National Research University Higher School of Economics

as a manuscript

Roman Chereshnev

HUMAN GAIT CONTROLLING SYSTEM USING MACHINE LEARNING METHODS SUITABLE FOR ROBOTIC PROSTHESES FOR PATIENTS SUFFERING FROM DOUBLE TRANSFEMORAL AMPUTATION

Ph.D. Dissertation Summary

for the purpose of obtaining academic degree
Doctor of Philosophy in Computer Science HSE

Moscow — 2019

This work was prepared at National Research University Higher School of Economics.

Academic Supervisor:	Attila Kertész-Farkas, PhD Docent, Faculty of Computer Science, National Research University Higher School of Economics

Subject of the dissertation

This thesis introduces a new system suitable for controlling robotic prosthetic of patients suffering at most double trans-femoral amputation, called GaIn (standing for Gait Inference) by means of machine learning techniques. The Author's idea is based on the observation that the correlation between the movements of the leg parts of healthy people – people without functional gait disorder during usual activities – is high, however, non-linear. Consequently, it is possible to infer the movements of both lower legs based on the movements of both thighs using machine learning methods. This idea has not been explored before. The GaIn system could be installed on microchip- or smartphone-controlled robotic leg prostheses that could be attached to patients in a non-invasive way to infer the movements of the lower limbs.

The relevance of research

Machine learning (ML) methods provide a general framework to adapt algorithms to certain tasks using a large collection of data. ML-based methods excel in several tasks, including image recognition, speech recognition, and product or service recommendation. This dissertation introduces novel machine learning methods for human activity recognition (HAR) problems.

Broadly speaking, HAR is a field that focuses on recognizing or analyzing the activities performed by humans [23]. Activity recognition may be useful in public surveillance for security reasons, in fall detection in elder care, as well as in gesture recognition, virtual reality, homeland security, robotics, exoskeletons, smart environments, etc. Human activity analysis can be useful in healthcare, for instance, in inpatient recovery monitoring after surgery, exoskeleton control, monitoring performance improvement, analyzing athletes' technique in sports, etc. Human activity analysis can be useful, for instance, in healthcare, in inpatient recovery monitoring after surgery, exoskeleton control, monitoring performance improvement, analyzing athletes' technique in sports, etc.

HAR methods are primarily based on two types of data: visual or sensory. In the first group, HAR methods are mostly based on images or videos captured by cameras. In the second group, the prediction of HAR methods is based on sensory data obtained from inertial sensors, such as accelerometers and gyroscopes of mobile phones or specifically mounted sensors on certain parts of the human body special wearable sensors on certain parts of the human body. The topic of this thesis falls into the second category and focuses on sensory data-based HAR.

There are three main areas of HAR: (1) gesture recognition, (2) recognition of activities of daily living, and (3) human gait analysis.

Gesture recognition (GR) mainly focuses on recognizing hand-drawn gestures in the air [24]. Patterns to be recognized may include numbers, circles, boxes, or Latin alphabet letters. Prediction is usually made on data obtained from smartphone sensors or special gloves equipped with inertial sensors, such as 3-axis accelerometers, 3-axis gyroscopes, and occasionally electromyography (EMG) sensors, to measure the electrical potential on the human skin during muscular activities.

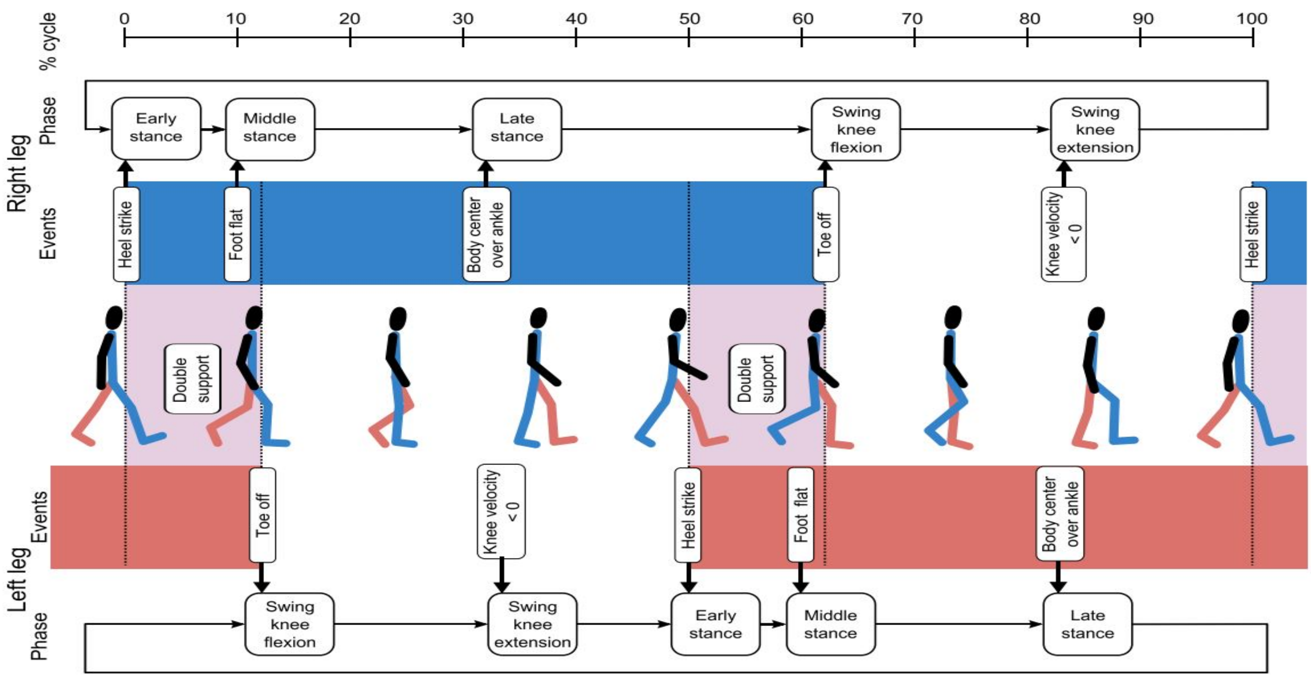


Figure 1: Phases of a full gait cycle during locomotion. Image source: [37].

Recognition of activities of daily living (ADL), on the other hand, aims at recognizing daily lifestyle activities [43]. For instance, an interesting research topic is recognizing activities in or around the kitchen, such as cooking; loading the dishwasher or washing machine; preparing brownies or salads; scrambling eggs; light cleaning; opening or closing drawers, the fridge, or doors; and so on. Often, these activities can be interrupted by, for example, answering phones. In this topic, on-body inertial sensors are usually worn on the wrist, back, or ankle; however, additional sensors, such as temperature sensors, proximity sensors, water consumption sensors, heart rate sensors, etc., can be employed as well.

Human gait analysis (HGA), in contrast, focuses not only on the identification of activities performed by the user but also on how the activities are performed [8]. This can be useful in health-care systems for monitoring patients recovering after surgery, fall detection, and diagnosing the state of, for example, Parkinson's disease, and even for increasing typing accuracy on touch screens during walking [29]. An unusual gait cycle can be evidence of disease; therefore, gait analysis is important in evaluating gait disorders, as well as neurodegenerative diseases such as multiple sclerosis, cerebellar ataxia, brain tumors, etc. Multiple sclerosis patients show alterations in step size and walking speed. Wearable sensors can be used to detect and measure gait-related disorders, to monitor patient's recovery, and to improve athletic performance. For instance, EMG sensors can be used to evaluate muscle contraction force to improve performance in running and other sport fields [9] or even for classification of fatigue degree for manual wheelchair users [26]. Emergency fall events can be detected with tri-axial accelerometers attached to the elderly people's waists.

HGI, also referred to as human gait trajectory prediction aims at predicting what the movements of amputated or injured leg parts (thigh, shank, or foot) would be for walking-related activities [37]. HGI methods are often hierarchical and consist of three layers. The first, called high-level control, aims at recognizing the current activity performed by the patient. Once the

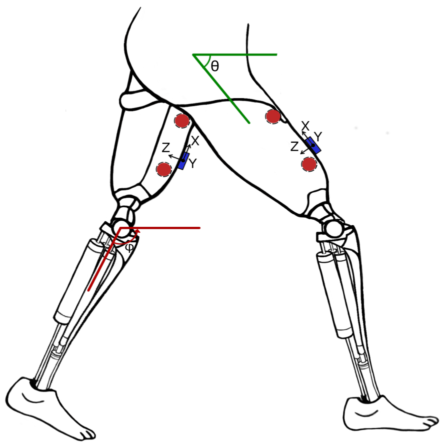


Figure 2: Concept of robotic prosthetic legs for patients suffering from double trans-femoral amputation. Circles show the location of EMG sensors, and boxes show the location of accelerometers and gyroscopes.

activity or the intention of the user is recognized, then the high-level controller commands the mid-level controller to infer the appropriate gait. The need for a high-level controller is explained by the fact that the locomotion task requires its own mid-level controller in most of the cases. Mid-level controllers generate the gait trajectory patterns for robotic prosthetic legs or exoskeletons. Mid-level controllers can be categorized into two types: phase-based and non-phase-based. Phase-based mid-level controllers consist of several models that infer gait for particular gait phase. The phases of the human gait are shown in Figure 1. After recognition of the current phase, the mid-level controller performs the appropriate actions. Non-phase mid-level controllers directly aim at predicting the desired gait trajectory, usually based on the physiological motion of the other leg, using linear regression models. The low-level controller carries out the physical control of the robotic legs at close to the hardware level. Even though HGI is closely related to HAR, advanced ML methods are not routinely used in this field, especially in mid-level controller design.

In this thesis, the Author introduces a new system called GaIn (standing for Gait Inference) that is suitable for controlling the robotic prosthetics of patients suffering at most double transfemoral amputation by means of machine learning techniques. The concept of this idea is illustrated in Figure 2. The Author's idea is based on the observation that the correlation between the movements of the leg parts of healthy people – people without functional gait disorder during usual activities – is high, yet non-linear. Figure 3 shows the non-linear correlation between the thigh and shank angles (of the same leg) during several gait cycles, measured during walking-related activities. The angles of the thigh and shank are measured to the horizontal line. Consequently, it is possible to infer the movements of both lower legs based on the movements of both thighs using machine learning methods. The GaIn system could be installed on microchip- or smartphone-controlled robotic leg prostheses that could be attached to patients in a non-invasive way to infer the movements of the lower limbs, as illustrated in Figure 2. Therefore, the GaIn system could help patients suffering partial or double lower limb amputation to move and walk by themselves. The GaIn system consists of two

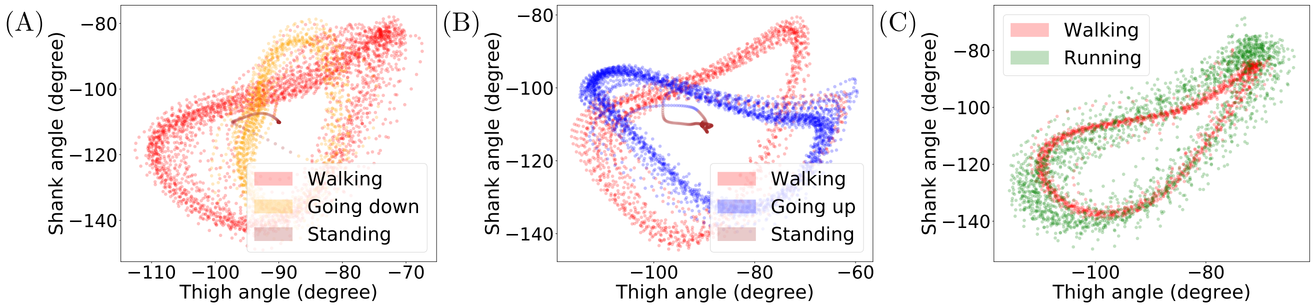


Figure 3: Correlation between shank and thigh movement over several gait cycles in different activities. The angles of the thigh and shank are measured to the horizontal line.

controllers: (1) a high-level controller, based on the RapidHARe method, for activity mode and patient intention recognition and (2) the non-phase based mid-level controller for gait inference. Both controllers were developed by the Author of this thesis. The first component is based on a dynamic Bayesian model and recognizes whether the patient is sitting, standing, or moving. In a sitting position, GaIn does not allow any gait inference to be performed, so the legs remain motionless. However, when thigh muscle activity is detected by electromyography sensors, the controller performs standing up activity. When the patient is standing and starts swinging one of his legs, then GaIn activates the gait inference procedure. When a person stands and wants to sit down, the high-level controller can predict his intention based on signals from his muscles. Because human movement is produced by neural mechanisms in the motor cortex of the human brain or spinal neural circuits [30] the Author believes that neurally inspired artificial neural networks could be suitable models for gait inference. Therefore, GaIn uses recurrent neural networks to infer human gait. In addition, GaIn was designed to be fast and computationally inexpensive, with low prediction latency. These features are necessary in order to be applied in mobile devices where energy consumption matters [7]. The Author notes that turning while walking involves rotating the torso, the hips, and the thighs at the hip joints but not the shanks [14]; therefore, our analysis does not involve examination of turning strategies. It should be noted that the methods related to the low-level controller and the actual construction of such robotic prosthetic legs are not part of this thesis.

The inference of the position of the shanks is made on the position (angle) and motion (angular velocity) of the thigh residual limbs, wherein the position and motion are determined using 3-axis accelerometers and 3-axis gyroscopes. In addition, as shown in the experiments, the GaIn system is capable of producing smooth inference for activity changes between several activity modes, including walking at various speeds, taking stairs up and down, sitting down and standing up, as well as running. It should be noted that EMG sensors are used only to recognize standing up or sitting down intention and not for gait inference.

Aims and objectives of research

The GaIn system could potentially be installed on microchip-controlled robotic leg prostheses that could be attached to patients in a non-invasive way to infer the movements of the lower limbs. In order to make GaIn efficient for use in portable real-time prediction systems, it should meet the following requirements:

A-1: **Low prediction latency**. Gain should respond quickly to sudden changes in user behavior in real-time.

A-2: **Fast and energy-efficient**. In order to be suitable for mobile and portable systems, GaIn is to be energy-efficient and computationally inexpensive.

A-3: **Smooth recognition**. GaIn should provide consistent recognition within a given activity mode and rapid transition in-between activity modes.

A-4: **Generalization**. GaIn should be accurate for new patients whose data was not seen during training.

A-5: **Accuracy.** The GaIn system should be developed using machine learning techniquesbecause these methods have demonstrated the ability to adapt to problem-specific tasks with high accuracy.

The GaIn method carries out the gait inference using accelerometer, gyroscope, and EMG sensors mounted on both thighs. These sensors are inexpensive and widely available.

Current approaches

Here, most relevant methods to this dissertation are discussed briefly.

The first artificial neural network-based (ANN) system to aid patients with spinal cord injuries was developed in 1995 by Sepulveda and his colleagues [33], who showed that ANNs are plausible models to restore muscle signals based on the joint flexion and extension at the hip, knee, and ankle. In addition, the proposed system obeyed voice control to switch between activity modes. The main conclusions of the article are that (1) one needs two separate neural networks for swing and stance phases and that (2) the ANN model requires calibration to the patient. In this PhD thesis, the Author shows that these conclusions are incorrect. First, the Author has built a single neural network which is capable of inferring the gait in both the swing and stance phases. However, the Author emphasizes that higher natural variance was observed in the swing phase for the same person than in the stance phase; however, very accurate gait prediction is not necessarily needed for the swing phase, because the more important supporting work is done by the standing leg. Also, note that voice-based control is not necessary to switch between walking and other activity modes. In addition, sitting down and standing up can be recognized from thigh muscle activities using EMG sensors. As for the second point, the Author suspects that Sepulveda and his colleagues used data from too few patients and thus their model did not generalize well. In this

PhD research work, an adequate number of people provided data, and the GaIn system obtained good generalization performance during the training.

Perhaps the best-known non-phase-based mid-level controller is the complementary limb motion estimation (CLME) developed by the group led by Martin Buss [38]. CMLE is based on the idea that the trajectory of a missing leg can be mapped from the movement and the position of the whole sound leg using linear transformations. Therefore, CLME uses information from the state of the whole sound leg and provides an inference method for patients suffering at most single-leg trans-femoral amputation. This work unfortunately has serious limitations: (1) This system was trained and tested on the same patient; therefore, the system's generalization performance is unknown. (2) The system was trained and tested only for walking on a treadmill and ascending stairs. (3) Sitting down and standing up were not considered or investigated. Contrary to the CMLE method, the GaIn system uses information from only the movements of the thighs, and it can be used with patients suffering from double leg amputation; GaIn was tested in natural environments in several walking-related activity modes, including the transitions between activity modes, sitting down and standing up. The GaIn system is demonstrated to have low generalization error for new users.

A reinforcement learning-based (RL) method for gait inference was published in January of 2019 by Wen et al. [39], after the Author of this thesis had completed his research project. Wen and his co-authors divided the full gait cycle into four sections and used a reinforcement learning algorithm to set up parameters of each of the four mid-level controllers. The authors achieved root-mean-square error of 3.99° 0.62°) (compared to the target) for two participants (one healthy and one one-side transfemoral amputee). The authors hypothesized that the feedback from knee kinematics and optimization state was reasonable as a first step towards autonomous mid-level gait control, but questions regarding the appropriate control objective remain open. Unfortunately, the authors tested their system only in laboratory conditions on a treadmill at a steady pace on a flat surface. One of the biggest drawbacks of their approach is that real-life systems should be trained for several ambulatory tasks, such as walking on grass, going up and down stairs, stopping and starting to walk, and so on. In addition, this approach requires having a good high-level controller to transmit impedance function from one locomotion activity mode to another.

The Author has compared the results of Wen et al. to those obtained with GaIn, and the comparison is summarized in . Note that, unfortunately, a direct comparison cannot be performed because the methods were tested on different data. On the one hand, Wen and his colleagues used one patient to calibrate and test their model in walking activity on a treadmill, and they obtained 3.99° root mean squared error (RMSE) for one leg. On the other hand, the Author of this thesis tested the GaIn system to predict the gait trajectory of one leg and used data from several participants in various ambulatory activity modes performed in real environments. GaIn was tested in walking with a subject whose data was not seen during the training, and it achieved 4.75° RMSE in this harder scenario. However, when GaIn was trained and tested with the same subject, it achieved an error as low as 3.58° during walking activity on average over several subjects. It should be noted that the smallest error that GaIn achieved was 2.37° with participant $ID = 6$. It also should be noticed that the GaIn system encapsulates gait trajectory prediction into one neural network model for several ambulatory activity modes, including starting and stopping walking as well, while the method by Wen et al. has been tested only in the walking scenario.

Based on an excellent review by Tucker et al. [37] from 2015, the main drawbacks of current gait inference methods are as follows:

B-1: Some methods assume a fully periodic gait process. It has been shown that this assumption is incorrect [15].

B-2: Several methods have been developed for only one activity. Moreover, these methods cannot adapt to changes in terrain, and they do not provide procedures to handle starting or terminating an ambulatory activity [22].

B-3: One complication with inference methods is whether they can handle gait inference safely when activity changes between gait phases [37].

B-4: Gait inference methods often require information about the subject, such as length of limbs, the position of the center of mass, and pelvis direction [18].

B-5: The desired impedance function depends on the locomotion task, as the dynamics and kinematics of the joints vary across different locomotion modes [11].

B-6: Current lower limb prosthesis controllers are not capable of transitioning automatically and seamlessly between locomotion modes, such as walking on level ground, stairs, and slopes [41].

Importance of work

Limb losses occur due to (a) vascular disease (54%) including diabetes and peripheral arterial disease; (b) trauma (45%); and (c) cancer (less than 2%) [44]. Up to 55% of people with a lower extremity amputation due to diabetes will require amputation of the second leg within 2–3 years. In the USA, about 2 million people live with limb loss. In the last 18 years, in Italy, there were 4877 arteriopathic patients who needed lower limb amputations as a consequence of their illness. Sixty-six percent of them were major amputations, of which 73% were transfemoral amputations while only 34% were partial foot or toe amputations [10].

The Author hopes the prosthesis will be a useful tool in combating disability discrimination as is called for under several human rights treaties, such as the Rights of Persons with Disabilities convention by the United Nations [16] and Equality Acts [4] in jurisdictions worldwide. These also mandate access to goods, services, education, transportation, and employment. The Author expects that the GaIn tool will be effective in helping patients tackle common obstacles such as stairs and curbs in urban areas.

The Author assumes that the GaIn system can potentially be useful for exoskeleton controls. Exoskeletons can provide augmented physical power or assistance in gait rehabilitation. In the former case, exoskeletons can be used to help firefighters and rescue workers in dangerous environments, nurses to move heavy patients [19], or soldiers to carry heavy loads. Rehabilitation exoskeletons can be used to provide walking support for elderly people or can be applied in the rehabilitation of stroke or spinal cord injury. The neuromuscular disease cerebral palsy, which affects the symmetry and the variability of walking, represents the main pathology that requires the use of exoskeletons/prostheses to rehabilitate walking.

Novelty and summary of the Author's main results

In this thesis, the Author introduces a new method called GaIn for predicting the movements of amputated leg parts for walking-related activities such as walking, taking stairs, sitting down, standing up, etc. This dissertation is supported by three articles, all of them published in international research journals as original articles.

The GaIn system comprises three main parts: (1) a dataset suitable for training and testing, (2) a high-level controller to recognize the patient's activity modes and intentions, and (3) a gait inference method to generate the trajectory for robotic prosthetic legs. Below, the novelty and the Author's results are summarized in three thesis points.

1. HuGaDB: the dataset for training the GaIn system [5]. Unfortunately, existing datasets for HGA and HAR were not adequate for the aim of this research project, because they did not contain detailed information on the movements of the parts of the legs. This dataset is unique in the sense that HuGaDB is the first to provide human gait data in great detail, mainly from inertial sensors, and contains segmented annotations for studying the transitions between different activities. The Author constructed the HuGaDB dataset, of which the main and novel characteristics are the following:

    (a) The HuGaDB dataset provides information about each part of the human leg during several walking-related activities in great detail, from inertial and EMG sensors. Six inertial sensors (each sensor consisted of one 3D-axis accelerometer and one 3D-axis gyroscope) were mounted on the left and right thigh, shin, and foot, respectively, and a pair of EMG sensors were mounted on the left and right thighs. Therefore, HuGaDB gives detailed information on how each part of the legs moves and how the parts move relative to each other.

    (b) The HuGaDB dataset contains continuous recordings of combinations of activities, and the data are segmented and annotated with the label of the activity currently performed. Thus, this dataset is suitable for analyzing both human gait and transition activities.

    (c) The data were collected from 18 participants in total. These participants were healthy young adults: four females and 14 males, average age of 23.67 (STD: 3.69) years, an average height of 179.06 (STD: 9.85) cm, and an average weight of 73.44 (STD: 16.67) kg. In total, they provide around 10 hours of data recording.

    (d) The HuGaDB article was published in Springer's Q2 journal *Lecture Notes in Computer Science*: [5] and it became quite popular among researchers. HuGaDB has been cited by [34, 20, 36, 3, 2] as of 29 March 2019.

2. RapidHARe: the Author developed a novel activity mode and intention recognition method used in GaIn as a high-level controller called RapidHARe [7]. This method is also suitable for HAR tasks in general.

   (a) RapidHARe is based on a dynamic Bayesian network. RapidHARe has low prediction latency (A-1),[1] is of fast and computationally inexpensive (A-2), provides smooth recognition (A-3), and generalizes well to new users (A-4).

   (b) RapidHARe outperforms all other state-of-the-art HAR methods in accuracy and speed (A-5). RapidHARe reduces the F_1-score error rate by 45%, 65%, and 63% and the accuracy error rate by 41%, 55%, and 62% when it is compared to artificial neural networks, recurrent neural networks, and hidden Markov models, respectively.

   (c) RapidHARe is used in the high-level controller to predict the patient's intention for stand up and sit down mainly from data obtained by EMG sensors placed on the skin over the vastus lateralis thigh muscles. The controller achieved 99% precision and recall in recognizing standing up intention and 99% precision and 68% recall in recognizing sitting down intention.

3. GaIn: a gait inference system that is suitable for controlling robotic prosthetic legs [6].

   (a) The GaIn framework can be used in lower limb prostheses for patients suffering from double transfemoral amputation, in exoskeleton design, etc. In contrast, most other methods are only suitable for controlling one prosthetic leg.

   (b) The GaIn system is based on the observation that the movement of the thigh and shin is highly but non-linearly correlated during regular walking-related activities. This is illustrated in Figure 3. No other method relies on this assumption; in fact, other methods usually extract more data from the sound leg as well.

   (c) GaIn infers the shin position based on the position and movement of the thighs using recurrent neural networks with long-short-term memory units. GaIn achieves a prediction error as low as 4.55° on average on natural terrain and generalizes well to new users. In contrast, other methods are often calibrated and tested on the same patient on treadmills.

   (d) The GaIn system does not assume a fully periodic gait (B-1)[2]; it can infer gait for several ambulatory activities (B-2, B-6), has small prediction error during activity transitions (B-3), and does not rely on information about the patients, such as length of limbs, weights, etc. (B-4). These are in contrast to some other methods in the scientific field.

   (e) The gait inference model for several ambulatory modes is encapsulated into one single neural network. Other approaches often use different mid-level controllers for different gait phases and activity modes.

   (f) The GaIn article was published in the *Sensors* journal, which is ranked as Q2 by Scopus.

[1] Cf. the list in section "Aims and objectives of research".
[2] Cf. the list of drawbacks in section "Current approaches".

Publications

The PhD candidate is the main author in all of these articles. All articles have been published in international research journals in English as original research papers. Ranking is based on Scopus and Web of Science. The independent citations are provided as of April 2019.

First-tier publications.

1. Chereshnev R., Kertész-Farkas A.: HuGaDB: Human gait database for activity recognition from wearable inertial sensor networks, *Lecture Notes in Computer Science* – Springer, 2017. – pp. 131–141. The journal is ranked by Web of Science as Q4 and by Scopus as Q2. This article has obtained five independent citations. HuGaDB article was presented at the 6th International Conference on Analysis of Images, Social networks and Texts and won the **best talk award**.

2. Chereshnev R., Kertész-Farkas A.: GaIn: Human gait inference for lower limbic prostheses for patients suffering from double trans-femoral amputation, *Sensors*, – 2018. – Vol. 18. – No. 12. The journal is ranked by Web of Science as Q2 and by Scopus as Q2. This article has been published recently and has not obtained any citations yet.

Second-tier publications.

3. Chereshnev R., Kertész-Farkas A.: RapidHARe: A computationally inexpensive method for real-time human activity recognition from wearable sensors, *Journal of Ambient Intelligence and Smart Environments*. – 2018. – Vol. 10. – No. 5. – pp. 377–391. The journal is ranked by Web of Science as Q4 and by Scopus as Q3. This article has obtained one independent citation.

Reports at conferences and seminars.

5. Roman Chereshnev: Energy efficient method of recognition of human activity in real time using inertial sensors and dynamic Bayesian networks, Research Seminar of the Graduate School of Computer Science, CS HSE, June 1, 2017.

6. Roman Chereshnev: Using hidden Markov models for human activities recognition in real time, Annual Interuniversity Scientific and Technical Conference of Students, Postgraduates and Young Specialists named after E.V. Armensky, MIEM HSE, February 19, 2018.

Summary of the dissertation by chapters

The thesis structured as follows. The first chapter contains an introduction defined the scope of this work, summarizes the current and most related state of the art of the filed, and highlights the novelty of the dissertation work. Chapter 2 provides a detailed review of the literature. Chapter 3 provides an overall of the main results and specifies the aims and research objectives. Chapters 4, 5, and 6 presents the main results in details. The whole thesis consists of 119 pages and includes 61 figures, 24 tables, 168 references, and one appendix.

The chapter 1: Introduction

This chapter introduces the scope of the dissertation and summarizes the novelty of the Author's PhD research work and results.

The chapter 2: Literature review

This chapter provides an overview of the history of HAR. The first part provides a chronological overview of the current HAR methods and datasets. The second part provides taxonomic overview of the methods proposed for gait inference. part provide a review of works that related to HGI there machine learning was used. Finally, the fourth part provides an overview on robotic prostheses controllers. Both high-level controllers and low-level controllers are described there.

The chapter 3: Overview of the GaIn system

This chapter provides an overall overview of the GaIn control system. The system's specification, aims, objectives, and main results are discussed there. The GaIn system provides a method for controlling robotic prosthetic legs for patients suffering at most double transfemoral amputation. The concept of this idea is illustrated in Figure 2. The Author's idea is based on the observation that the correlation between the movements of the leg parts of healthy people − people without functional gait disorder during usual activities − is high. Consequently, it is possible to infer the movements of both lower legs based on the movements of both thighs using machine learning methods. The GaIn system employs a recurrent neural network with long-short-memory (LSTM) cells to infer the shank movement during walking-related activities.

Sitting down and standing up intentions cannot be recognized from thigh movements. In fact, these sitting-related activities drive thigh movements. Therefore, GaIn applies EMG sensors placed on the skin over the vastus lateralis the thigh muscles; therefore, the patient can signal her/his sitting down or standing up intentions by increasing thigh muscle activity.

The GaIn control system takes the input data from triaxial accelerometer and gyroscope sensors and EMG sensors located on both thighs. The GaIn control system consists of two major parts: (i) a high-level controller, which recognizes the user's current or the intended activity, and (ii) a mid-level controller, which performs the appropriate actions: sitting down, standing up, or gait inference.

The high-level controller orchestrates the mid-level controller via the following rules:

- When the user is sitting, then the high-level controller does not allow the mid-level controller to infer gait, and both legs remain motionless. If an adequate amount of electrical activity from both thigh muscles is recognized by the high-level controller based on data from the EMG sensors, then the mid-level controller system performs the standing up procedure.
- When the user is standing, then the high-level controller can (i) keep the user in a standing

position, (ii) get the mid-level controller to start gait inference if one leg starts swinging, or (iii) get the mid-level controller to perform a sitting down procedure if the electrical activity of both thigh muscles is suddenly high and both thighs have a similar position.

- When the user is walking, running, or taking the stairs, then the high-level controller keeps the mid-level controller performing gait inference using a recurrent neural network or perform stopping and standing position.

- When the user suddenly stops, then the high-level controller commands the mid-level controller to stop the procedure and keeps the patient in a standing position.

Figure 4 shows the possible transitions between different activities. For instance, if the user is walking, then the system cannot perform a sitting down activity without first stopping and standing. When the user is sitting, then GaIn cannot infer walking-related activities without first standing up and standing.

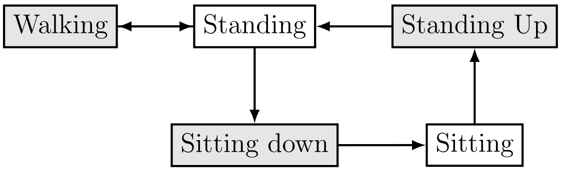


Figure 4: Activity transition graph of the GaIn control system.

Incorrect activity mode or intention recognition may pose safety issues. When the GaIn system incorrectly recognizes a standing up activity while the user is sitting, then the system simply stretches the robotic prosthetic leg, resulting in no harm to the patient. However, when a sitting down intention is predicted while the user is simply standing, then the patient will fall and may suffer serious injury. Thus, it is more important to achieve low false alarm (high precision) than low missed alarm (high recall) rates for the sitting down activity. Therefore, the decision threshold was calibrated so that the activity recognition module achieved a low false alarm rate (precision) at the expense of high missed alarm (recall). This is a trade-off between precision and recall. As a consequence, users may need to produce clearer and longer signals to the system for sitting down, but the Author expects that this will results in causing fewer injuries from falling.

The GaIn system could potentially be installed on microchip-controlled robotic leg prostheses that could be attached to patients in a non-invasive way to infer the movements of the lower limbs, as illustrated in Figure 2. Therefore, the GaIn system could help patients suffering single or double lower limb amputation to move and walk by themselves. However, in order to make GaIn efficient in portable real-time prediction systems, it should meet the following requirements:

1. **Low prediction latency**. GaIn should respond quickly to sudden changes in user behavior in real-time.

2. **Fast and energy-efficient**. In order to be suitable for mobile and portable systems, GaIn is to be energy-efficient and CPU-friendly.

3. **Smooth recognition**. GaIn should provide consistent recognition within a given activity mode and rapid transition in-between activity modes.

4. **Generalization**. GaIn should be accurate for new patients whose data was not seen during training.

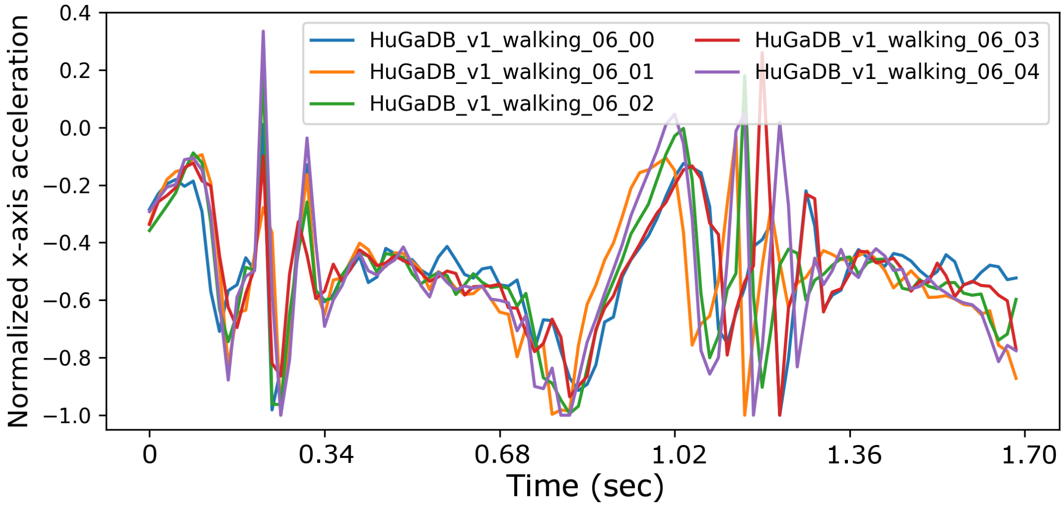
Low prediction latency. The first requirement ensures that the model has low latency; therefore, activity prediction can be made instantly based on the latest observed data. Therefore, bidirectional models, such as bidirectional LSTM RNN [24] or dynamic time warping [27] methods, are not appropriate for this project aims for two main reasons. First, these bidirectional methods require a whole observed sequence before making any predictions, which would increase their latency. Second, the prediction they make on a frame is based on subsequent data. Standard hidden Markov models have become the *de facto* approach for human activity recognition [28], and they yield good performance in general. However, they do so at the expense of increased latency in prediction, because Viterbi algorithms use the whole sequence, or at least some part of it, to estimate a series of activities (i.e., hidden states), and their time complexity is polynomial. Therefore, HMMs are not adequate for on-the-fly prediction, because the latency of these methods can be considered rather high.

Fast and energy efficient. Continuous sensing and evaluating by CPU-intensive prediction methods rapidly deplete a mobile system's energy. Therefore, the second point requires the system to be energy-efficient enough for mobile-pervasive technologies. Several approaches have been introduced for this problem. Some methods aim to keep the number of necessary sensors low by adaptive selection [42] or based on the activity performed [12] for accurate activity prediction. Other approaches aim to reduce the computational cost by feature selection [1], feature learning [32], or proposing computationally inexpensive prediction models such as C4.5, random forest, or decision trees [35].

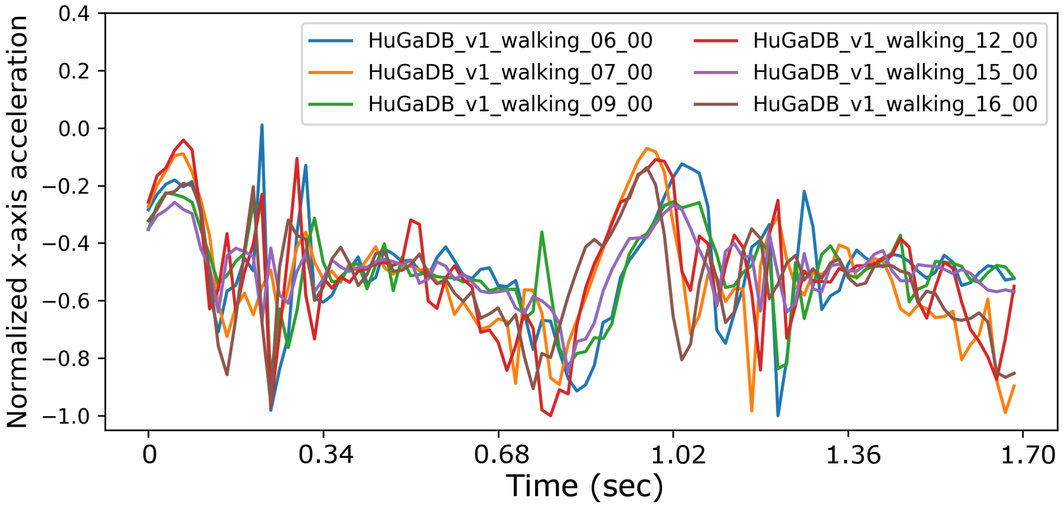
Smooth recognition. This point is to ensure that the activity recognition method provides consistent prediction within the same activity mode, but changes rapidly when the activity mode has changed. Lester et al. [25] pointed out that single-frame prediction methods such as decision stumps or support vector machines are prone to yielding scattered predictions. However, human activity data are time series data in nature, and subsequent data frames are highly correlated. This tremendous amount of information can be exploited simply by sequential models such as HMM and RNN, or by incorporating the sliding-window technique in single-frame methods (e.g., nearest-neighbor). In fact, Mannini and his co-authors [28] pointed out that the continuous-emissions HMM-based sequential classifier performs systematically better than its simple single-frame GMM counterpart (99.1% vs. 92.2% accuracy). Actually, the proposed sequential classifier beats its tested single-frame competitors overall (the best single-frame classifier is the nearest mean classifier, which achieves up to 98.5% accuracy). This highlights the relevance of exploiting the statistical correlation from human dynamics.

Generalization to new users. People walk in different ways, and thus, human gait cycles vary. Figure 5 shows the variance of various gaits for the same person (A) and for various people (B). Therefore, it is essential that machine learning systems be robust against this natural variance and their performance be comprehensively evaluated with new patients whose data have not been seen during the training. Unfortunately, the Author observed that many HAR methods in the scientific literature have been validated with mixed data, i.e., training and testing datasets are distinct but contains data from the same users. Thus, those evaluations are not adequate to assess how their systems would perform with new users. The performance of the GaIn control system was evaluated using a supervised cross-validation approach [21]. In this approach, data from a designated participant were held out for tests, and the rest of the data from the other participants were used for training. Thus, this approach gives a reliable estimation of how well the GaIn system would perform for a new patient whose data have not been seen before. The GaIn control system was optimized so that it performed the best on the new patient's data.

Finally, note that, when the HuGaDB data were recorded a few years ago, some variance in sensors, installation was allowed. The location and the orientation of the sensors were not precisely regulated on purpose. This provided some variance in the data, and this makes the GaIn system more robust to sensor installation in practice and provides better generalization for the machine learning algorithms. This also will give the patients more freedom in putting the sensors on.



(A) Single user



(B) Various users

Figure 5: Gait cycle variance during walking. (A) Gait cycles produced by the same user multiple times. (B) Gait cycles produced by different users. Legend indicates the source of the data. Data are scaled to the range $[-1, +1]$. Data are taken from the HuGaDB dataset [5].

Main results. The Author's overall results of gait inference using high- and mid-level controllers can be seen in a video at `https://youtu.be/aTeYPGxncnA`, from which two screenshots are shown in Figure 6. Many videos have been generated based on different data recorded from different participants, but the Author did not see visually notable differences in the videos. The reason this particular example was chosen is that these data contain a variety of activities during a relatively short time.

Figure 7 shows the inference for a continuous series of standing up, sitting down, and a few walking-related activities. This figure consists of two parts: the first part (from 4.2 seconds to 20 seconds) shows sitting-related predictions by the high-level controller, while the second part

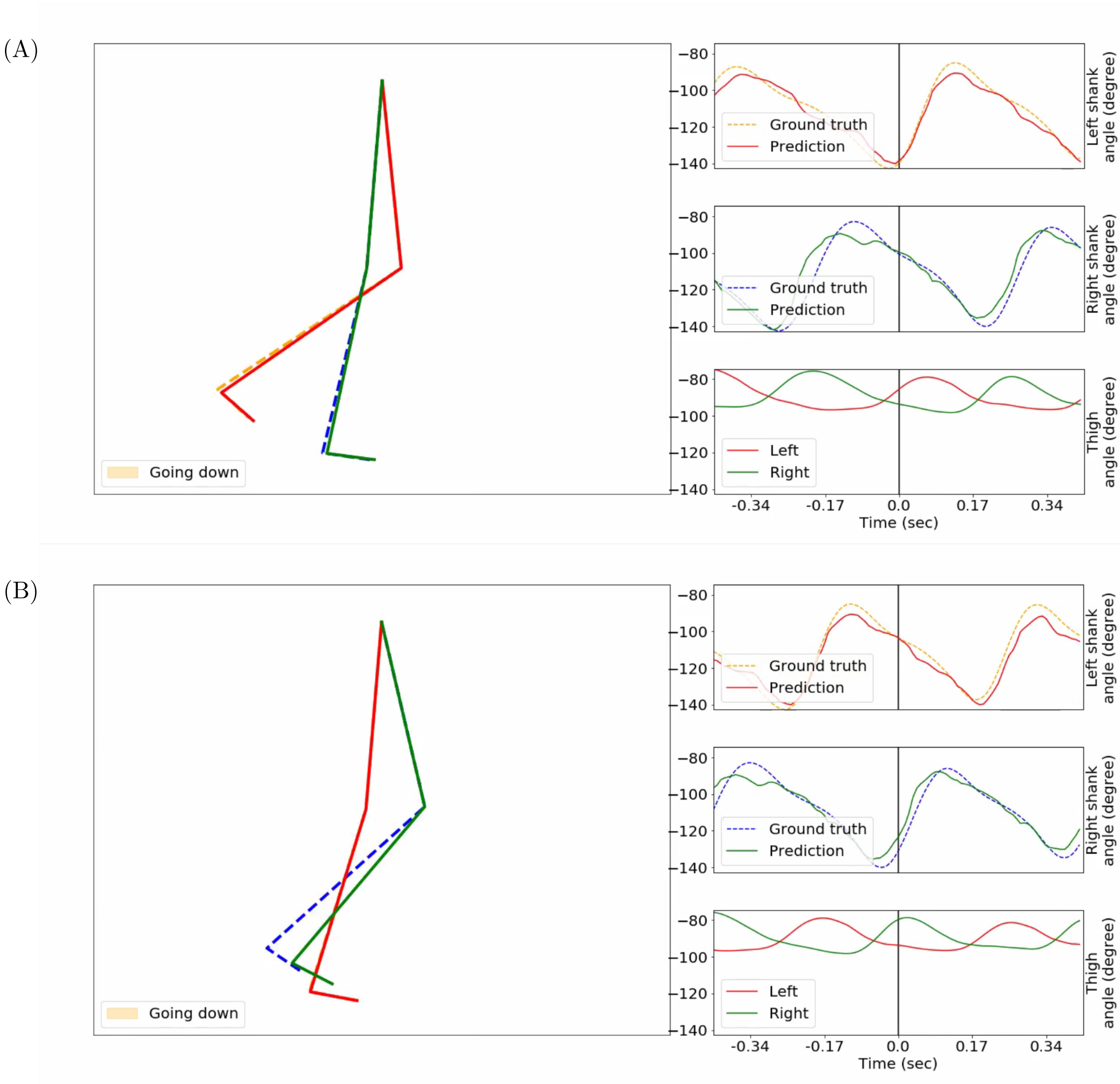


Figure 6: Screenshot of GaIn during gait inference. Around 56 data frames add up to 1 second. See the full video at: `https://youtu.be/aTeYPGxncnA`.

(from 21 seconds) shows shank movement inference by the mid-level controller for walking-related activities. In the first part, the high-level controller is supposed to predict sitting-related activity modes. The activity modes are indicated by the color of the background. The true modes are shown at the bottom, while the predicted activity modes are shown at the top. Here, the activity modes were recognized correctly albeit with around a 1-second lag. The activity modes are recognized mainly based on the variance in the EMG signals (solid dark and light green lines) and the position of the shanks are irrelevant here. It should be noted that the length of the sitting down and standing up activities in the figures is irrelevant here because the length would depend on how the robotic prosthetic legs performed these movements once the patient's intention was recognized.

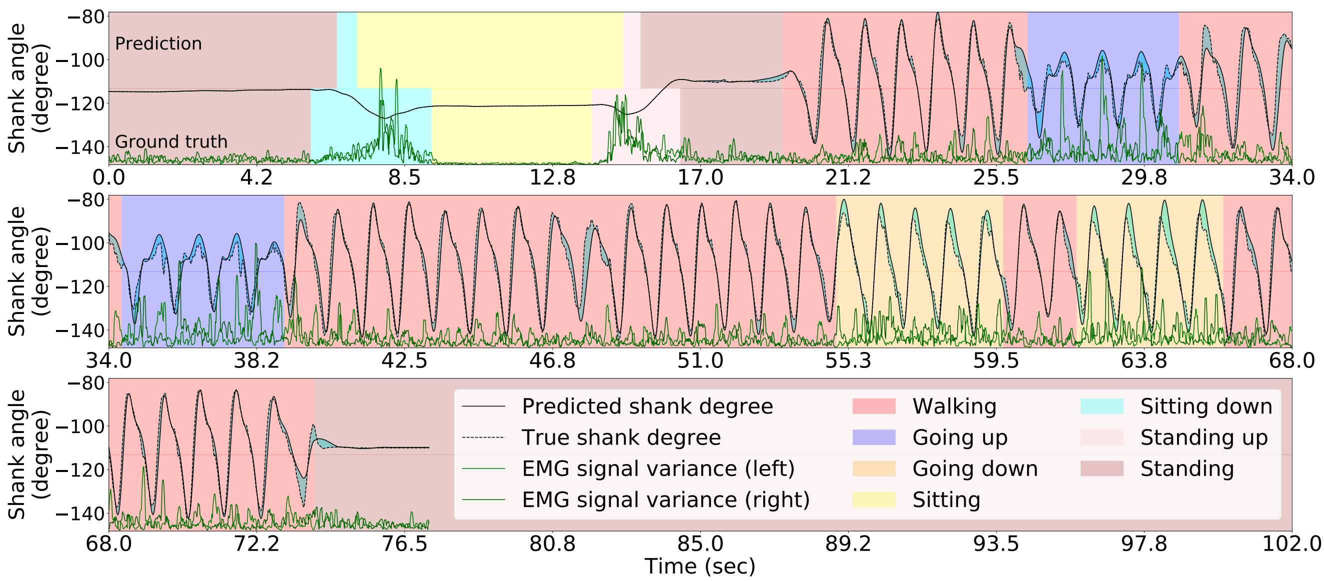


Figure 7: Gait inference and activity recognition using GaIn.

The Chapter 4: Dataset for gait inference

The Author created a new dataset suitable for studying human gait in great details, because existing datasets for HGA and HAR were not adequate for the aim of this research project due to the lack of detailed information on the movements of the parts of the legs. Thus, for this thesis project there was collected HuGaDB dataset.

HuGaDB is a human gait data collection for analysis and activity recognition consisting of continues recordings of combined activities, such as walking, running, taking stairs up and down, sitting down, and so on; and the data recorded are segmented and annotated. This dataset is unique in the sense that it is the first to provide human gait data in great detail mainly from inertial sensors and contains segmented annotations for studying the transition between different activities.

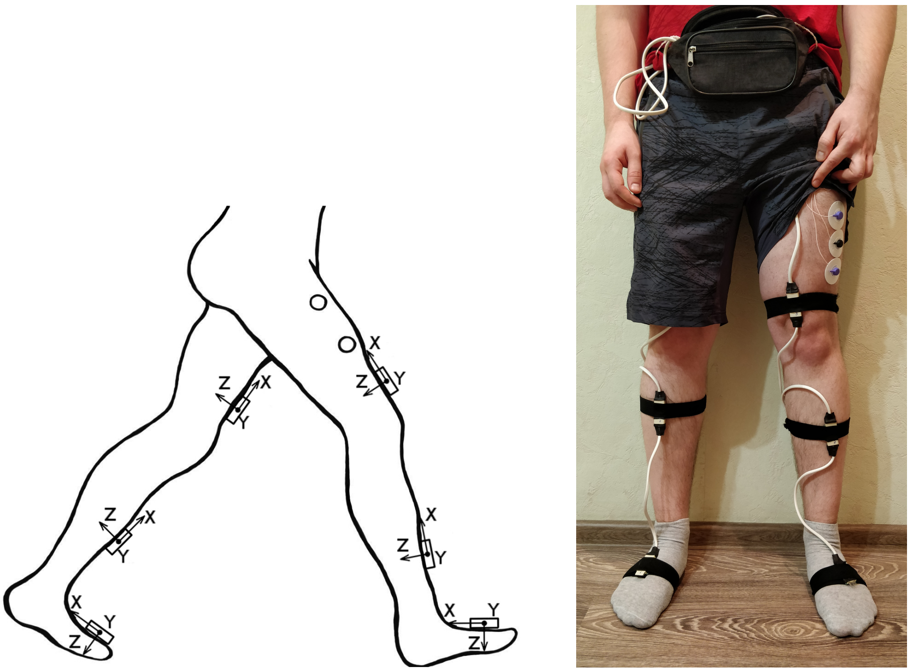
Table 1: Characteristics of HuGaDB

ID	Activity	Time sec (min)	Percent	Samples	Description
1	Walking	11544 (192)	32.15	679073	Walking and turning at various speeds on a flat surface
2	Running	1218 (20)	3.39	71653	Running at various paces
3	Going up	2237 (37)	6.23	131604	Taking stairs up at various speeds
4	Going down	1982 (33)	5.52	116637	Taking the stairs down at various speeds and steps
5	Sitting	4111 (68)	11.45	241849	Sitting on a chair; sitting on the floor not included
6	Sitting down	409 (6)	1.14	24112	Sitting on a chair; sitting down on the floor not included
7	Standing up	380 (6)	1.06	22373	Standing up from a chair
8	Standing	5587 (93)	15.56	328655	Static standing on a solid surface
9	Bicycling	2661 (44)	7.41	156560	Typical bicycling
10	Up by elevator	1515 (25)	4.22	89144	Standing in an elevator while moving up
11	Down by elevator	1185 (19)	3.30	69729	Standing in an elevator while moving down
12	Sitting in car	3069 (51)	8.55	180573	Sitting while an travelling by car as a passenger
	Total	35903 (598)	100.00	2111962	

The main purpose of this dataset is to provide detailed gait data to study how the parts of the legs move individually and relative to each other during activity modes such as walking, running, standing up, etc. A summary of the activities can be found in Table 1. This dataset contains continuous recordings of combinations of activities, and the data are segmented and annotated with the label of the activity currently performed. Thus, this dataset is also suitable for analyzing human gait and activities between activity mode transitions.

In data collection, there were used MPU9250 inertial sensors and electromyography (EMG) sensors created in Laboratory of Applied Cybernetic Systems at BiTronics Lab (`www.bitronicslab.com`), Moscow Institute of Physics and Technology. All sensors are powered from a battery, that helps to minimize electrical grid noise.

In total, three pairs of inertial sensors and one pair of EMG sensors were installed symmetrically on the right and left legs with elastic bands. A pair of inertial sensors were installed on the rectus femoris muscle 5 centimetres above the knee, a pair of sensors around the middle of the shinbone at the level where the calf ends, and a pair on the feet on the metatarsal bones. Two EMG sensors were placed on vastus lateralis and connected to the skin with three electrodes. The locations of the sensors are shown in Figure 8. In total, 38 signals were collected, 36 from the inertial sensors and 2 from the EMG sensors.



(A) (B)

Figure 8: Location of Sensors. (A) EMG sensor are shown as circles while boxes represent inertial sensors. (B) Mounted sensors. The black waist bag contains the Ardurio driver.

The Chapter 5: High-level controller of GaIn

The Author develped a fast and computationally inexpensive high-level controller for the GaIn system and it is introduced and discussed in this chapter. The controller is based on RapidHARe model developed by the Author [7]. RapidHARe is a dynamic Bayesian network, whose structure is shown in Figure 9. The states, i.e., activities, denoted by S and the probability of a state $s(t)$ at a given time t with respect to a given observed context window $v(t), v(t-1), \cdots, v(t-K)$ of length K, is formulated by

$$P(s(t) \mid v(t), v(t-1), \cdots, v(t-K)) = \frac{\prod_{k=0}^{K} P(v(t-k) \mid s(t)) P(s(t))}{\sum_{n=1}^{N} \prod_{k=0}^{K} P(v(t-k) \mid s(t)=n) P(s(t)=n)}. \tag{1}$$

Certainly, at the beginning of performance, when $t < K$, the context window is adjusted. RapidHARe does not use different *a priori* class probabilities for different $P(s(t))$. Thus, the model does not bias toward some states that are abundant in the training data. Therefore, the activity prediction should be based fully on the data, and the state probabilities $P(s(t))$ can be omitted from Eq. 1.

The state being performed at time t can be predicted as follows:

$$\hat{s}(t) = \underset{s(t)}{\operatorname{argmax}} \left\{ P(s(t) \mid v(t), v(t-1), \cdots, v(t-K)) \right\}. \tag{2}$$

Since the optimum of Eq. 2 is invariant to normalization, the normalization factor can be omitted from Eq. 1. This gives a very simple model for activity prediction in the following form:

$$\hat{s}(t) = \underset{s(t)}{\operatorname{argmax}} \left\{ \prod_{k=0}^{K} P(v(t-k) \mid s(t)) \right\}. \tag{3}$$

This model can be implemented using the rolling-window technique for real-time continuous activity recognition; thus, the model remains fast for large Ks, and redundant calculation of $P(v(t-k) \mid s(t)); (k > 0)$ can be avoided by using tables.

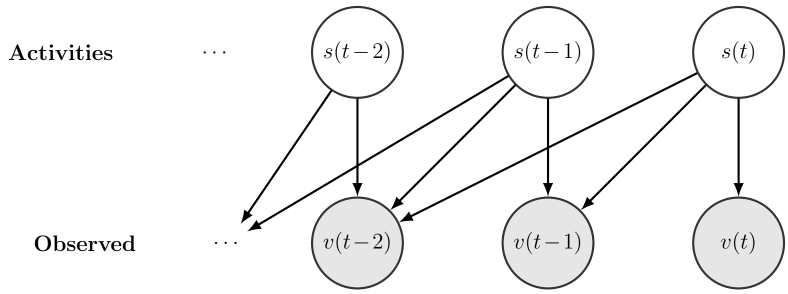


Figure 9: Illustration of an unfolded dynamic Bayesian network w.r.t. an activity series.

The distribution $P(V \mid S)$ with respect to a given state is modeled with Gaussian mixture models (GMMs), and its parameters are trained using the expectation-maximization method. The training of GMMs was straightforward because training data were segmented.

GaIn high-level controller uses three RapidHARe models to recognize standing up and sitting down intentions.

Sitting-Standing module. The first RapidHARe module, denoted $\mathcal{C}_{\rm ss}$, is to recognize if the user is (1) sitting, (2) standing, or performs (3) other walking-related activity modes. This module uses one Gaussian component for each activity modes, respectively, based on four input features, namely: the raw x and z-axes accelerometer data from left and right thighs The length of the context window K was 20.

Sitting-Down module. The second module, denoted $\mathcal{C}_{\text{sd}}$, is to recognize sitting down intention vs. walking during standing from EMG sensor data and the differences of the accelerometer data. The sitting-down intention was modeled with five Gaussian components while standing and walking activity modes were modeled with two Gaussian components, respectively. The prediction with this module is based on the standard deviation of the EMG signal changes compared to a ten past references ($\gamma_{10}(t)$) and the difference of the thigh positions. The difference of the thigh positions is useful in distinguishing sitting down intention from walking. The length of the context window K was 20.

Standing-Up module. Finally, the third module, denoted $\mathcal{C}_{\text{su}}$, is to recognize the users intention to stand up from sitting position based on EMG sensor data. The intention was modeled with 10 Gaussian components, while sitting was modeled with one Gaussian component. The input of this module are the standard deviation of the EMG signal changes compared to a five past references ($\gamma_5(t)$) as it is used in the previous model. The length of the context window K was 20.

The activity recognition was evaluated with $Precision = \frac{TP}{TP+FP}$ and $Recall = \frac{TP}{TP+FN}$ metrics, where TP, FP, and FN denote the number of the true positive, false positive, and false negative predictions, respectively. In addition, the F_1 scores were calculated and reported.

The goal of GaIn high-level controller is to understand whether the person intends to sit down or sitting down. The triggering may be not as fast as healthy users' performance. However, in this work, if the system predicts intention with some lag it is counted as TP result. Moreover, all high-level controller metrics were calculated based on person intention, not based on data samples. Thus, TP is counted, when activity correctly predicted (or triggered) during the same ground truth activity. FP is counted when activity predicted (or triggered) during other ground truth activity. And finally, FN is counted when GaIn missed an activity recognition.

Table 2: Mean classification results

Metric	Standing up	Sitting down	Standing	Sitting
Recall	0.99	0.68	0.99	0.99
Precision	0.99	0.99	0.99	0.99
F_1	0.99	0.77	0.99	0.99

The results, summarized in Table 2, show that standing and sitting position recognition can be achieved with high accuracy; however, it is easier to recognize standing up intention than sitting down intention. The GaIn system achieved 99% recall and 99% precision for recognizing standing up intention, but it achieved only 68% recall and 99% precision for sitting down activity. The reason is that the muscle activity in both thighs is very low in a sitting position, thus it is effortless to recognize standing up intention form the sudden increase in muscle activity. However, muscle activity is already present in a standing position, which makes it more challenging to distinguish a patient's simple balancing or walking efforts from a sitting down intention. Nevertheless, incorrect activity prediction can result in different impacts on the patient. When the GaIn system incorrectly recognized a standing up activity while the user is sitting, then the system simply stretched the robotic prosthetic leg, resulting in no harm to the patient. However, when a sitting down intention is predicted while the user is simply standing, then the patient would fall and may suffer serious injury. Thus, it is more important to achieve lower false alarm (high precision) than missed alarm (high recall) rates for sitting down activity. Therefore, the decision threshold was calibrated so that the activity recognition module achieved as high as 99% precision at the expense of a recall, which decreased to 68%. As a consequence, users may need to produce clearer and longer signals to the system for sitting down, but this results in GaIn causing fewer injuries from falling.

Overall, RapidHARe is a simple and fast model that consumes little energy to recognize human activities recognition. Moreover, RapidHARe can be used in other applications. The Author tested RapidHARe model on the classification task based on HuGaDB dataset [5]. In comparative tests, RapidHARe appeared to be an extremely fast predictor, one and a half times faster than artificial neural networks methods, and more than eight times faster than recurrent neural networks (RNNs) and hidden Markov models (HMMs). Moreover, in performance, RapidHARe achieves an F1 score of 94.27% and accuracy of 98.94%, and when compared to ANN, RNN, HMM, it reduces the F1-score error rate by 45%, 65%, and 63% and the accuracy error rate by 41%, 55%, and 62%, respectively. Therefore, RapidHARe is suitable for real-time recognition in mobile devices [7].

The Chapter 6: Mid-level controller of GaIn

The Gain mid-level controller aims to infer human gait and to predict shanks movements. It should be noticed, that GaIn has only one mid-level controller for all gait activities and phases.

The shanks movement prediction was modeled with recurrent neural networks (RNNs) with long-short-term memory (LSTM) units [17]. RNNs are universal mathematical tools for modeling statistical relationships in sequential data. The RNN consisted of 50 LSTM hidden units in one hidden layer. The learning objective for the RNN was to minimize the squared error between the predicted and the true shank angle. For the training, the input sequential data were chunked into 15 long data segments. The RNN uses a 4-component input vector, in which each component corresponds to the angle and the angular speed of the left and right thighs, respectively.

Raw data obtained from the gyroscope and accelerometer sensors were filtered with a moving average. This was performed to remove the bias drift of inertial sensors [13]. The gait inference method is based on the thigh angle and angular speed data in the sagittal plane. The initial angle degrees for thigh and shank are calculated based on the accelerometer data and Earth gravity [31]. Formally, the start angle of the left thigh (θ) is calculated with

$$\theta^{L}_{start} = \arctan\left(\frac{a_{(l,t,y)}}{\sqrt{a^2_{(l,t,x)} + a^2_{(l,t,z)}}}\right), \tag{4}$$

where $a_{(l,t,y)}$, $a_{(l,t,x)}$, and $a_{(l,t,z)}$ denote the values of the accelerometer sensors located on left thigh. The start angle of the left shank (ϕ) is calculated via

$$\phi^L_{start} = \arctan\left(\frac{a_{(l,s,y)}}{\sqrt{a^2_{(l,s,x)} + a^2_{(l,s,z)}}}\right), \tag{5}$$

where $a_{(l,s,x)}$, $a_{(l,s,y)}$, and $a_{(l,s,z)}$ denote the values of the accelerometer sensors located on left shank. The angular velocities are from the gyroscope data. Using the angular velocities of left thigh and shank $\omega_{(l,t,y)}$ and $\omega_{(l,s,y)}$ at time t, respectively, the angles of thigh $\theta(t)$ and shank $\phi(t)$ at time t can be calculated as follows [31]:

$$\theta^L(t) = \theta^L_{start} + \int_0^t \omega_{(l,t,y)}(t)dt, \tag{6}$$

$$\phi^L(t) = \phi^L_{start} + \int_0^t \omega_{(l,s,y)}(t)dt. \tag{7}$$

The variables for the right leg $\theta^R(t)$, $\phi^R(t), \theta^R_{start}$, ϕ^R_{start} are calculated the same way, but with information obtained from right leg. Consequently, the gait inference module can be formulated as

$$y(t) = R(v(t)), \tag{8}$$

where $v(t) = [\theta^L(t), \theta^R(t), \omega_{(l,t,y)}(t), \omega_{(r,t,y)}(t)]$ and $y(t) = [\phi^L(t), \phi^R(t)]$ contains the angle prediction for the right and left shanks at time t, respectively, and R denotes a recurrent neural network with LSTM units. It should be noted that the index "t" is overriding here and not to be confused. It stands for both "tight" in $\omega_{(l,t,y)}$ and $a_{(r,t,y)}$ and denotes "time" in $\theta^L(t)$, and $\phi^L(t)$.

The results for gait inference are shown in Figure 10 for various walking-related activities such as walking, running, and taking the stairs up and down. The dashed lines show the true angle of the shank, while the solid line shows the prediction for the shank angle. The line segments going upward correspond to swing phases and line segments going downward correspond to stance phases in the gait cycle. The error, the difference between the true and the predicted movements, is indicated by the shaded area. It appears that the errors occur at the peaks and troughs which correspond to the approximately turning point between the swing and stance phases. The color of the background indicates the activity performed. Note that these activity labels were not incorporated into the training procedure; they are presented simply for illustration purposes. The prediction errors for different activities are listed in Table 3. The error was calculated for each activity overall data of all users. The average of the prediction errors for the shank angles across different activities is 4.55 degree. Figure 11 shows the coordination and coordination variability of the true (red) and predicted (blue) shank angles with respect to the thigh angles. This scatter plot shows that the predicted shank angles are in accordance with the true shank angles. However, the predicted shank angles do not span over the range of the true angles in some cases. For instance, in plot C, the predicted shank angles do not reach the extremes of the true angles. This is the error which occurs at peaks and troughs in Figure 10.

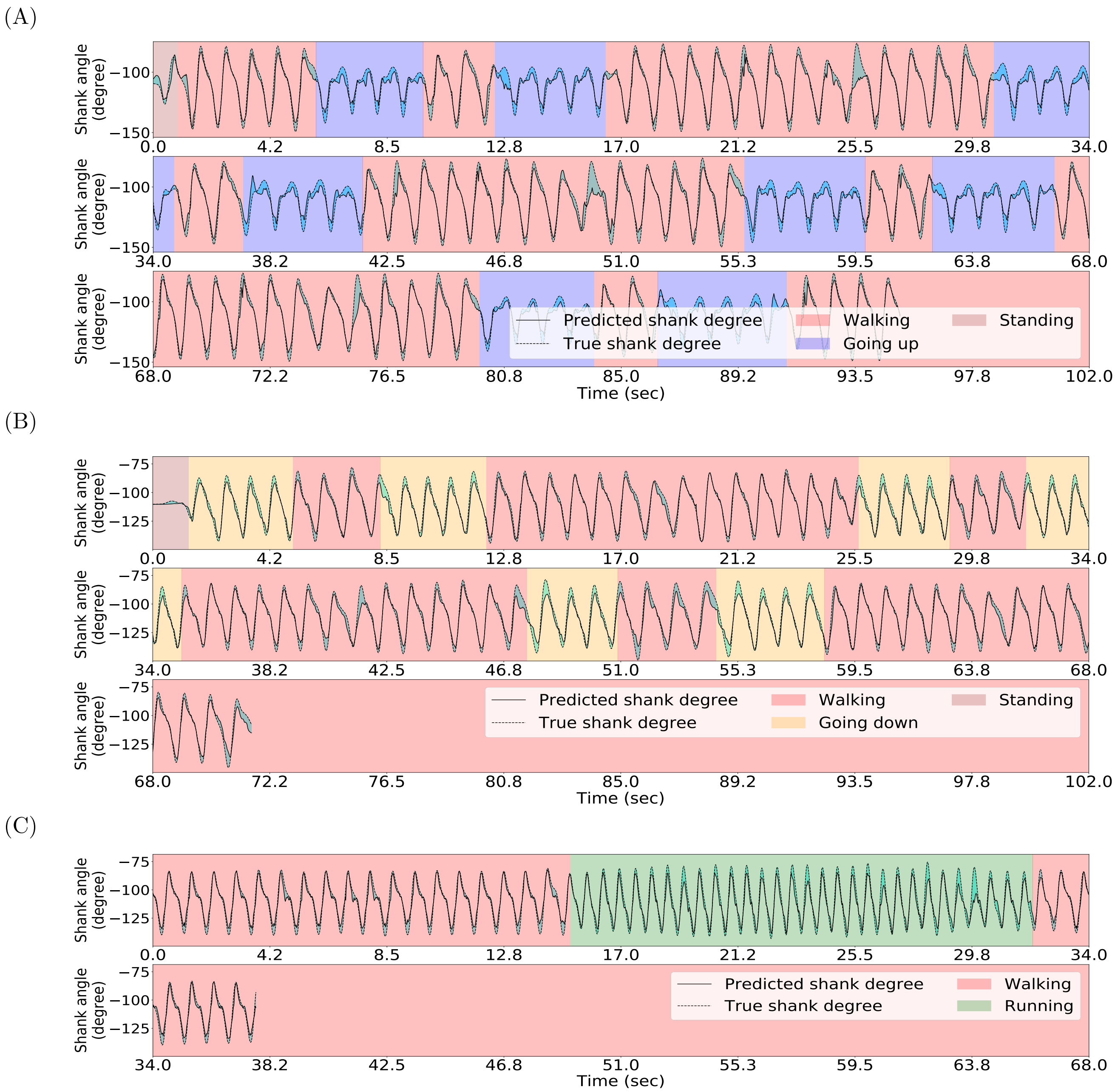


Figure 10: GaIn inference for various walking-related activities. The activity is indicated by the background color for the reader, but this information was not used in the methods. The shank degree is predicted based on thigh angles (not shown). Solid black line shows the predicted, the dashed line shows the true angles of the right shank, while the shaded area between them indicates the prediction error. Plots for the left leg are similar.

Table 3: Gait inference error

	Walking	Running	Going up	Going down	Standing	Mean
Mean	4.988	5.648	5.820	5.148	1.174	4.555
Std	0.910	2.212	1.299	1.158	0.457	1.207

Error measured in absolute difference between the true and the predicted shank angles in degrees.

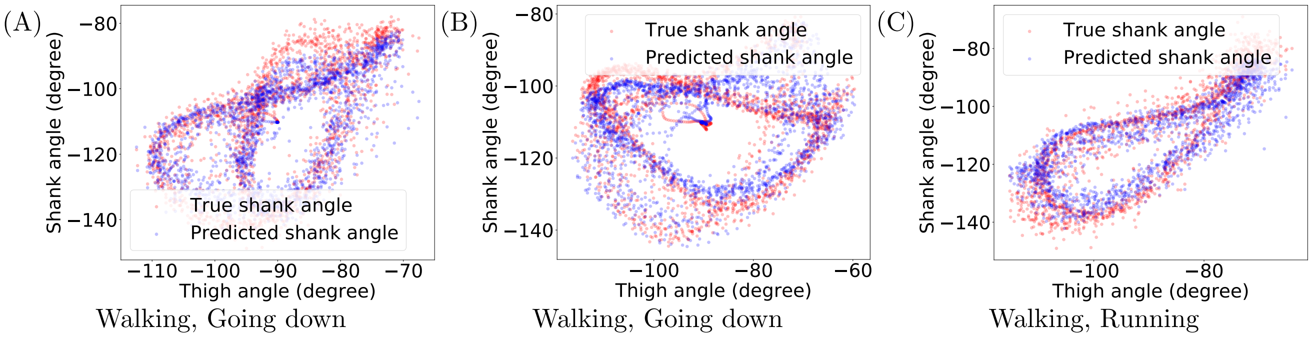


Figure 11: Predicted and true shank angles as function of thigh position over several gait cycles in different activities. The input data used was the same as at Figure 3. The caption below each figure indicates the types of activities performed on the plot.

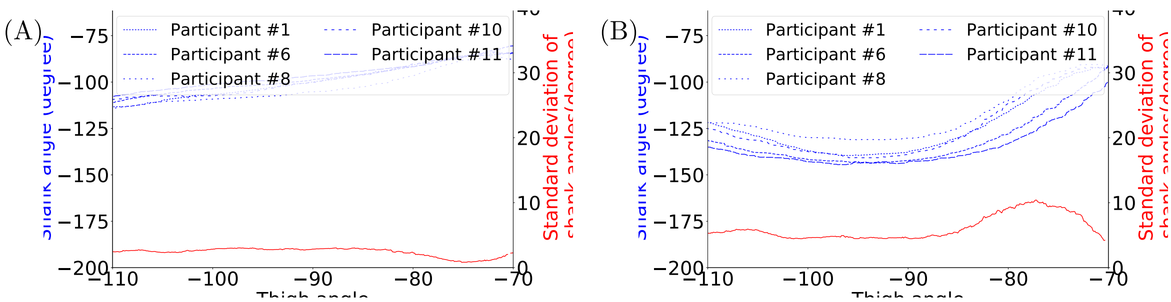


Figure 12: Shank angles of different participants in stance phase (A) and swing phase (B).

People walk differently, resulting in variance in gaits. Moreover, gait varies over different cycles for the same person as well. Figure 3 shows this natural variance. This variance prevents in achieving 100% accuracy in gait prediction for someone's gait based on other people's gait data. It has also been noticed that variance in the swing phase is larger than in the stance phase [40]. This is as expected, since the stance phase is more important in walking stability, while legs may move more freely in the swing phase [40]. This fact is also observed in HuGaDB. In Figure 12, panel A shows the shank angles of the gait cycle in the stance phase (blue lines) and the variance (red line) and panel B shows the same information for the swing phase. The figure shows that the variance is higher in the swing phase. Therefore, higher prediction error is expected for the swing phase than for the stance phase. In fact, the mean shank degree prediction error across all activities is 4.783 (STD: 1.171) in the stance phase and 6.182 (STD: 1.680) in the swing phase. Table 4 shows detailed prediction errors for different activities.

Table 4: GaIn inference error

	Walking	Running	Going up	Going down	Mean
Swing phase					
Mean	5.826	6.420	6.738	5.744	6.182
Std	1.0817	2.750	1.437	1.452	1.680
Stance phase					
Mean	4.268	4.967	5.140	4.758	4.783
Std	0.800	1.700	1.215	0.969	1.171

Error measured in degrees.

We closely examined the error around activity changes; for instance, when a walking user started running. We measured the gait inference errors in a range of ± 15 data samples (equivalent to half of a second) around the true activity change. We found that the shank degree prediction error is 5.44°, which is not especially larger than general. The detailed results for different activity transitions are shown in Table 5.

Table 5: Average shank degree prediction error at activity transitions.

Activity transition	Mean	Std
Walking → Running	5.79	2.297
Walking → Going up	5.34	1.417
Walking → Going down	5.68	0.959
Walking → Standing	4.50	0.742
Running → Walking	5.31	2.352
Going up → Walking	5.15	1.661
Going up → Standing	7.24	0.837
Going down → Going up	6.21	0.479
Going down → Walking	6.22	1.734
Standing → Going up	5.75	1.331
Standing → Walking	4.20	3.065
Standing → Going down	6.11	2.242
Mean	5.44	1.471

The degree error was measured in ± 15 sample interval (around half a second long range) at the true activity transition border.

The Chapter 7: Conclusions

This part summarizes and concludes the main results of this thesis. In addition, questions are considered that remain open and require further research. Possible directions of future work, developing the results of the thesis, are also given in this part.

Bibliography

[1] Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra, and Jorge L Reyes-Ortiz. Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine. In *International Workshop on Ambient Assisted Living*, pages 216–223. Springer, 2012.

[2] Abeer A Badawi, Ahmad Al-Kabbany, and Heba Shaban. Daily activity recognition using wearable sensors via machine learning and feature selection. In *2018 13th International Conference on Computer Engineering and Systems (ICCES)*, pages 75–79. IEEE, 2018.

[3] Abeer A Badawi, Ahmad Al-Kabbany, and Heba Shaban. Multimodal human activity recognition from wearable inertial sensors using machine learning. In *2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, pages 402–407. IEEE, 2018.

[4] David Bell and Axel Heitmueller. The disability discrimination act in the uk: Helping or hindering employment among the disabled? *Journal of health economics*, 28(2):465–480, 2009.

[5] Roman Chereshnev and Attila Kertész-Farkas. Hugadb: Human gait database for activity recognition from wearable inertial sensor networks. In *International Conference on Analysis of Images, Social Networks and Texts*, pages 131–141. Springer, 2017.

[6] Roman Chereshnev and Attila Kertész-Farkas. Gain: Human gait inference for lower limbic prostheses for patients suffering from double trans-femoral amputation. *Sensors*, 18(12):4146, 2018.

[7] Roman Chereshnev and Attila Kertész-Farkas. Rapidhare: A computationally inexpensive method for real-time human activity recognition from wearable sensors. *Journal of Ambient Intelligence and Smart Environments*, 10(5):377–391, 2018.

[8] Prudhvi Tej Chinmilli, Sangram Redkar, Wenlong Zhang, and Tom Sugar. A review on wearable inertial tracking based human gait analysis and control strategies of lower-limb exoskeletons. *Int Rob Auto J*, 3(7):00080, 2017.

[9] Buddhika de Silva, Anirudh Natarajan, Mehul Motani, and Kee-Chaing Chua. A real-time exercise feedback utility with body sensor networks. In *Medical Devices and Biosensors, 2008. ISSS-MDBS 2008. 5th International Summer School and Symposium on*, pages 49–52. IEEE, 2008.

[10] Maurizio Falso, Silvia Zani, Eleonora Cattaneo, Marco Zucchini, and Franco Zucchini. Triamf protocol as an innovative tool in the comprehensive treatment and outcome evaluation of lower limb amputees before and after prosthesis use. *Journal of Novel Physiotherapy and Rehabilitation*, 3:1–24, 2019.

[11] Woodie C Flowers and Robert W Mann. An electrohydraulic knee-torque controller for a prosthesis simulator. *Journal of biomechanical engineering*, 99(1):3–8, 1977.

[12] Dawud Gordon, Jurgen Czerny, Takashi Miyaki, and Michael Beigl. Energy-efficient activity recognition using prediction. In *Wearable Computers (ISWC), 2012 16th International Symposium on*, pages 29–36. IEEE, 2012.

[13] Farid Gulmammadov. Analysis, modeling and compensation of bias drift in mems inertial sensors. In *Recent Advances in Space Technologies, 2009. RAST'09. 4th International Conference on*, pages 591–596. IEEE, 2009.

[14] Kazunori Hase and R.B. Stein. Turning strategies during human walking. *Journal of Neurophysiology*, 81(6):2914–2922, 1999.

[15] Jeffrey M Hausdorff, CK Peng, ZVI Ladin, Jeanne Y Wei, and Ary L Goldberger. Is walking a random walk? evidence for long-range correlations in stride interval of human gait. *Journal of Applied Physiology*, 78(1):349–358, 1995.

[16] Aart Hendricks. Un convention on the rights of persons with disabilities. *Eur. J. Health L.*, 14:273, 2007.

[17] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[18] Shuuji Kajita, Fumio Kanehiro, Kenji Kaneko, Kiyoshi Fujiwara, Kensuke Harada, Kazuhito Yokoi, and Hirohisa Hirukawa. Biped walking pattern generation by using preview control of zero-moment point. In *ICRA*, volume 3, pages 1620–1626, 2003.

[19] Hiroaki Kawamoto, Stefan Taal, Hafid Niniss, Tomohiro Hayashi, Kiyotaka Kamibayashi, Kiyoshi Eguchi, and Yoshiyuki Sankai. Voluntary motion support control of robot suit hal triggered by bioelectrical signal for hemiplegia. In *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, pages 462–466. IEEE, 2010.

[20] A Keçeci, A Yildirak, K Özyazici, G AyluÇtarhan, O Ağbulut, and i Zincir. Gait recognition via machine learning. In *International Conference on Cyber Security and Computer Science (ICONCS'18)*, 2018.

[21] Attila Kertész-Farkas, Somdutta Dhir, Paolo Sonego, Mircea Pacurar, Sergiu Netoteia, Harm Nijveen, Arnold Kuzniar, Jack AM Leunissen, András Kocsor, and Sándor Pongor. Benchmarking protein classification algorithms via supervised cross-validation. *Journal of biochemical and biophysical methods*, 70(6):1215–1223, 2008.

[22] Taisuke Kobayashi, Kosuke Sekiyama, Yasuhisa Hasegawa, Tadayoshi Aoyama, and Toshio Fukuda. Unified bipedal gait for autonomous transition between walking and running in pursuit of energy minimization. *Robotics and Autonomous Systems*, 103:27–41, 2018.

[23] Óscar D Lara and Miguel A Labrador. A survey on human activity recognition using wearable sensors. *Communications Surveys & Tutorials, IEEE*, 15(3):1192–1209, 2013.

[24] Grégoire Lefebvre, Samuel Berlemont, Franck Mamalet, and Christophe Garcia. Inertial gesture recognition with blstm-rnn. In *Artificial Neural Networks*, pages 393–410. Springer, 2015.

[25] Jonathan Lester, Tanzeem Choudhury, Nicky Kern, Gaetano Borriello, and Blake Hannaford. A hybrid discriminative/generative approach for modeling human activities. In *IJCAI*, volume 5, pages 766–772, 2005.

[26] Wenfeng Li, Xinyun Hu, Raffaele Gravina, and Giancarlo Fortino. A neuro-fuzzy fatigue-tracking and classification system for wheelchair users. *IEEE Access*, 5:19420–19431, 2017.

[27] Jiayang Liu, Lin Zhong, Jehan Wickramasuriya, and Venu Vasudevan. uwave: Accelerometer-based personalized gesture recognition and its applications. *Pervasive and Mobile Computing*, 5(6):657–675, 2009.

[28] Andrea Mannini and Angelo Maria Sabatini. Machine learning methods for classifying human physical activity from on-body accelerometers. *Sensors*, 10(2):1154–1175, 2010.

[29] Josip Musić, Daryl Weir, Roderick Murray-Smith, and Simon Rogers. Modelling and correcting for the impact of the gait cycle on touch screen typing accuracy. *mUX: The Journal of Mobile User Experience*, 5(1):1, 2016.

[30] Kimitaka Nakazawa, Hiroki Obata, and Shun Sasagawa. Neural control of human gait and posture. *The Journal of Physical Fitness and Sports Medicine*, 1(2):263–269, 2012.

[31] Mark Pedley. Tilt sensing using a three-axis accelerometer. *Freescale semiconductor application note*, 1:2012–2013, 2013.

[32] Thomas Plötz, Nils Y Hammerla, and Patrick Olivier. Feature learning for activity recognition in ubiquitous computing. In *IJCAI Proceedings-International Joint Conference on Artificial Intelligence*, 2011.

[33] Francisco Sepulveda and Alberto Cliquet Jr. An artificial neural system for closed loop control of locomotion produced via neuromuscular electrical stimulation. *Artificial organs*, 19(3):231–237, 1995.

[34] Pekka Siirtola, Heli Koskimäki, and Juha Röning. Openhar: A matlab toolbox for easy access to publicly open human activity data sets. In *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*, pages 1396–1403. ACM, 2018.

[35] Jørgen Skotte, Mette Korshøj, Jesper Kristiansen, Christiana Hanisch, and Andreas Holtermann. Detection of physical activity types using triaxial accelerometers. *Journal of Physical Activity and Health*, 11(1):76–84, 2014.

[36] Y. Sun, G. Yang, and B. Lo. An artificial neural network framework for lower limb motion signal estimation with foot-mounted inertial sensors. In *2018 IEEE 15th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, pages 132–135, March 2018.

[37] Michael R Tucker, Jeremy Olivier, Anna Pagel, Hannes Bleuler, Mohamed Bouri, Olivier Lambercy, José del R Millán, Robert Riener, Heike Vallery, and Roger Gassert. Control strategies for active lower extremity prosthetics and orthotics: a review. *Journal of neuroengineering and rehabilitation*, 12(1):1, 2015.

[38] Heike Vallery and Martin Buss. Complementary limb motion estimation based on interjoint coordination using principal components analysis. In *2006 IEEE Conference on Computer Aided Control System Design, 2006 IEEE International Conference on Control Applications, 2006 IEEE International Symposium on Intelligent Control*, pages 933–938. IEEE, 2006.

[39] Yue Wen, Jennie Si, Andrea Brandt, Xiang Gao, and He Huang. Online reinforcement learning control for the personalization of a robotic knee prosthesis. *IEEE transactions on cybernetics*, 2019.

[40] David A Winter. The biomechanics and motor control of human gait: normal, elderly and pathological. 2. *University of Waterloo, Waterloo*, 1991.

[41] Aaron J Young, Ann M Simon, Nicholas P Fey, and Levi J Hargrove. Intent recognition in a powered lower limb prosthesis using time history information. *Annals of biomedical engineering*, 42(3):631–641, 2014.

[42] Piero Zappi, Clemens Lombriser, Thomas Stiefmeier, Elisabetta Farella, Daniel Roggen, Luca Benini, and Gerhard Tröster. Activity recognition from on-body sensors: accuracy-power trade-off by dynamic sensor selection. In *Wireless sensor networks*, pages 17–33. Springer, 2008.

[43] Mi Zhang and Alexander A Sawchuk. Human daily activity recognition with sparse representation using wearable sensors. *IEEE journal of Biomedical and Health Informatics*, 17(3):553–560, 2013.

[44] Kathryn Ziegler-Graham, Ellen J MacKenzie, Patti L Ephraim, Thomas G Travison, and Ron Brookmeyer. Estimating the prevalence of limb loss in the united states: 2005 to 2050. *Archives of physical medicine and rehabilitation*, 89(3):422–429, 2008.