outputs. Although certain gait anomalies (steppage (foot-drop), slap, and diplegic) have given the maximum TP rates, their FP rates exceed 0.5, which means context-awareness cannot be implemented on opposite reference and surface results. In addition to this, both have decent earliness histogram, which has been described in Figure 44.

In conclusion, the comparison of 6 different case scenarios allows acknowledging that context-awareness can be considered only in certain circumstances. According to the above-mentioned results, the context has importance for some gait abnormalities, especially, both adaptive and fixed reference patterns with the same real-time streaming data. However, the opposite hard and soft reference-data models allow saying that context does not have an impact. The best F1 score for each testing procedure is given:

- F1 = 1 for steppage (adaptive reference with incoming hard surface data),
- F1 = 0.814 for steppage (adaptive reference with incoming sand surface data),
- F1 = 0.869 for steppage (fixed hard reference with incoming hard surface data),
- F1 = 0.8 for steppage (fixed sand reference with incoming sand surface data),
- F1 = 0.85 for steppage (fixed hard reference with incoming sand surface data),
- F1 = 0.96 for steppage (fixed sand reference with incoming on hard surface data).

6. DISCUSSION

This chapter has been organized to discuss the limitations of the project during the experimental procedures and development parts, also includes the desired future improvements that can increase the scope area by considering higher performance and better outcomes.

6.1 Limitations

Although the project has completed successfully and quite significant results have been achieved, it is needed to emphasize some limitations as below:

- Only limited MLA can be implemented for gait analysis: the better performance of each algorithm highly depends on the specific placement of sensor devices;
- The project is only focused on the healthy subject in the same age group, however, the diversity of age groups can assist to get better analysis of gait abnormalities;
- A medium scale dataset is implemented during the implementation of MLA;
- The particular Shimmer S3 wearable multi-sensor devices have certain limitations (Short Bluetooth communication range, missing data points, impact of battery voltage level) affecting the data collection process, which has to be considered;

6.2 Future improvements

It has been mentioned before that this thesis topic is the part of a research and development project which is called "Closed-loop communication system to support highly responsive neuromuscular assistive stimulation", therefore the scope area of future improvements are quite wider and diverse.

- Different age groups will be involved in the data collection procedures for getting a high amount of dataset for MLA;
- Not only from the healthy subjects but it is also intended to collect data from patients who suffer from gait abnormalities;
- Possible ML methods and algorithms will be implemented to provide the diversity of better analysis understanding;
- Existing detection algorithm will be ported to the smartphone or wearable devices with integrated FES device;

- The notification about context change will be sent directly to embedded FES device which follows proper reference pattern and stimulate accordingly

SUMMARY

The arisen problems of gait abnormalities are quite problematic and affect the daily activities, performance, and psychology of the neuromuscular diseases patients. The conducted researches have shown that certain technological improvements had been done in this field, but still, there are some tasks like fall prediction and context-awareness that are not considered on the same performance level as fall detection. In this thesis, the author has performed a comprehensive investigation of these missing parts.

The instrumented gait analysis was conducted to collect a certain amount of datasets for the further testing of machine learning algorithms. To get comparable results, the data collection process was completed on different surfaces by both 23 years elderly healthy men and women subjects. Two wearable multi-sensor devices were used to get data from 2 different positions of the foot and encountered challenges about the data collection process have been described in the thesis.

The development of the BLE radio beacon prototype was needed to broadcast information about the walking surface properties either to the functional electrical stimulation devices or user mobile phone applications. The data advertising in beaconing mode is considered significant from the economic, ergonomic, and technological aspects, therefore the importance of this and the development process, a developed prototype has been described, hardware and software selections are explained.

The testing process of short frame tracking anomaly detection provided comparable results according to ROC curves and pattern deviation discovery earliness histograms, which allow acknowledging in which cases context-awareness must be considered. The abnormalities detection scenarios have been conducted over the adaptive and fixed gait patterns on different walking reference surfaces. Altogether it can be said that context-awareness has importance for some gait abnormalities in 4 different scenarios. However, the tested opposite reference-data models showed that context cannot help any of the abnormalities. Actual measurement data and comparable results assist to acknowledge that this thesis can be a good motivation to expand the scope of gait analysis for further improvements.

KOKKUVÕTE

Tekkivate kõnnihäirete probleemid on üsna problemaatilised ja mõjutavad neuromuskulaarsete haiguste patsiendide igapäevaseid tegevusi, võimekust ja psühholoogiat. Läbiviidud uuringud on näidanud, et selles valdkonnas on teatavaid tehnoloogilisi saavutusi, kuid siiski on mõned ülesanded, näiteks kukkumise ennustamine ja kontekstiteadlikkus, mida ei peeta samal tehnoloogilisel tasemel olevaks kui kukkumise tuvastamine. Käesolevas lõputöös on teostas autor nende puuduvate osade põhjaliku uuringu.

Instrumentaalne kõnnaku analüüs viidi läbi, et koguda teatud hulk andmeid edasiseks masinõppealgoritmide katsetamiseks. Võrreldavate tulemuste saamiseks viisid andmete kogumise protsessi erinevatel kõnnipindadel läbi 2 tervet täiskasvanut (M+N) keskmise vanuses 23 eluaastat. Kahte mitme anduriga seadet kasutati liikumisandmete saamiseks kahest erinevast jala asukohast ning lõputöös on kirjeldatud andmete kogumise protsessiga seotud probleeme.

BLE raadiomajaka prototüübi väljatöötamine oli vajalik teabe edastamiseks kõnnipinna omaduste kohta kas funktsionaalse elektrilise stimulatsiooni seadmele või kasutaja mobiilseadme irakendusele. Majaka režiimis toimuvat andmete edastamist peetakse majanduslikust, ergonoomilisest ja tehnoloogilisest aspektist oluliseks, seetõttu kirjeldatakse seda töös, kirjeldatakse loodud prototüüpi, selgitatakse riist- ja tarkvara valikuid.

Lühikese ajaaknaga erinevate anomaaliate avastamise testimisprotsess andis võrreldavaid tulemusi ROC kõverate ja kõrvalekalde tuvastusaja histogrammide alusel, mis võimaldab hinnata, millistel juhtudel tuleb arvestada kontekstitundlikkusega. Kõnni kõrvalekallete tuvastamise stsenaariumid viidi adaptiivselt häälestuva ja fikseeritud kõnnimustri suhtes erinevatel võrdluspindadel ning kokkuvõttes võib öelda, et kontekstitundlikkus on oluline mõne kõrvalekalde puhul nelja testitud stsenaariumi korral. Tulemustest lähtudes saab siiski järeldada, et kontekstitundlikkus ei paranda oluliselt kõnni kõrvalekallete tuvastamist. Reaalsed mõõtmiste andmed ja õrreldavad tulemused kinnitavad, et käesolev väitekiri võib olla heaks motivatsiooniks kõnni analüüsi ulatuse laiendamiseks edasisteks täiustusteks.

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