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Master's Thesis in Embedded Systems

Micro-Activity Recognition using Wearables for Human Augmentation

Luis Alfonso Gonzalez Godinez

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TU Delft Delft University of Technology

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Embedded Software Section
Faculty of Electrical Engineering, Mathematics and Computer Science
Delft University of Technology
Mekelweg 4, 2628 CD Delft, The Netherlands

Luis Alfonso Gonzalez Godinez
l.a.GonzalezGodinez@student.tudelft.nl

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Author
Luis Alfonso Gonzalez Godinez (l.a.GonzalezGodinez@student.tudelft.nl)
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Graduation Committee

Prof. Dr. K. G. Langendoen (Chair)	TU Delft
Dr. Venkatesha Prasad R (Supervisor)	TU Delft
A.U.N. Srirangam Narashiman (Daily Supervisor)	TU Delft
Dr. ir. Arend L. Schwab (External Member)	TU Delft

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Abstract

Wearable devices have paved way for several context-aware applications in the field of health-care and sports to improve the well-being of users and their performance for human augmentation. During rehabilitation patients need accurate feedback that can empower and improve the speed of recovery. On the other hand competitive athletes need a reliable, flexible and real-time feedback on their performance and technique. In this thesis, we present a framework capable of performing *Micro-Activities Recognition* (MAR) by decomposing complex activities. These models employ data only from the wearable devices. We present two real-world applications, *viz.,* (i) the analysis of the *Lunge* exercise performed during knee rehabilitation and (ii) the study of the *Stroke* activity in long-track speed skating.

Hitherto, most of the models used additional data such as camera and 3D tracking for identifying activities. The models proposed in this thesis aims to go one step forward to understand fine-grained activity (micro-activity) information. In knee rehabilitation, we proposed models to identify the exercise performed by the patient and its micro-activities. Providing feedback in these systems is non-trivial due to the overlapping labels. The feedback provided using the models proposed is based on the labels that are highly similar. In speed skating, we aim to identify the micro-activities of the stroke to determine its frequency, and other characteristics of the speed skaters. The model identified the top signal/IMU that can classify a stroke and its micro-activities accurately. The top signal identified the correct number of strokes across all laps. The model was also able to classify a stroke performed in straight and curve sections. Furthermore, the average length and offset values of a stroke for a complete lap is 5.4% and 135 ms respectively.

In this thesis, we derive fine-grained activity information using data from IMUs. The models identified the top signal that maximizes the micro-activity recognition among all the signals. This information can be used to determine the optimal placement of IMUs and also to reduce the data collection/processing. The fine-grained information obtained using MAR can provide meaningful feedback for human augmentation systems.

'Science, my lad, is made up of mistakes, but they are mistakes which it is useful to make, because they lead little by little to the truth."

– Jules Verne, A Journey to the Center of the Earth

Preface

I am proud to present the product of my thesis as part of the Embedded Software group in order to obtain my master in Embedded Systems. This research allow me to put in practice many of the skills developed in the program. Keen on the topics of wearable technology and with a personal interest in sports, I am glad to say I am satisfied with the main topic of my thesis. I was able to understand the process of research and analytical thinking. I gained more knowledge in the areas of machine learning, embedded software, data processing and sport engineering. Together with my supervisor, we work on a real-life solution, proposing a framework that aims for the augmentation of ths capabilities of a user.

This master has been one of the biggest challenges of my career but definitely one of the greatest experiences. This could not have been possible with the people that I met along the way. For this I want to give my gratitude to my family and friends whose support and affection accompany me. To the instructions of my professor Koen Langendoen and finally, with especial remarks, to Akshay S. N who's guidance and dedication as supervisor help me on the production of this project.

Luis A. Gonzalez G.

Delft, The Netherlands
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Contents

Chapter 1

Introduction

The advent of ultra-low power microelectronics and computer systems has led to real-time monitoring of human activities [2]. The ability to observe, measure and track how individuals function in their daily living is fully possible now with the help of Internet of Things (IoT) and wearable devices [1]. Specifically, recognition of human activities has enabled the development of several context-aware applications to improve well-being of the users. Numerous *Human activity recognition systems* are developed to quantify various daily activities performed by users [3, 4] e.g., number of steps, working/sleeping hours, heart rate, etc.

Human activity recognition systems can be broadly classified into two ways *viz.,* (i) external and (ii) wearable [21] as shown in Fig. 1.1. External system requires deployment of sensors in a pre-defined location e.g., training room, laboratory, etc. Inference of activities performed is based on the interaction between these devices and users. This includes deployment of cameras, sophisticated custom hardware and gesture recognizers. The installation cost of the external system is high and also requires complex processing to infer activities performed. In contrast, wearable sensors are attached to the user to identify the performed activities in wearable systems. Inertial measurement units (IMUs) are capable of measuring human biological data, such as physiology and motion. A typical IMU includes: (i) system-on-chip low-power microprocessor, (ii) wireless interface, (iii) MEMS-based IMUs, such as accelerometer, magnetometer and gyroscope, (iv) sensors such as temperature, humidity and heart rate, (v) actuators such as auditory or haptic feedback, (vi) external data storage, and (vii) a power management system (Li-ion battery).

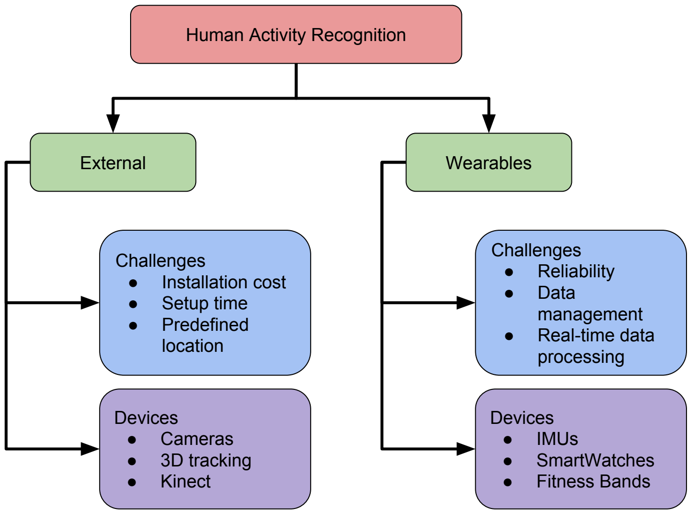


Figure 1.1: Human activity recognition systems.

Several IMU based systems such as Moov[1], X-IMU[2] and Xsens[3] are now commercially available for tracking human activities[4]. The concept of using technology to enhance the performance capabilities of a human is known as **Human Augmentation** [5]. Companies such as *Athos*[5] or *Beast*[6] use IMUs along with *activity recognition models* to track and coach users, e.g. different exercises of a fitness program. Further, several machine learning tools have been widely used for activity recognition [9] to distinguish different activities performed by the user [8, 16] such as walking, running, swimming and rowing [6]. Feedback such as walking speed, total time, distance covered, number of steps, etc., are provided to raise awareness and enhance the performance.

Hitherto, most of the human activity recognition models concentrated on identifying general activities such as walking, running, jumping, cycling and sleeping [54]. While these models provide necessary information on the activities performed, it does not provide fine-grained details during the activity. Recently, Yan et al. [10] proposed a model to break down a complex activity performed by users into *Micro-activities* to improve the accuracy of activity recognition. Further, analyzing micro-activities can be useful to understand the actions performed by a user during an activity, analyze user behavior and finally to provide feedback to improve the activity performed. Iden-

[1] www.moov.cc
[2] www.x-io.co.uk
[3] www.xsens.com
[4] We use the words humans and users interchangeably.
[5] www.liveathos.com
[6] www.thisisbeast.com

tification and analysis of micro-activities is a crucial component in several health and sports related applications for human augmentation.

The use of IMUs in *Human Augmentation* poses several challenges. Some of these challenges are: (i) Reliability: since most of the IMUs are low-cost, the data obtained from these sensors may not be completely reliable; (ii) Data collection/management: high-frequency data coming from IMUs needs to be transmitted to an embedded system or smart phones for processing with low-latency or stored locally with limited in-built memory; (iii) Real-time data processing: the data collected from different IMU poses a challenge on computation in embedded systems such as Raspberry Pi, smart phones and smart watches; (iv) Different sensors: IMUs used in different applications vary with the type of sensors used. Hence interoperability and understanding semantics of the data from different sensors is crucial [11], [12].

Our objective is to develop a framework that employ wearables for human augmentation. Analysis on data obtained from wearables is used to provide coaching to enhance user performance. In this thesis, we introduce a general framework for *Micro-activity Recognition* (MAR) to provide real-time feedback. The framework can be implemented on embedded systems such as Raspberry Pi, Arduino and smart phones/watches. The framework consists of several building blocks and was evaluated with data collected from two applications *viz.,* (i) Knee rehabilitation and (ii) Speed Skating. The framework can be extended to other applications by adding necessary domain-dependent information. We now provide a brief introduction to the two applications considered in this thesis for human augmentation.

Knee Rehabilitation: During knee rehabilitation patients need accurate and periodic feedback on their physiotherapy, ideally as soon as possible. The quality of this feedback to users can empower and improve the speed of the patient's recovery. Analyzing the micro-activities performed by patients can also help the practitioner to increase his expertise and improving their therapy programs. We specifically analyzed one of the most common knee rehabilitation exercise, the lunge. The motivation of this problem is to overcome the fact that patients receive little or no feedback when they perform these exercises away from the clinic resulting into a slow recovery. We present a methodology that provides accurate feedback on the exercises performed by the patients during knee rehabilitation. Specifically, we propose a two-stage methodology; first, we identify the activity (exercise) performed and its corresponding micro-activities. Second, we classify the micro-activities to a set of labels that represent the exercises performed.

Speed Skating: It is a competitive form of ice skating, where skaters race each other. In this competitive sport, skaters use the feedback given by the coaches to correct their technique and improve their performance. Most of the remarks done by the coaches rely on qualitative observations and may not be accurate. Several efforts have been proposed to use wearables and other sensors to monitor skaters and improve their performance. Moreover, most of these systems aim to understand what is the time taken for a lap and corresponding speed timings. In this thesis we aim to understand each activity (strokes) in speed skating to provide feedback and improve the performance of skaters. Specifically, we identify the micro-activities within a stroke like *glide*, *push* and *reposition*. We aim to provide feedback on these micro-activities to improve skaters technique and eventually increase the performance.

In this thesis, we employed real-world data collected from several participants for the above applications. The data acquisition system for knee rehabilitation includes a knee coach composed of *two* IMUs and for speed skating, *seven* IMUs were used together with force sensors and 3D tracking. Note that, the data collection is not part of this thesis. We used the data collected by Dutch coast [13] for knee rehabilitation and we used data collected by STW project [14] for speed skating. In both applications several participants were involved during data collection along with a domain expert to provide annotations.

Thesis Outline

This thesis is organized as follow. We first introduce the problem related to micro-activity recognition and propose a generic framework in Chapter 2. In Chapter 3 we present details of knee rehabilitation application. We first enumerate specific problems of this case and describe our approach to identify the micro-activities of the lunge exercise to provide feedback during rehabilitation. In Chapter 4, we provide a brief introduction to speed skating and the different activities involved. Further, we describe our approach to identify and analyze micro-activities in a stroke to provide feedback. Chapter 5 describes the experimental evaluation of the MAR models proposed for both the applications. Finally, we conclude in Chapter 6 and state proposals for future work.

Chapter 2

Problem statement

Smart devices such as wrist bands, smart watches and wearables are increasingly being used to analyze user activities and behavior modeling [7]. These devices monitor users in their daily routines, fitness routines, competitive sports and health care to collect activities performed and provide associated statistics [3]. These statistics enable users to analyze their activities and possible ways to achieve their goals like running a kilometer every day, counting the number of steps walked, performing fitness exercises and so on.

2.1 Related work

Most of the wearable devices fail to identify similar activities performed by the user and further do not provide fine-grained information on the activities performed [15]. Analyzing activities at micro-level enables a unique view in understanding user activity and to provide detailed feedback for enhancing user performance. Some of the challenges involved in micro-activity recognition (MAR) using wearables are: (i) The efficacy of the MAR model will depend on the dataset used for training, e.g. number of data samples, diversity, consistency, validation data, etc.; (ii) Use of appropriate machine learning approach to analyze micro-activities, since each application/domain requires different type of micro-activities to be recognized; (iii) Near real-time identification of micro-activities calls for low-latency data communication between IMUs and the embedded devices, distributed data processing and online algorithms; (iv) Since micro-activities can be defined in several ways, MAR models require domain experts to provide information on the micro-activities. Hence identifying micro-activities across multiple applications is challenging. We now describe the problems associated in MAR for knee rehabilitation and speed skating.

Knee rehabilitation: There are around 10.4 M patients visiting doctors for common knee injuries such as fractures, dislocations, sprains and ligament tears every year [44]. Most of the knee injuries can be successfully treated through rehabilitation exercises and some may require surgeries. After an injury or surgery, physical therapy for rehabilitation include exercises that are designed to improve strength of the knee muscles [18]. Patients attend regular sessions with the therapist during the early rehabilitation stages. Apart from the periodic visits, patients must also perform the targeted exercises regularly at home. This eventually quickens the process of rehabilitation. The therapist monitors the patient progress in the clinic; however patients have no feedback when performing the exercises in their home. This might lead to longer recovery process or cause further injury if sufficient care is not taken [17].

Several research efforts considered the use of various hardware to recognize the exercise performed by patients and to provide feedback [53, 48, 47]. The standard approach to measure the performance of a patient involves the measurement of the knee angle with a tool called goniometer [19]. Most often, this is done by observation since electronic goniometers/torsiometers [1] are capable of measuring the knee angle only in motion. Current techniques employ expensive hardware like kinect health or video processing to track patient activities and provide feedback on how well the exercises are performed [45, 46]. To this end, recent research works aim to determine the knee angle using low-cost sensors. Torsiometers and flex-sensors [52] have a good accuracy in determining the knee angle but are difficult to setup [48, 23]. Other techniques employ expensive hardware like kinect health [22] or video processing [25] to track patient activities and provide feedback on how well the exercises are performed [45, 46]. Dejnabadi et al. [51] and Tomaru et al. [53] make use of IMUs like magnetometers, gyroscopes and accelerometers to determine the knee angle. They employ kalman filters to estimate the angle towards ground in a 3D space. Another approach employs artificial neural networks along with IMUs for measuring the knee angle [47]. Ahmadi [20, 24] considers the use of an automatic activity classification using random forest approach. Most of the proposed techniques in literature aim to understand the knee angle using the IMUs. However patients have little knowledge on knee angle based feedback. Hence, we aim to analyze the micro-activities in a exercise to determine the position of the knee and use pre-defined labels to classify how accurately each participant performed the exercise.

There are many exercises to be performed during knee rehabilitation based on the injury. In this thesis, we focus on the lunge exercise. Lunges are one of the common knee rehabilitation exercise performed to increase the knee

[1] e.g. http://www.biometricsltd.com/gonio.htm

strength and control. To eliminate the labor intensive process mentioned previously, we design a system that can collect information on how patients perform knee rehabilitation exercise. Further, we develop a methodology to identify the exercise and its corresponding micro-activities to provide accurate feedback for the patients. This enables them to perform the exercise as described by the therapist and also understand what they are doing wrong. In Chapter 3, we provide detailed overview of the lunge exercise and the methodology to identify micro-activities involved in lunges.

Speed skating:
Speed skating is a competitive sport where athletes are timed for a set distance on an ice rink. In speed skating, the performance of the skaters can be monitored by comparing time, e.g lap time, and making remarks by observing their technique. Monitoring an athlete at all points of an long-track ice rink (typically 400 m) is difficult. Furthermore, when there are more than one skater on the ice rink, it is very hard to identify and analyze the techniques at various parts of the lap. Speed skaters performance is generally examined by the use of video analysis. During training, skaters perform several laps with different techniques and based on the feedback received by the expert. This training period is later analyzed to understand the pitfalls and to improve the performance of the skater.

The performance of speed skating depends on the mechanical power output delivered by the skater and the power required to overcome the frictional forces [39]. In speed skating the total power output is the product of work per stroke and stroke frequency [33]. Particularly stroke frequency is used to identify the skating velocity. Each stoke consists of three different phases *viz.,* glide, push-off and repositioning phase [40, 30]. Most of the related work on improving speed skaters performance studies the delivered power output by skaters using the kinematic characteristics such as knee angle, trunk angle and push-off angle [28]. In [32], multiple digital cameras and radio-frequency identification tags was used for data acquisition and to measure kinematic characteristics of speed skaters. Ahmadi et al. [24] uses a *motion analysis framework* to recognize activities by integrating classifiers (such as Lazy IBk, Naive Bayes, and random forest) with signal processing for analyzing performance and techniques of speed skaters. A three dimensional inverse skater model to analyze speed skating motion on the straight part of the ice rink is proposed in [35]. Recent works [34, 36, 37] consider IMUs deployed on the speed skaters along with several sensors on the skate to identify kinematic characteristics and analyze the performance of speed skaters. Recent projects target providing real-time feedback for better skating performance[2] [14] by analyzing the data collected from several professional speed skaters.

[2]http://skatescience.nl/

In this thesis, we employ the data collected in [14] to determine stroke frequency. Furthermore, we develop semi-supervised methodology to analyze IMU data to derive the micro-activities (glide, push-off and repositioning) within a stroke. The objective is to classify the different phases/micro-activities in a stoke to be able to provide detailed information to the skaters. Identifying the number of strokes, length of a stroke and different phases in a stroke is useful for coaches to understand the technique of the speed skaters. This can further be used to analyze the performance and compare techniques with other skaters.

Therefore, to summarize, the research questions we try to answer in this thesis are: (i) How to identify micro-activities in different applications with minimal domain knowledge? (ii) Which IMU sensors are most optimal to identify micro-activities? (iii) What type of feedback can be provided for human augmentation using IMU data?

2.2 General framework

To address the above research questions, in this thesis we propose a generalized framework on *Human activity recognition.* This framework is employed to identify micro-activities and to provide feedback. Fig. 2.1 shows the proposed generalized framework with building blocks *viz.,* (i) data collection, (ii) data processing, (iii) modeling (iv) ranking model and (iv) evaluation & feedback.

Data Collection: Each application requires data collected at various levels and different granularities. Some of the data sources are *viz.,* (i) External sensors such as cameras for video/image capture, kinect and 3D tracking; (ii) IMU sensors, e.g., accelerometer, magnetometer, gyroscope; (iii) Environmental data, e.g. temperature, barometric pressure, light intensity; and (iv) Qualitative data provided by an domain expert (e.g., physiotherapist, coach) with annotations and labels.

Data Processing: The raw data from the above sources may include outliers, noise, different units, etc. Hence, most often the data needs to be processed before applying any data modeling techniques. Use of filters such as low-pass and kalman filters help to reduce noise, drift and outliers. Furthermore, when qualitative data is available the raw data can be annotated with labels for data modeling. After processing the raw data, significant features such as *min, max, mean, standard deviation, zero-crossings and fundamental frequency* can be obtained. Feature extraction enables to reduce the amount of data stored or transmitted for data modeling.

Modeling: Data modeling is a crucial step in activity recognition. Prevalent research has proposed various modeling techniques for activity recogni-

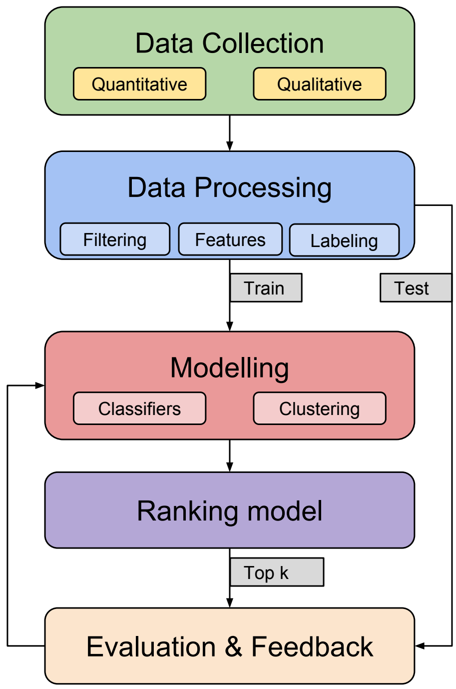


Figure 2.1: General framework diagram for Activity recognition

tion. These include various classifiers (*KNN, iBk , decision trees, rules* and clustering techniques such as *Expectation-maximization* (EM) and *k-means* (KM).

Ranking Model: The main objective of the ranking model is to rank the signals/sensor data that can provide the best outcome for activity/micro-activity recognition. Ranking the signals/data is a fundamental problem in information retrieval. Typically, ranking is performed based on certain accuracy/error metrics. Several ranking models have been proposed in literature and it depends on the application [26, 27]. Some of the well known ranking models are AdaRank, RankBoost, Combined Regression and ranking (CRR) and BayesRank. In Chapter 3 and 4, we describe the ranking models employed for micro-activity recognition in knee rehabilitation and speed skating.

Evaluation/Feedback: The evaluation block uses the model developed to determine the activity/micro-activity labels. This block utilize the top-k results/signals to evaluate new or existing data. Using only top-k signals will allow for real-time evaluation and comparing with ground truth. The information on the activities/micro-activities identified are then utilized to provide feedback.

In summary, the main contributions of this thesis are:

1. We propose a methodology to accurately classify the exercises performed by the patients during knee rehabilitation. The proposed ranking model determines the most influential features that can accurately identify the set of labels that are similar to the exercise performed (Chapter 3).

2. We propose a methodology for stroke classification using IMU data from speed skaters. The proposed model can distinguish different phases within a stroke to analyze the techniques employed by the skaters (Chapter 4).

3. We describe in detail the empirical evaluation of the proposed models by utilizing real data sets collected from various participants (Chapter 5).

Chapter 3

Knee Rehabilitation

In this chapter, we employ IMUs to assist human augmentation for enhancing human productivity and restoring capabilities of the human body. Specifically, we address the problems involved in physical therapy during knee rehabilitation of patients. Generally, the therapist monitors the patient progress in the clinic; however patients have no feedback when performing the exercises in their home. This might lead to longer recovery process or cause further injury if sufficient care is not taken.

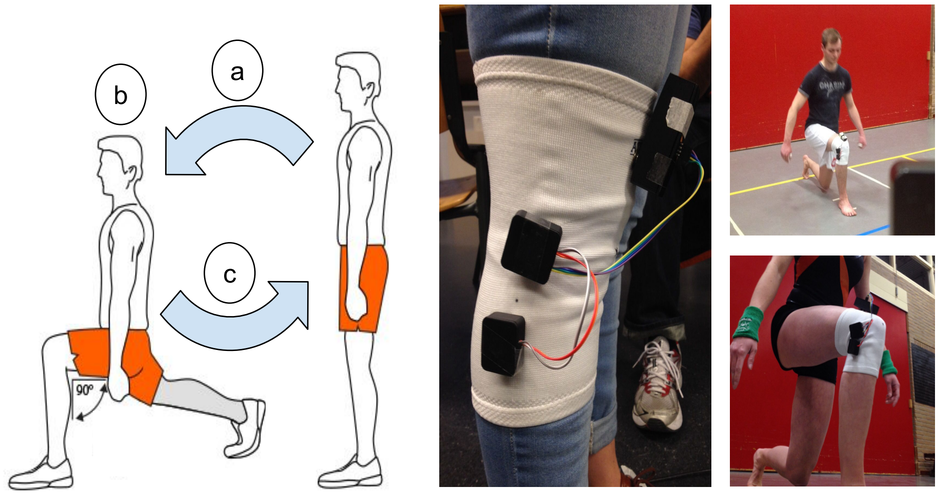
This labour intensive process has several limitations *viz.,* (i) the therapist is not aware of how accurately the exercises are performed by the patients; (ii) patients have no feedback on the exercises performed and their suitability thus they require regular visit to the doctors; (iii) patients may lose motivation when performing exercises at home due to lack of feedback; and (iv) doctors need to keep track of the exercises and specific details for each patient. Recent research efforts have deployed several wearable devices on human body to monitor different exercises performed by the patients. These solutions collect data from various IMUs such as accelerometer, gyroscope and magnetometer to determine the knee joint angle, movement techniques, and other temporal aspects of gait [47, 48].

Feedback provided using these mechanisms can be broadly classified into the following: (i) *knee angle based–* this indicates the deviation of knee movements compared to the correct positions; and (ii) *activity label based–* this classifies the exercises to one of the labels defined by the therapist and appropriate feedback is provided based on the identification. Even-though the above approaches aim to provide information on the exercises performed, patients often cannot relate directly to the exercises. For example, feedback on the knee joint angle cannot be understood by the patients to correct the exercises performed. Similarly, labels obtained by the therapist are generally a rough approximation. Feedback based on the identified label may not be accurate as there could be multiple labels associated with the same exercise performed [44]. The labels are defined by the therapist using visual inspections and are generally ill-defined. Current approaches apply binary classification to identify the closest label based on the exercise performed [49]. This results in providing inaccurate feedback to the patients. The activity label based feedback systems has two major challenges,

1. *Composite activity* – An exercise in rehabilitation is not a simple activity. Many exercises are composed by several instances of simple activities, i.e., a composite activity consists of a series of several micro-activities. For example, a lunge exercise involves stepping forward, steady position and stepping back. Hence activity recognition needs to consider micro-activities performed during an exercise.

2. *Overlapping labels* – Most of the labels defined are based on the visual inspection of the therapist. These labels are generally overlapping due to the approximation and inconsistency in definition of labels across therapists. Hence label based feedback systems need to identify multiple related labels rather than a single label to provide accurate feedback.

In this Chapter, we address the above issues and present a methodology that provides accurate feedback on the exercises performed by the patients during knee rehabilitation. Specifically, we propose a two-stage methodology; first, we identify the composite activity performed and its corresponding micro-activities. Second, we classify the micro-activities to a set of labels that represent the exercises performed. A knee band comprising of IMUs is developed to collect data related to the lunge exercise performed. Furthermore, we propose a novel mechanism to classify the micro-activities to one or more labels defined by the therapist using the data collected. Finally, based on the identified labels, appropriate feedback is provided to the patients on the lunge exercise. For instance, if the lunge exercise performed is classified as "instable" label – refers to the instability in the end position of legs – the feedback provided to the patient includes the part of the lunge which was instable due to excessive movements or vibrations. This feedback can be provided via the mobile phone or in-home displays or web-based applications in near real-time. Note that the methodology presented here is applicable to other exercises in knee rehabilitation.



(a) Lunge exercise (b) Knee band with WIMUs

Figure 3.1: Lunge exercise and the knee band used for data collection.

3.1 Activity: Lunges

Lunges are one of the most common knee rehabilitation exercise performed to increase the knee strength and control after an injury. Each lunge exercise is a composite activity, which includes several micro-activities, (a) step forward, (b) steady position and (c) step backward. Fig. 3.1(a) shows the different micro-activities involved while performing a lunge exercise. Hitherto, most of the feedback systems only identified either a lunge exercise was performed or not [24]. However, each lunge is composed of several micro-activities and identifying the micro-activities correctly can enhance the feedback systems.

3.2 Data collection

The data acquisition setup includes a knee band, which contains two IMUs and an Arduino board for data processing. The data was collected with the help of Dutch-Coast company [13]. The placement of IMUs depend on the positions that can provide the maximum information of the performed lunge exercise. We identified two positions, one on the upper leg and the other on the lower leg, which captures the position and movement of the corresponding leg [47]. Each IMU consists of 3-axis accelerometer, gyroscope and a magnetometer. Fig. 3.1(b) shows the knee band worn by the patient. We used LSM9DS0 from ST micro[1] as the IMU. LSM9DS0 has a linear

[1]LSM9DS0 product sheet [online] https://www.adafruit.com/products/2021.

acceleration full scale of $\pm 2g$ *to* $\pm 16g$, a magnetic field full scale of ± 2 *to* ± 12 gauss and an angular rate of ± 245 *to* ± 2000 dps. This enables to track the motion accurately. Furthermore, 16 bit range with sampling rate of 50 Hz was used for data collection. The sensed data is then transmitted to the Arduino board using Bluetooth Low Energy (BLE).

The knee band developed is portable and can be used by the patients anywhere. We collected data from six participants, four males and two females. Participants from different age groups were chosen for this study in order to provide variations in the data collected. Each participant was asked to perform their normal routine during rehabilitation, which includes a 10 min warm-up followed by several lunges. In total around 200 lunges were performed by the participants. Furthermore, video footage from the data collection session was recorded for ground truth information. A therapist analyzed the lunge exercise performed by the participants and with the help of video footage and each lunge performed by the participant was labeled. The labeling was to classify how accurately each participant performed the lunge exercise. Eight labels were defined *viz.,*

- ***Over*** indicates the over flexion of the knee. In this application, the knee cap is beyond the position of the foot due to over-leaning in the forward direction.
- ***Knee In*** (KI) indicates that the knee flexes were inside the body. This is due to bad rotation of knee or wrong leg angles while performing the lunge.
- ***Knee Out*** (KO) indicates that the knee flex is outside the body.
- ***Instable*** (Ins) indicates the instability in the end position of legs due to excessive movement or vibration.
- ***OverIns*** refers to Over instable, which is a combination of Over and Instable.
- ***Good*** indicates that the lunge exercise was performed properly.
- ***Small*** indicates that a small step was used during the lunge. Producing a short angle flexion of the knee.
- ***Fast*** indicates that the lunge is done faster than average, leading to a short time in the steady phase.

The data collected was segmented into repetitions during post-processing. The sensors were calibrated to identify the starting position i.e., standing straight. Furthermore, a simple automated segmentation method that identifies the starting position was employed to segment the data collected into

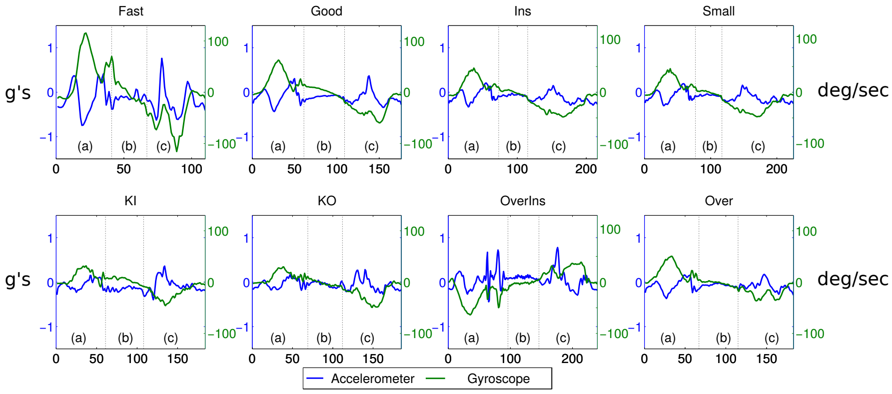


Figure 3.2: Accelerometer and gyroscope raw data from IMUs for different labels.

repetitions. Fig. 3.2 shows the raw accelerometer and gyroscope data for different labels along with the micro-activities. The different micro-activities are labeled as (a), (b) and (c) corresponding to stepping forward, steady position and stepping backward respectively. The x-axis represents the sample numbers.

3.3 Micro-activity Recognition

Activity classification is used to identify the exercise performed during the rehabilitation. This can be further used to evaluate the performance of the exercise. In this section, we first describe a traditional approach to classify lunges. Furthermore, we propose two methodologies, (i) Average Signal Model (ASM) and (ii) Ranking Model (RM) to classify the lunge exercise.

3.3.1 Traditional classifier

Fig. 3.3(a) shows the traditional classifier model used to classify lunges performed during rehabilitation. As mentioned previously the collected data from IMUs are segmented to repetitions, where each repetition represents a lunge. The data is split according to 90-10 rule where 90% of the data is used for training and the remaining 10% of the data is used for testing. Several features were extracted from each lunge repetition and a classifier model is developed using the features extracted. We employed three classifiers: NaiveBayes (NB), decision trees (J48), and K-nearest neighbor (IBk) for classifying each repetition. During evaluation, each repetition was evaluated to the closest label.

The traditional classifier has several drawbacks. First, since the entire lunge is used for classification, micro-activity recognition is not possible. This results in considering activities which may not be significant. For ex-

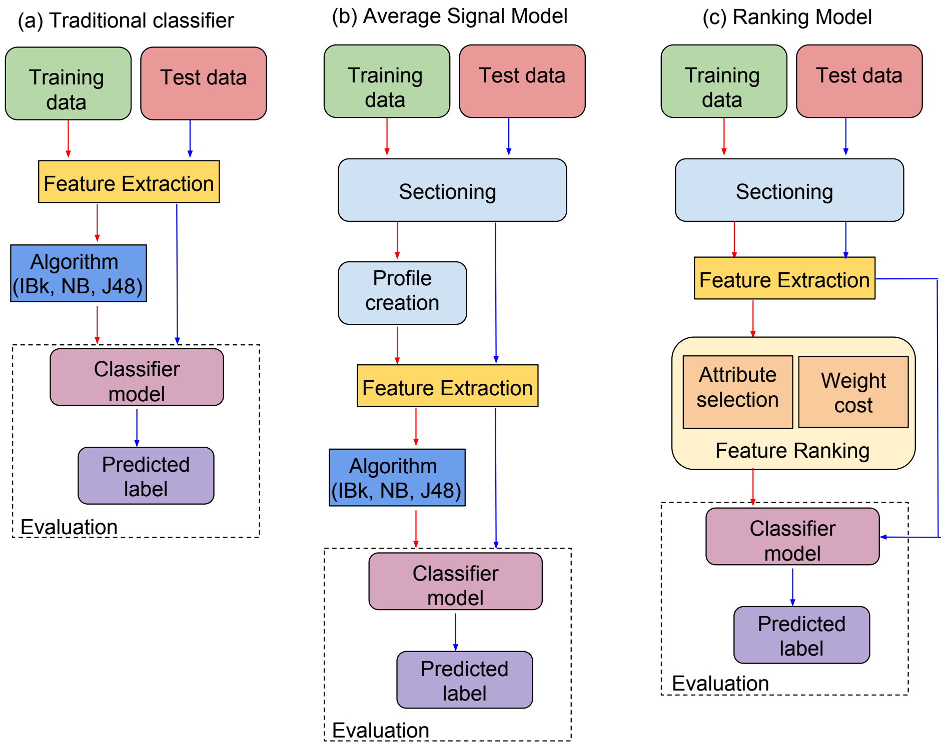


Figure 3.3: Proposed micro-activity classification models.

ample, in a lunge stepping forward and stepping backward are not crucial. However, the lunge steady position is the most significant micro-activity that can provide more information on how good the lunge was performed. Second, the traditional classifiers are generally binary i.e., it classifies a repetition to a label or not. However, most of the labels defined in rehabilitation and other human augmentation applications have multiple overlapping labels. Hence, classifiers should not only identify the closest label but also similar labels for each repetition. Third, due to the biased results to one of the labels, the feedback provided may not be accurate.

3.3.2 Average Signal Model

To overcome the above issues, we propose average signal model (ASM) that first sections a composite activity into micro-activities and then classifies the test data by comparing it to the average signal for each label. Fig. 3.3(b) shows the proposed ASM model. The major components are: sectioning, profile creation, feature extraction and evaluation.

Sectioning: The objective of sectioning is to determine the micro-activities from the composite activity. For example, a lunge exercise has three sections *viz.,* forward, steady and backward as shown in Fig. 3.1. We employ an unsupervised clustering approach to determine the different sections from each repetition. Clustering approaches such as Expectation Maximization (EM) and k-means (KM) with different configurations was empirically evaluated across all labels and repetitions. EM clustering with 3 clusters was able to accurately identify the sections (or micro-activities) across all repetitions.

Profile creation: This component determines an average signal for each label in the dataset. The objective is to create a golden profile for each label, which can be used during classification of a new repetition. We select the steady state of the lunge from the sectioning. Since the steady state of the lunge is the crucial micro-activity, we focus only on this micro-activity. Profile creation first determines the average length of the steady state for each label. Since, each repetition may have varying time, we apply time wrapping (DTW) to stretch or shrink the micro-activity such that all the repetitions of a label have the same length. We then merge all the corresponding signals for that label to obtain an average signal. For example, we determine the average length of steady state for all good lunges and then merge all accelerometer x signals of the good repetitions into one. Finally, the merged signal represents the golden profile for that label. This merged profile for each label can be used to compare and identify the similarity between the lunges.

Feature extraction: Several features from golden profile of each label are then extracted for classification. The extracted features include fundamental frequencies (FFT), mean crossing, standard deviation, root mean square, max, minimum, mean, and size (n samples). Furthermore, features, such as signal difference between two signals and root mean square of difference were also extracted. We employed three classifiers, NB, J48, and IBk for classifying each repetition of a lunge using the average signal.

Evaluation: In this block, a repetition is evaluated with the average signal of each label. The label that is similar to the repetition is then selected as its corresponding label.

ASM model sections a composite activity into micro-activities. Furthermore, the test data is compared across all golden profiles of each label and the closest label is selected. However, ASM model still cannot identify labels that are similar. Consequently, any mis-classification will result in providing inaccurate feedback.

3.3.3 Ranking model

Ranking model (RM) aims at determining the set of labels that represent the test data. The objective of the proposed model is to extend binary classifiers previously proposed to determine the set of labels that are close to the test data. Since, the labels across micro-activities are generally overlapped identifying the set of labels that are similar enables appropriate feedback to patients. Fig. 3.3(c) shows the ranking model along with its components. The functionality of sectioning and feature extraction block remains the same as ASM. A feature ranking block is added to identify the most influential features for each label. This information is further utilized to determine the set of labels that are similar.

Feature Ranking: In ASM all the features were used to classify the test data. This results in inclusion of features that are similar or noisy, resulting in poor classification accuracy. Feature ranking block identifies the most influential features for each label. This saves computation time and considers only features that are important for that label.

In order to identify features that are influential for a particular label, we apply weighted cost along with attribute selection ranking tool from WEKA [50]. The attribute selection ranking provides a set of features that are most influential across all labels. However, since we want the features that are influential for each label, a weight cost is applied that penalizes a feature during mis-classification. This ensures we derive the most influential features for each label. This also helps in faster convergence. Finally, we use this ranked features for each label to build a classifier model. The resulting model includes the probability density function (PDF) of a feature across labels.

Evaluation: The test data is first sectioned and corresponding features from the steady state of lunge is extracted. The top-k feature vectors that are obtained from the feature ranking block are used for evaluation. We select the set of labels that has high values for the corresponding features, e.g., labels within 0.2% of standard deviation. The resulting list of labels indicates the labels that are closest to the test data.

The ranking model determines the labels that accurately represent the test data using the feature ranking method proposed. The feature ranking method ensures that the feature, which improves the classification accuracy is selected. Furthermore, by calculating the probability density function (PDF) for each top feature, one can select the set of labels that are similar rather than selecting one label (generally the one with highest value). Feedback systems can now exploit this to provide feedback based on the set of labels determined for a repetition.

In Chapter 5 we describe the evaluation methodology and present the classification accuracy of identifying different micro-activities. In the next Chapter, we present the details of MAR model for stroke classification in speed skating.

Chapter 4

Speed Skating

Speed skating is a competitive sport where athletes are timed for a set distance on an ice rink. A typical long-track for international competitions has a distance of 400 m per lap according to the regulations of the International Skating Union (ISU) [31]. Each lap is composed of four sections *viz.,* two straight and two curves as shown in Fig. 4.1. In speed skating, the skater gains forward propulsion by pushing side wards each leg, each cycle of the leg is called *stroke*. A complete left and right stroke together is called a *cycle*. Furthermore, a stroke can be further classified into three types *viz.,* straight, curve and transition. A transition stoke could be described as the stroke in-to-the curve and out-of-the curve.

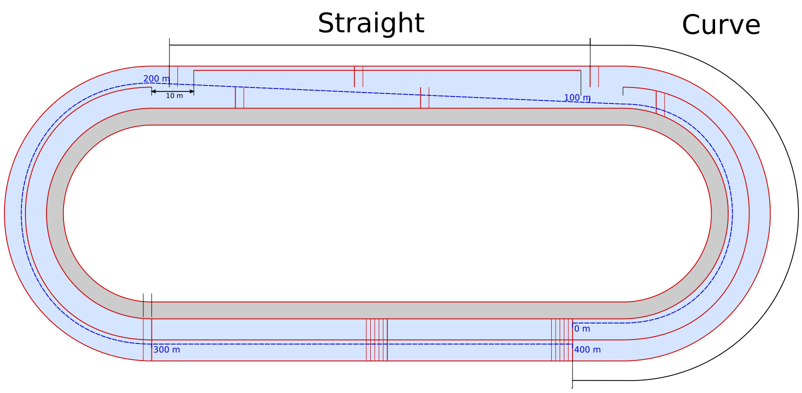


Figure 4.1: 400 m Speed skating rink [42].

Several research efforts have concentrated to analyze speed skaters movement to improve their performance and technique [32]. Specifically, work per stroke, stroke frequency, and speed of skaters are monitored and analyzed to provide detailed feedback. However, most of the techniques proposed employ either expensive hardware such as camera modules or 3D tracking [34] to know these features and other kinematic characteristics such as knee

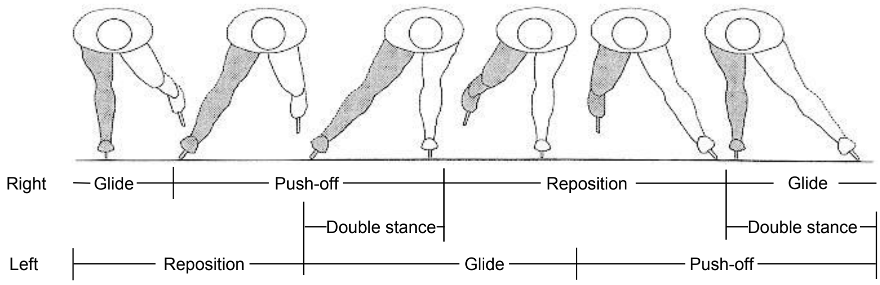


Figure 4.2: Phases of a stroke: push-off phase, glide phase and reposition phase [30]

angle, trunk angle and push-off angle [30, 41]. While these techniques are already in practice they also require lot of data processing to obtain information about the performance. Recent works [36, 37] employ IMUs and force sensors to understand the stroke frequency, mechanical power output, and other kinematic characteristics. We build on top of the existing techniques to determine the number of strokes in a lap, length of each stroke and the different phases of the stroke.

In this thesis, we aim to identify and classify a stroke using *only IMUs data* for providing feedback to skaters. In speed skating each stroke has three phases *viz.,* glide, push-off and reposition. We adapt our framework described in Chapter 2 to identify strokes, classify into straight and curve. Furthermore, our model can identify the different phases of a stroke (i.e., micro-activities). Identification of these micro-activities can be useful to obtain detailed information on the technique employed by the speed skaters. Furthermore, analyzing the length of a stroke and frequency of a stroke will provide fine-grained information to improve the performance of the skaters. In this chapter, we present the details of a stroke along with its micro-activities followed with description of the data collection procedure. Finally, we describe the model proposed to identify and classify strokes.

4.1 Activity: Strokes

In this section we describe in more detail the strokes and its different micro-activities. Fig. 4.2 shows the different phases of a stroke. The three micro-activities are:

- ***Glide***(G) In this phase the body is supported over one leg, being the transition between reposition and push-off.

(a) IMU sensors on skaters body [43].

(b) Force sensors on the skate.

Figure 4.3: Location of sensors deployed during speed skating.

- ***Push-off*** (P) Right after the glide phase the skater pushes sidewards away from the body extending the leg almost completely. The Push-off finishes when the skate is lift off from the ice.

- ***Reposition***(R) The skate is retracted back to the center of the body. In this phase the skate is on the air, thus the force sensors register it's minimum value.

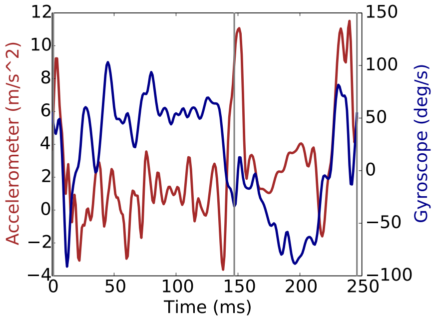
The intersection of the final part of the Push-off of one leg and the first part of the other leg's Glide, is called *Double stance* (DS) [35]. During double stance both skates are in contact with the ice. The distinction between the left and right stroke can also be seen in Fig. 4.2. Further, each left/right stroke has an independent *Glide, Push-off, Reposition* (GPR) cycle. Moreover, each stroke can belong to straight section or curve or transition.

4.2 Data collection

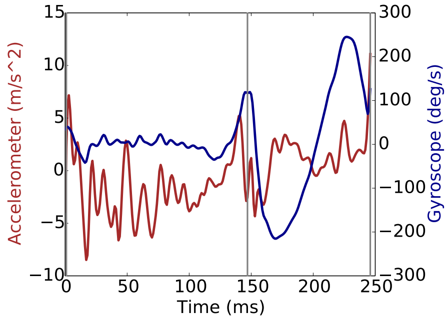
We employ the data set collected in a STW project called *Real-time feedback for better skating performance* [14]. In this project, a wearable body suit sensor system along with 3D tracking system was employed to collect data from several speed skaters [36, 38].

The wearable body suit consists of *seven* motion capture Shimmer IMUs[1] and *four* force sensors. Fig. 4.3a shows the distribution of the Shimmer IMUs on skaters body. There is a IMU on upper back of the skaters followed with two sensors on the lower leg, upper leg and on each skate. Fig. 4.3b shows

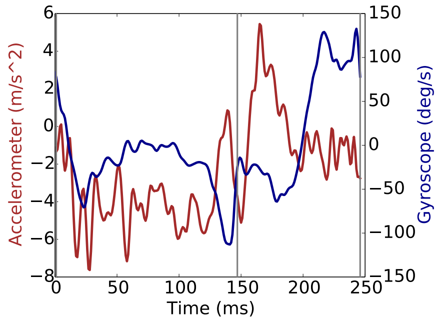
[1]Shimmer: http://www.shimmersensing.com



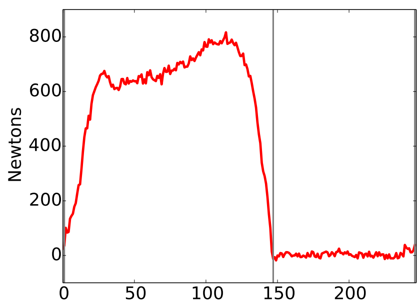
(a) Right skate IMU



(b) Right lower leg IMU



(c) Rigth upper leg IMU



(d) Rigth leg stroke Force

Figure 4.4: Raw accelerometer, gyroscope and force data.

the location of the instrumented skates' [37] force sensors. Each skate has two force sensors one in the front and the other in the back. This results in 54 signals from 7 IMUs (each consists of accelerometer, gyroscope) and 4 force (all with 3-axis) sensors. The 3D tracking includes Qualisys systems[2] for accurate data collection of biomechanics coordinates in a 3D space.

The IMUs and force data from the skaters were collected for the complete lap. However, the qualisys tracking system recorded a 50 m straight section of the ice rink. Hence qualisys data is available only on a part of straight section. The data from both the systems had a common timestamp with a sampling frequency of 100 Hz. The qualisys data was used to label the straight part and to synchronize the data collected. Four skaters, two female ($P1$,$P2$) and two male ($P3$,$P4$) participated in the data collection process. We utilized 29 laps of straight section data from all the four participants and two complete laps from $P2$ and $P3$ for our analysis.

Fig. 4.4 shows the raw accelerometer, gyroscope and force data from

[2]Qualisys: http://www.qualisys.com/

3 IMUs on right leg and the force sensor data of the right skate for a stroke. Note that, analyzing force data with simple machine learning tools can already derive micro-activities. However, in this thesis we aim to use data only from IMUs (accelerometers and gyroscopes) for stroke and micro-activity recognition.

4.3 Micro-activity Recognition

Pattern recognition techniques such as classification and clustering are widely used to recognize activities [29]. The key challenge is to find the proper mechanism that employs minimal data to identify the activity and its micro-activities. In this section we describe the approach used to identify strokes and its micro-activities. We restrict the classification of strokes to only straight and curve sections. Since there is no clear definition of a transition section we classify all the strokes as either straight or curve. In an ideal scenario, the first and last stroke of the curve could be termed as transition. Furthermore, we identify the combination of *Glide, Push-off* (GP) and *re-position* micro-activity from the IMUs data. Note that, we do not employ force data for identification of micro-activities.

The proposed MAR model for stroke recognition employs semi-supervised clustering mechanism to recognize the various micro-activities using IMU data. Fig. 4.5 shows the proposed *Signal Ranking Model* (SRM) for stroke identification. The different building blocks of the model are:

Data: We used data from three sources *viz.,* (i) IMUs, (ii) 3D tracking system (iii) Force sensors. However, we use only IMUs data for micro-activity (GP and R) recognition. The force and 3D tracking data was used as ground truth to evaluate the accuracy of our models. The raw data from the IMUs are pre-processed with a low pass filter to remove any outliers, gaps, and eliminate partial data.

Clustering: To identify the different micro-activities, we employ an semi-supervised clustering mechanism like Expectation Maximization (EM). EM algorithm takes the IMU signal data to derive a *cluster sequence*. Moreover, other clustering mechanisms like K-means and Support Vector Machines (SVM) can also be used at this stage by specifying the number of clusters equivalent to the micro-activities to be recognized. The number of clusters from EM will determine the micro-activities and the length of each cluster sequence represent the length of the micro-activity. Fig. 4.6 shows an example of cluster sequence using EM clustering mechanism on a IMU signal (Right Skate Gyroscope Z) with a filter of 1.5 Hz. The cluster sequence is compared with the right skate force data (ground truth). The grey lines mark the ground truth point for the beginning and end of a micro-activity. The combination of two cluster sequences (GP and R) represent a stroke.

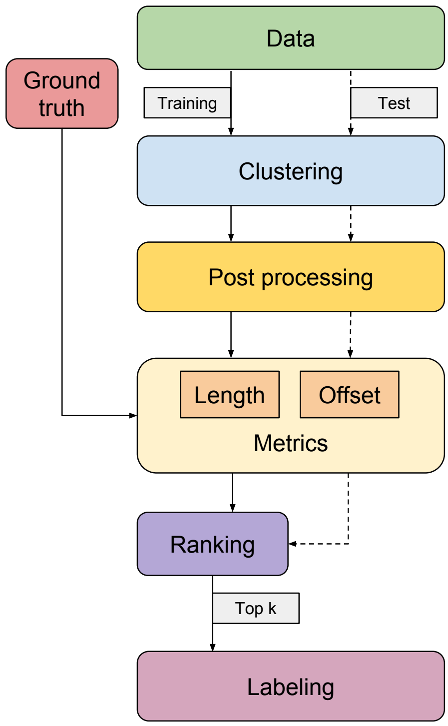


Figure 4.5: Signal ranking model along with training and testing phase

Post Processing: During our analysis, we found that IMU signals at the beginning of the lap has some variation/noise. This may be due to the initial impact of skate in the ice or the data collection error. Hence we discarded few initial data samples from the cluster sequence. The algorithm computes the length of the first cluster sequence and if the length of the sequence is less than 50 frames, we discard the first cluster sequence. In Fig. 4.6, the first cluster sequence (blue dotted line) is less than 50 samples and hence is eliminated before evaluating the micro-activities. We selected 50 frames since, average micro-activity in speed skate is always greater than 50 frames.

Ranking model: The wearable body suit has 7 IMUs with 2 sensors (i.e., 3-axis accelerometer and gyroscopes) resulting in 42 signals, it is important to identify the top signals that can accurately identify micro-activities. To this end, we propose two metrics that can be used to evaluate the cluster sequences obtained against the ground truth. The ranking model aims to select top-k signals that maximizes the micro-activity recognition and minimize the metric value. The two metrics considered in this ranking model are *length* and *average offset*.

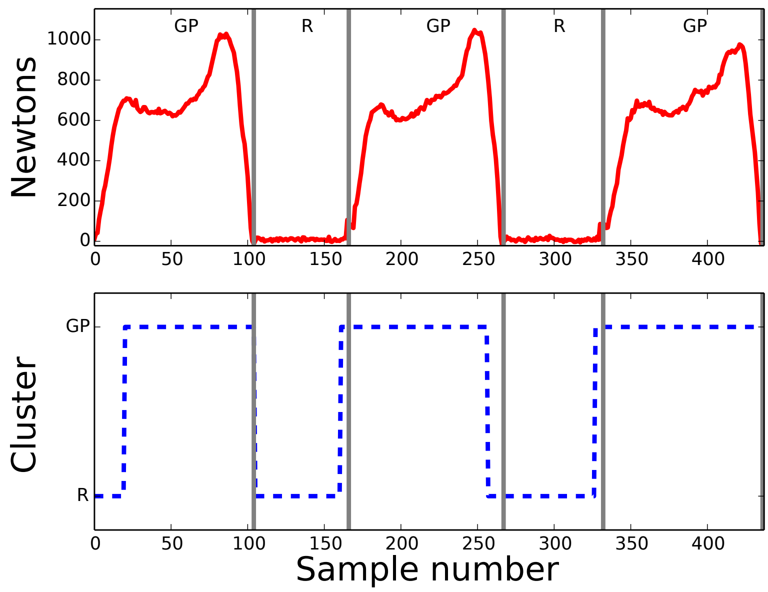


Figure 4.6: Cluster sequence of a IMU data vs Ground truth (force data)

- Length: The length metric is the difference between the length of the stroke from ground truth and the length of the stroke obtained from the cluster sequence. The average length metric for all the sections (N) of a lap is defined as,

$$\frac{\sum_{n=1}^{N} abs(\frac{len(GT_n)-len(C_n)}{len(GT_n)})}{N} \tag{4.1}$$

  where $len(GT_n)$ is the length (in frames) of the ground truth micro-activity and $len(C_n)$ the length of the cluster.

- Average offset: The average offset metric identifies the average delay in start of the micro-activity as compared with the ground truth. It is given by,

$$\frac{\sum_{n=1}^{N}(GT\_Start_n - C\_Start_n)}{N} \tag{4.2}$$

where GT_Start_n is the start point time (ms) of the ground truth and C_Start_n) is the start point of the cluster. We compute length and average offset metric for each micro-activity (GP and R) and the stroke across all signals. Furthermore, we rank the signals based on the metric values obtained. Fig. 4.7 shows the length and offset error for a stroke.

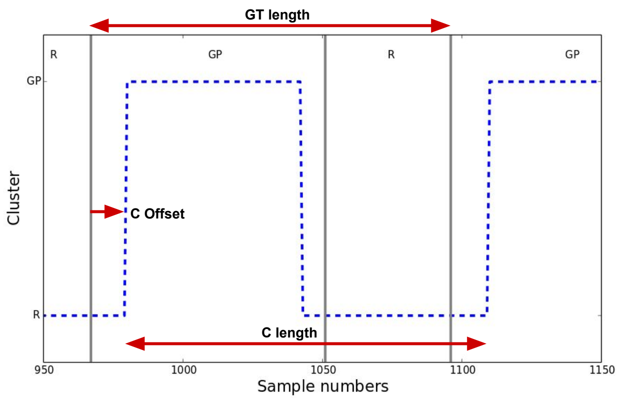


Figure 4.7: Example of offset and length error values.

Labeling: We calculated a series of features such as, *mean, min/max, standard deviation*, etc., for the top-k signals. These features are used to identify the labels of the micro-activities by comparing against the ground truth to obtained the labels for each cluster as GP or R. With the top-k signals we then compute various statistics such as number of strokes in a lap, length and offset of a stroke, GP and R micro-activities.

In the testing phase, new data from IMUs of a different participant is utilized to determine the micro-activities. In this case, we only use the top-k signal derived in training period from all the IMU signals for micro-activity recognition. Fig. 4.5 shows the flow of training and testing phase.

In the next Chapter, we discuss the accuracy of stroke and micro-activity detection. Furthermore, we provide detailed analysis on classification of strokes into straight and curve section along with possible feedback provided to the skaters.

Chapter 5

Evaluation and results

5.1 Knee rehabilitation

5.1.1 Lunge classification

The first step in providing feedback to the patients is by determining if a lunge was correctly performed or not. To this end, we applied K-nearest neighbor (IBk) classifier to distinguish a lunge from other activities such as walking, running and jumping performed during rehabilitation. The classifier accuracy of identifying a lunge was close to 96%. The high classification accuracy obtained is mainly due to the unique characteristic of lunges i.e., different micro-activities such as stepping forward, steady state and stepping backwards.

After identification of lunge exercise performed, we applied an automated segmentation method to determine individual repetition of lunges as described in Section. 3.2. For each individual repetition, we applied the traditional classifier to classify the test repetition to one of the labels defined by the therapist. We employed three classifiers *viz.,* IBk, J48 and NB to determine the labels. IBk performs better than the other classifiers with an average classification accuracy of 24.8% across all labels. The poor classification accuracy is due to the inability of standard classifiers in identifying the micro-activities of lunge. Since the step-forward and step-backward micro-activities across all labels are similar, traditional classifiers cannot distinguish them across labels. Hence identifying different micro-activities and using the right micro-activities for classification is crucial to get accurate classification of lunges.

Average Signal model

ASM model first sections the composite activity into micro-activities. We employed a clustering approach to determine the different micro-activities. The semi-supervised method first identifies the clusters that correspond to the micro-activities. These clusters are then labeled with the help of a domain expert. To identify the correct cluster configuration (a combination of signals and parameters), we developed a brute force algorithm to empirically derive the best configuration. The different parameters evaluated were the clustering mechanisms (EM, K-means), the number of clusters (2,3,4,5) and the smoothing parameter (low-pass filter of 10, 15 and 20Hz). The smoothing parameter ensure outliers and noisy data points are eliminated. The number of clusters indicate the number of micro-activities present in the composite activity. For the lunge exercise, we found EM clustering with 3 clusters and 15 Hz smoothing parameter to correctly identify the three micro-activities of lunge accurately across different labels. Furthermore, we merged all the signals of a particular label to derive its corresponding golden profile. The test data was evaluated with the golden profile across multiple classifiers. The average classification accuracy of identifying the corresponding label for NB, J48 and IBk were 39.6%, 45.2% and 51.8%, respectively. IBk classifier has better performance than other classifiers and the detailed accuracy of each label is described in Table. 5.1. The metrics employed to study the efficacy of the classifiers are:

- *True positives* indicate the number of labels that was correctly classified.

- *False positives* indicate the number of labels that were incorrectly classified,

- *Precision* is the number of true positives divided by the total number of elements labeled as belonging to a particular label.

- *Recall* is the number of true positives divided by the total number of elements that actually belong to a label.

- *F-measure* indicates the accuracy of the classifier and it is the harmonic mean of precision and recall.

Table. 5.1 shows the TP, FP, precision, recall and F-measure for each label using IBk classifier. It can be seen that for some labels the accuracy is high (e.g. 100% for fast) and for others the accuracy is as low as 40%. Moreover, ASM classifies a repetition to only one of the label and eliminates the others. Hence a mis-classification may result in providing a completely wrong feedback to the patients during rehabilitation. Hence, feedback systems should determine the set of labels that are similar to the test data, particularly when the exercise is composed of several micro-activities and overlapping labels.

Table 5.1: Classification accuracy across labels for ASM and ranking model.

	Labels	Fast	Ins	KI	KO	OverIns	Good	Over	Small	Mean
	TP Rate	1.00	0.60	0.50	0.00	0.00	0.57	0.80	0.67	0.52
	FP Rate	0.00	0.10	0.04	0.00	0.00	0.32	0.05	0.04	0.07
ASM	Precision	1.00	0.60	0.50	0.00	0.00	0.40	0.80	0.67	0.50
	Recall	1.00	0.60	0.50	0.00	0.00	0.57	0.80	0.67	0.52
	F-measure	1.00	0.60	0.50	0.00	0.00	0.47	0.80	0.67	0.50
	TP Rate	0.13	0.30	0.22	0.40	0.00	0.36	0.56	0.22	0.27
	FP Rate	0.00	0.00	0.00	0.19	0.00	0.00	0.18	0.00	0.05
RM	Precision	1.00	1.00	1.00	1.00	0.33	0.62	0.00	1.00	0.74
	Recall	1.00	0.57	0.60	1.00	1.00	1.00	0.00	0.67	0.73
	F-measure	1.00	0.73	0.75	1.00	0.50	0.77	0.00	0.80	0.69

Ranking model

Unlike ASM, ranking model aims to determine the set of labels that represent the test repetition. Fig. 5.1 shows the Top-5 features that are influential for each of the labels. We employed attribute selection ranking with weighted cost matrix from WEKA tool to obtain the top features that are important for each label. The attribute selection ranking performs an exhaustive search over all features to identify the top features. Then a weighted cost matrix ensures mis-classifications are highly penalized. This ensures that the obtained features will certainly improve the classification accuracy for each label. Furthermore, to select the set of labels, we compute the probability distribution function for each feature across labels. This allows one to identify the set of labels that are closest.

Rank	Fast	Ins	KI	KO	OverIns	Good	Over
1	13_SigDiff	12_RMS	13_RMS	13_Max	3_Mean	13_Max	13_Max
2	13_SigRMS	13_RMS	13_Max	13_RMS	15_Mean	13_Mean	13_RMS
3	8_StdDev	12_SigRMS	14_SigDiff	13_Mean	15_Max	13_RMS	13_Mean
4	12_RMS	12_Max	13_Mean	12_RMS	15_Min	12_RMS	13_Min
5	8_SigRMS	16_Mean	14_SigRMS	12_SigRMS	3_Max	12_SigDiff	12_SigRMS

Figure 5.1: Top-5 features selected for each label.

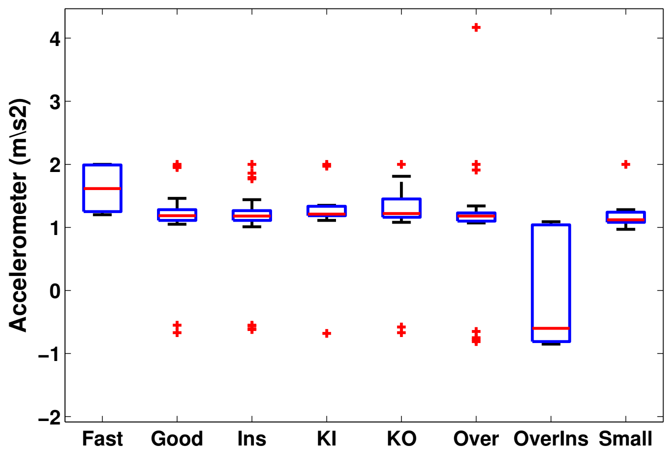


Figure 5.2: Boxplot of probability distribution of *3_Mean* across labels.

Fig. 5.2 shows the values for a feature 3_*mean* (corresponding to the accelerometer x-axis on the lower leg IMU) across all labels. It can be clearly seen that for *OverIns* label this feature is unique. This enables the classifier to determine the corresponding label based on the top features obtained.

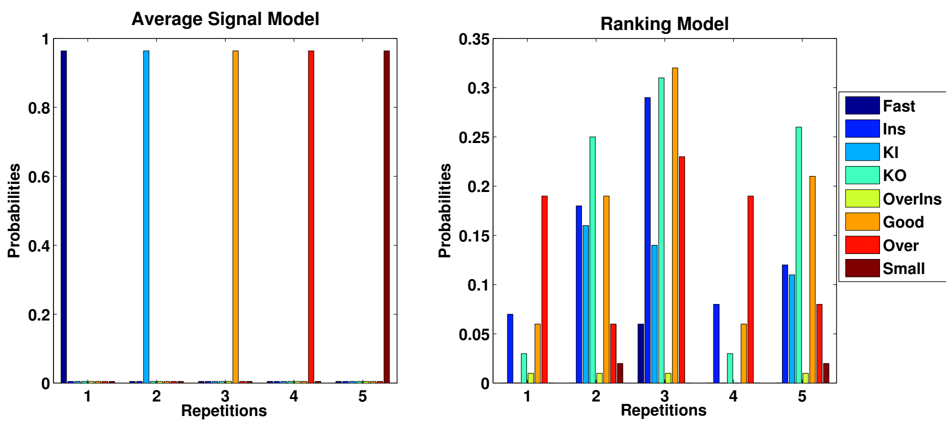


Figure 5.3: Evaluation of 5 repetitions across labels using ASM and RM.

Fig. 5.3 shows the probability distribution for 5 test repetitions across different labels with average signal and ranking models. It can be clearly seen that ASM is completely biased to one of the labels and mis-classifications will lead to providing inaccurate feedback to the patients. However, for ranking model using the probability we can identify a set of labels that are similar. This can be seen in Fig. 5.3 where for some repetitions only one label has high probability and for other repetitions more than one label has similar probabilities. For example, Repetition 1, 4 was clearly identified as

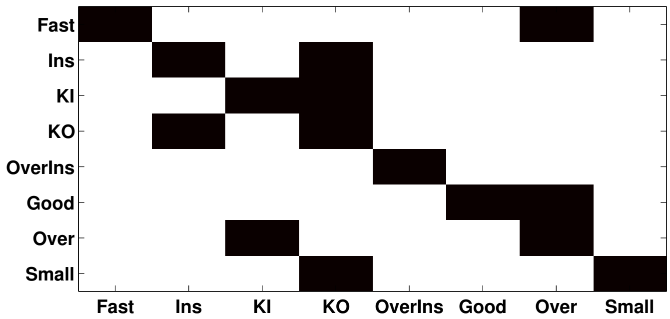


Figure 5.4: Set of labels derived using ranking model that are overlapped.

a *Small* lunge, whereas, in Repetition 3, it can be seen that the probability of being *Instable* or *KO* or *Good* is similar. Hence labels that have similar probabilities are selected as the predicted labels. Feedback is provided to patients based on the obtained set of labels rather than a single label.

Finally, Fig. 5.4 shows the set of labels that are overlapped. The colored column block indicates that the label is similar to the corresponding row label. Note that this mapping between labels may vary depending on the training data. This allows our proposed methodology to be adaptive and learn new patterns in the collected data over time.

Table. 5.1 shows the TP, FP, precision, recall and F-measure obtained using the ranking model with top-3 features. The higher accuracy is due to the classification of test data to a set of labels that are similar. The average accuracy across all labels is around 70% with high precision of 74%.

5.1.2 Feedback

The key challenge in human augmentation is providing near real-time feedback to users regarding the activities performed. Providing feedback is non-trivial, especially when there exists micro-activities, due to the overlapping labels. In traditional feedback systems, based on the identification of the labels, appropriate recommendation is provided to the patients. For example, if the label predicted is *Over* the feedback includes, (i) keep your upper body straight, you may be leaning forward too much, (ii) your forward step might be too short, (iii) you might be lowering your body too much. Similarly, if the label identified is *Instable* the feedback includes, (i) Do the exercise slower, to get more control (ii) do not step too hard on the front leg, etc.

Since there exists multiple labels representing the same micro-activity performed, identifying only one label or a mis-classification may lead to inaccurate feedback. To overcome this, we proposed a micro-activity classifier that identifies a set of labels that represent the activity performed. Fig. 5.3

shows the labels that are similar from the collected data using IMUs. Feedback is provided based on the labels that are highly similar. For example, if the predicted label of a test repetition is *Over and Instable* label, then the system selects feedback corresponding to these two labels. Furthermore, based on the probabilities associated to each label, the feedback system can select the associated recommendations accordingly. This allows users to know what went wrong when the lunge exercise was performed. The hypothesis here is that by providing feedback from the set of labels increases the accuracy compared to that of a single label based feedback.

The corresponding feedback is provided to the users on their phone or in-home displays. This allows users to know in real-time how accurately exercises were performed. Furthermore, it allows users to know how they can improve themselves. This significantly enhances the recovery process and eliminates the frequent visits to the therapist. The feedback can also be sent to the therapist who can then adapt the feedback to provide more personalized recommendations.

5.2 Speed skating

5.2.1 Stroke classification

In Chapter 4 we described our signal ranking model (SRM) to classify different phases in a stroke. The combination of glide, push-off and reposition phases forms a stroke in speed skating. SRM model identifies the different micro-activities using only IMUs data. As described in Section 4.1, in speed skating there can be a stroke in straight section of the lap and in the curve section. The modeling presented here can distinguish both types of strokes. We first describe the evaluation of strokes in straight section and then provide results for the total lap.

Stroke: Straight section

In Section 4.2 we mentioned that the dataset collected in [14] includes 29 straight section data from 4 speed skaters. For these 29 straight section data, we also had the Qualisys data along with force data was used as ground truth. Specifically, $P1$ contributed to 3 laps, $P2$ to 9, $P3$ to 10 and $P4$ to 7. In this section, we consider only the straight section of the lap for micro-activity recognition.

Ground truth: The force data and Qualisys data together was used to derive the strokes, length of a stroke and the identification of GP and R. The ground truth information was also provided as part of the dataset [36, 38].

Signal ranking model (SRM)

SRM model takes the IMU data from the wearable body suit of the skater to determine the stroke frequency, length of the stroke and its micro-activities. The raw signal data was pre-processed by applying a Butterworth filter (with values of 0.5, 1.0, 1.5, 2.0 and 2.5 Hz). This pre-processed signal data was used by clustering algorithm to obtain the cluster sequence. We used EM and K-means (KM) clustering algorithms to obtain the cluster sequences. The number of cluster was set to 2, on the grounds that there are two micro-activities (GP & R). The resultant cluster sequences was then processed to filter initial noise as described in SRM model.

The number of clusters represent the number of micro-activities, the length of a cluster sequence represent the length of the micro-activity. For all cluster sequences, we then computed the length and offset values using Eq. 4.1 and Eq. 4.2 respectively. Specifically, we computed 3 combinations of length and offset values for GPR, GP and R. GPR represents a complete stroke and GP and R represents the micro-activities, the corresponding metrics are:

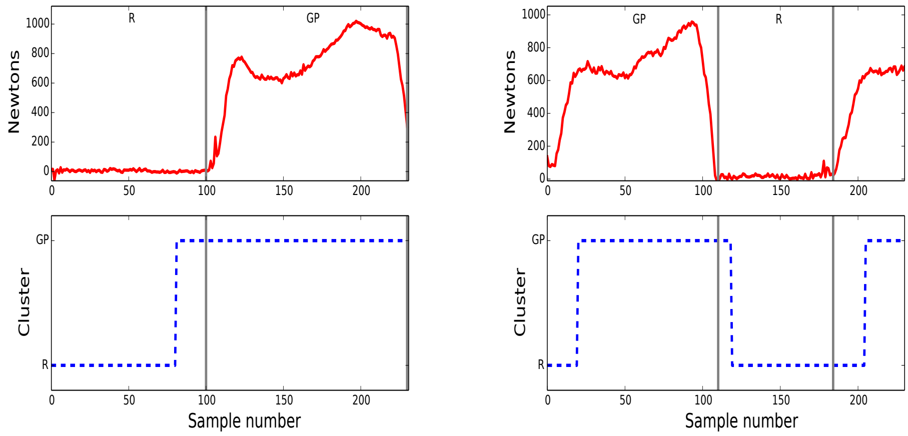
- *Length GPR* indicates the difference between the length of GPR from ground truth and SRM model.
- *Offset GPR* indicates the difference between the start of the GPR from ground truth and SRM model.
- *Length GP* indicates the difference between the length of GP micro-activity and the length of GP obtained from SRM.
- *Offset GP* indicates the difference between the start of the GP from ground truth and the start of GP obtained in SRM.
- *Length R* indicates the difference between the length of R from ground truth and SRM model.
- *Offset R* indicates the difference between the start of R from ground truth and SRM model.

The length metric takes a non-negative value, lower the value the better is the signal performance. The offset metric is a integer where a negative value indicates the micro-activity starting earlier than the actual start and a positive value indicates the micro-activity starting later than the actual start. The 42 signals from 7 IMUs was then ranked based on the length and offset metrics. The top-5 signals for both length and offset metrics were the same. Table 5.2 shows the top-5 signals for the strokes found by the SRM.

Table 5.2: Top-5 signals along with cluster configurations.

Top	Sensor location	Signal	Low Pass filter (Hz)	Cluster Method
1	Right Skate	Gyroscope Z	1.0	KM
2	Right Upper leg	Accelerometer Z	1.0	KM
3	Right Upper leg	Accelerometer Z	1.5	KM
4	Right Upper leg	Accelerometer Z	2.0	KM
5	Right Skate	Gyroscope Z	1.5	KM

Fig.5.5 shows an example of the ground truth force stroke data of a right skate along with the cluster sequence obtained from SRM for the top signal. Fig. 5.5a shows the length metric of a stroke. It can be seen that the length error for GPR (total stroke) is 0. Further, micro-activities GP and R has a length error of 15% and 20% respectively. Similarly, Fig. 5.5b shows the offset metric for a stroke. The total stroke (GPR) has an offset error of 200 ms (20 frames).

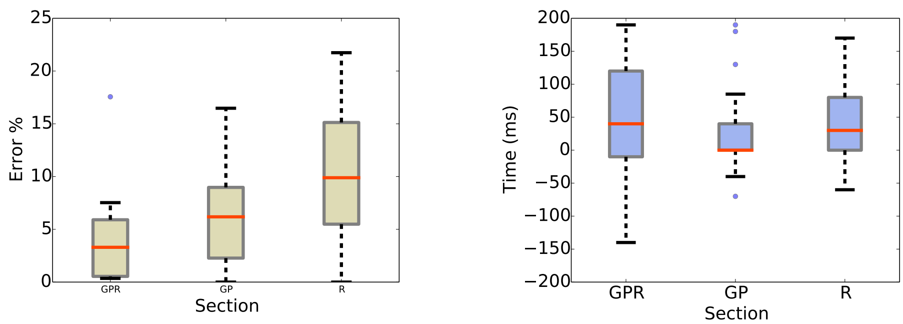


(a) Length error

(b) Offset error

Figure 5.5: Stroke Error examples.

Fig. 5.6 shows the box plots of the length and offset values of the top signal (Right Skate, Gyroscope Z) evaluated for all the 29 straight sections. It can be seen in 5.6a that, the difference between the ground truth stroke length and derived stroke length is less than 4%.



(a) Length error

(b) Offset error

Figure 5.6: Length and offset errors top signal for all users across all laps.

Furthermore, the number of strokes obtained using our SRM model matches the total number of strokes in ground truth. Fig. 5.6b shows the offset values for GPR, GP and R micro-activity. The average offset value for GP and R is close to 46 ms and 54 ms respectively. The minimum values for GP and R are 0, see Table 5.3.

Table 5.3: Top 1 metric values.

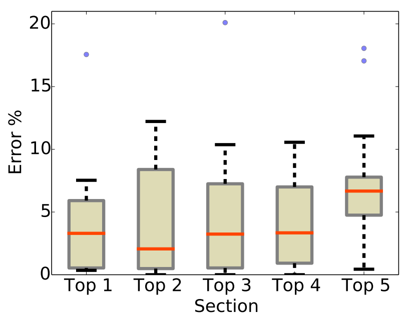
Top 1	Length (%)			Offset (ms)		
ft.	GPR	GP	R	GPR	GP	R
AVG	3.9	6.5	10.3	70	46	54
Max	17.6	16.5	21.7	190	230	170
Min	0.4	0.0	0.0	10	0	0

In summary, the length and offset values obtained for all 29 straight sections are very low, indicating the good performance of SRM model.

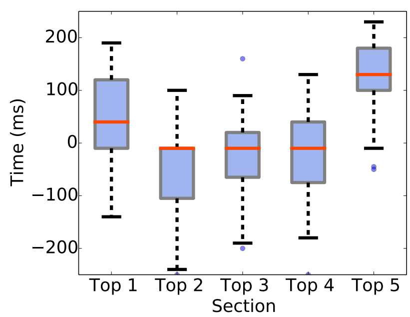
Table 5.4 shows the average length and offset values of all 29 straight sections for each signal in Table 5.2. It can obtain that, the average length and offset values for the top-5 signals are 8.5% and 84 ms respectively.

Table 5.4: Average length & offset of top 5 signals for all laps

	Length (%)			Offset (ms)		
Signals	GPR	GP	R	GPR	GP	R
1	3.9	6.5	10.3	70	46	54
2	4.2	8.2	10.7	73	109	64
3	4.5	9.4	11.3	95	101	96
4	5.3	11.0	11.0	95	91	96
5	6.6	8.1	16.5	142	63	68



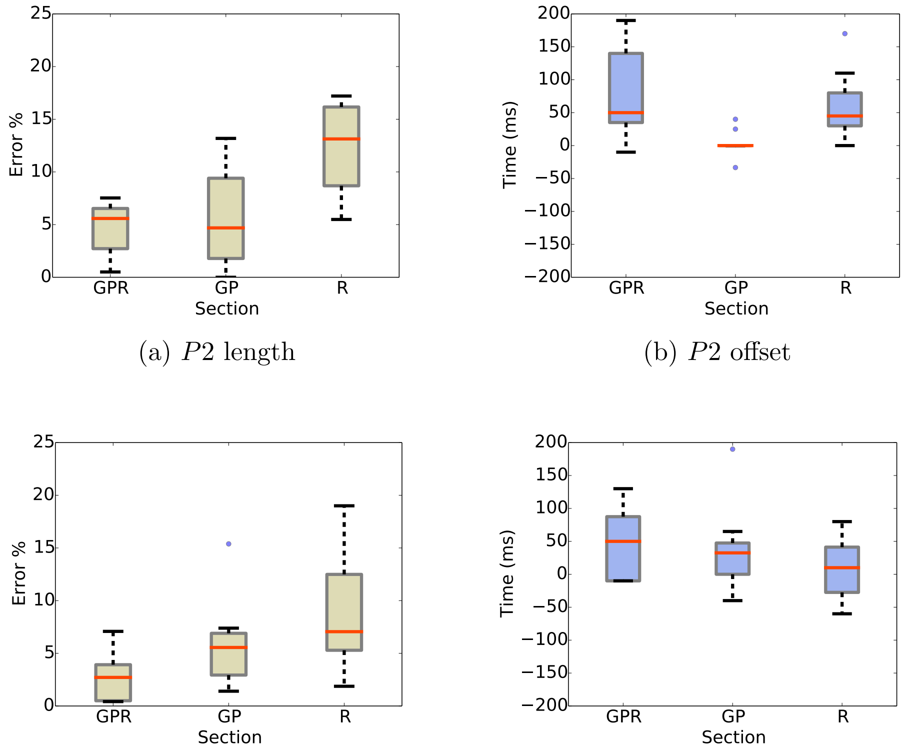
(a) Length error



(b) Offset error

Figure 5.7: Metric values of top 5 signals for all users across all laps (GPR/stroke).

The distribution of length and offset values for top-5 signals is shown in Fig. 5.7. It is worth noticing that the 1st and 5th top signals come from the same sensor (Right skate, Gyroscope Z) but different configuration (1.0 and 1.5 for the Low pass filter), they have a smaller distribution on their offset error than the signal from the Right Upper leg, Accelerometer Z sensor.



(a) $P2$ length (b) $P2$ offset

(c) $P3$ length (d) $P3$ offset

Figure 5.8: Length and offset error of $P2$ and $P3$

These differences are due to the position of the IMU and it's signal. Strokes are determined by whether the skate is on the ice or not, therefore it makes sense that an IMU on the skate will show a more correlated pattern to the skating strokes.

Finally Fig. 5.8 shows the length and offset distribution of two skaters, $P2$ and $P3$. The length and offset values are lower for $P3$ as compared to $P2$. However, the proposed SRM model used the same top-signal obtained from other participants. Further, the number of strokes was correctly identified for both the skaters. Hence, using just the IMU data the proposed model can derive the number of strokes, stroke length and also identify the micro-activities. The evaluation indicates that not all the IMUs may be required for detection of strokes. Further, with the above results we can identify the optimal placement of IMU for accurately classifying a stroke and different micro-activities. Consequently, resulting in deploying fewer IMUs, lesser data processing and communication.

Stroke: Total lap

In the previous section, we considered only the straight section of the lap for classification of strokes. In this section, we use the same analysis for the complete lap. Thus, we evaluate the top signal obtained from straight section analysis for all the sections in a lap. As shown in Fig. 4.1 in Chapter 4, there are 2 straight and curve sections in a lap. Since, the dataset does not have the ground truth for the total lap, we utilized the ground truth information derived by Eline et al. [14]. They analyzed the total lap data along with force and other sensors data to derive the ground truth information. This information was used to compare the number of strokes and micro-activities obtained from SRM with only top-signal data.

Since a complete lap includes different sections (straight and curve), we applied a two-level clustering for distinguishing strokes from these parts. The steps involved are:

1. The complete lap data of the top-signal was used to derive the cluster sequence. The SRM model aimed at identifying the different micro-activities i.e. GP and R. The combination of GP and R was represented as a stroke. In the next step, we describe the procedure to distinguish between the stroke in straight and curve section.

2. The length of each stroke obtained from the previous step was calculated. We used the length of a stroke to further classify if the stroke is in straight or curve section. In general, the length of the stroke in the curve section is smaller than the length of the stroke in straight section. Fig. 5.9 shows the length of the stroke in straight and curve sections. On average, a straight stroke takes 1950 ms while the curve is around 1390 ms in our dataset.

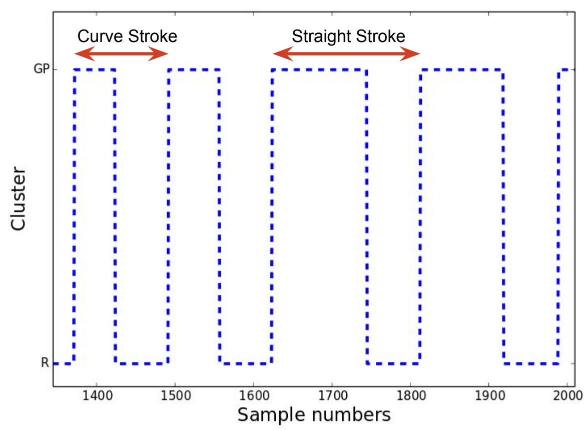
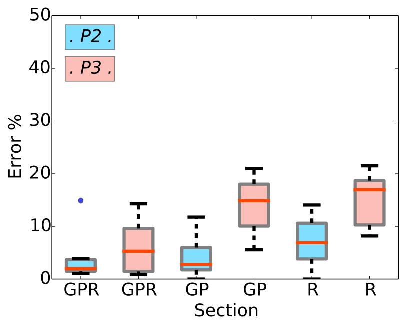
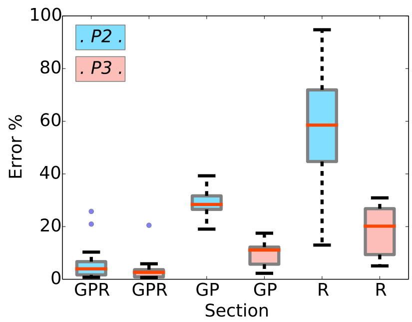


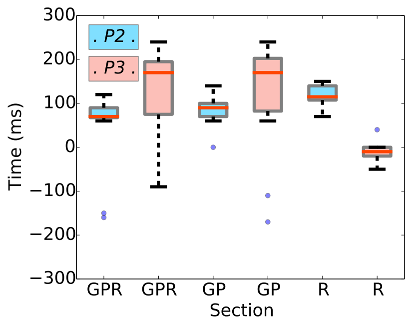
Figure 5.9: Curve and straight sections strokes.



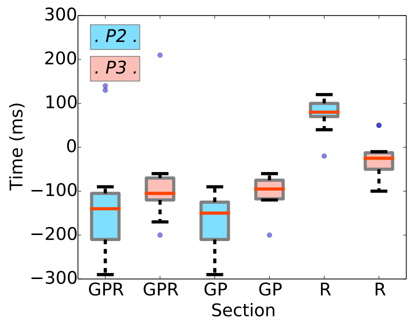
(a) Length Straight



(b) Length Curve



(c) Offset Straight



(d) Offset Curve

Figure 5.10: Metrics value for a complete lap.

The above approach used only the top-signal to derive the type of stroke, number of strokes, length of stroke and the GP, R micro-activities. From the dataset collected, we used 2 total laps from two skaters for stroke classification.

Fig.5.10 shows the length, offset values for straight and curve section for two skaters. The cluster sequences and the corresponding length and values are obtained based on the top signal derived previously. The SRM model correctly identifies the total number of strokes in straight and curve sections for both the skaters. Furthermore, the average length error in straight and curve for $P2$ is 20% and 119 ms respectively. Similarly, the average length error for straight and curve is 11.3% and 101 ms for $P3$. It can be seen that, the average length values for straight section is much lower than curve section across all total stroke, GP and R. Note that, the curve section was never modeled before in our analysis. This error could be reduced by training the SRM model in curve section. Furthermore, the offset in straight section is generally positive as compared to offset values in the curve section. This information can be considered in our modeling to further reduce the offset values. Table 5.5 shows the length and offset errors for two skaters across the total lap, only straight and curve sections.

Table 5.5: Length & offset error percentage values

	Length (%)			Offset (ms)		
User	GPR	GP	R	GPR	GP	R
$P2$ Straight	4.2	4	14.2	95	84	116
$P2$ Curve	6.6	29.1	55.7	162	165	80
$P2$ Lap	5.5	17.4	37.3	132	127	96
$P3$ Straight	6.1	14.1	15.2	149	162	18
$P3$ Curve	4.2	9.6	18.6	123	103	47
$P3$ Lap	5.2	12	16.8	136	135	31

5.2.2 Feedback

Currently, coaches give feedback by timing each lap or section of the lap, ideally this feedback should be given near real-time. For example, the skater should know if his current speed is right, too fast or too slow, in which sections he is losing time, which phase (G,P,R) he has to improve, etc. With the proposed approach one can identify the number of strokes, the length and the micro-activities GP and R. This information can be used to analyze the technique of the skater, their performance and possible ways to improve. For example, we can provide feedback to skaters such as i) number of strokes done in each section *strokes per minute*; (ii) length of a stroke; (iii) which section is the skater losing time as compared to others. Furthermore, the proposed modeling can be used to compare the techniques across skaters and to improve the performance. By identifying the GP section on both leg strokes it is possible to compute the double stance (DS) frequency.

The proposed model has low length and offset error indicating the good performance in classifying the stroke. Furthermore, we proposed an adaption technique to improve the accuracy of classification of micro-activities and strokes.

Finally, the proposed model can be implemented on embedded devices such as Raspberry Pi, Arduino and smart phones/watches/glass to provide feedback to skaters. recent efforts use systems such as google glass [55] or haptic [56] to provide feedback. Also, the SRM model can be adapted to provide near real-time feedback and the latency depends on the data communication and processing limitations of the hardware.

5.3 Discussions

In this thesis, we presented a ranking based model for identifying micro-activities in various applications. Specifically, we adapted the generic framework to identify micro-activities in two applications (i) knee rehabilitation and (ii) speed skating. Several strategies were proposed to accurately identify different micro-activities, however there still exist some challenges.

- **Sensors** The selection of IMUs and their placement is highly dependent on the application [11]. For knee rehabilitation, two IMUs were sufficient for the analysis of the Lunge exercise. However, for stroke classification in speed skating 7 IMUs were deployed. Moreover, to identify other characteristics such as knee angle, force, etc. the position of the IMUs play an important role. In both applications we determine the most optimal IMU placement that maximizes the accuracy of detecting the micro-activity we are interested. However, for other activities the placement of IMUs may vary. Furthermore, since the dataset was not collected as part of the thesis, there may exist other placement position for IMUs which can maximize the micro-activity classification.

- **Data labeling** Accurately labeling composite activities is non-trivial due to the micro-activities involved. Hence classification approaches presented should consider overlapping labels, inconsistent labels and similar labels during evaluation. The approach for knee rehabilitation described in this paper is agnostic to the number of labels. Thus, the ranking model can determine the set of labels that can accurately represent the test data. In speed skating micro-activities are well defined and the validation with quantitative ground truth. Yet we had to group two micro-activities (G & P) in order to work with the data, due to lack of precise distinction between these.

- **Feedback systems** Providing near real-time feedback is a crucial component in human augmentation systems. However in the case of rehabilitation, most systems analyze the entire composite activity performed as a whole, leading to inaccurate feedback systems. This thesis identifies the set of labels rather than a single label. To improve the accuracy, more distinctive labels or proper feedback for set of labels should be done. For speed skating we provide feedback in terms of number of strokes, length of a stroke and the different phases. However, other information such as knee angle, force, speed, etc., may also be useful. The proposed models can be extended to provide other key statistics for the skaters.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

The main research objective of this work was to present a framework that can analyze user activities using wearables and provide feedback to enhance the performance capabilities of users. In this thesis, we proposed variants of ranking model to identify the micro-activities performed by user. Analyzing micro-activities provides a unique view in understanding user activity. Furthermore, the proposed models were able to identify the most significant signals and the IMUs required to identify these micro-activities. We considered two real-world applications and demonstrated the efficacy of the models proposed. The ranking models was adapted for each application to identify the micro-activities. The information obtained from analyzing these micro-activities was used to provide feedback to users (patients and skaters) to enhance their performance. This thesis is a step towards identification of fine-grained user activity information to provide accurate feedback.

In Chapter 3, we presented a system that helps in faster rehabilitation of knee injury patients using a wearable knee band comprising of two IMUs. We described a novel methodology to accurately classify the exercises performed by the patients. Unlike the existing systems, the techniques presented in this thesis can identify the micro-activities involved in a particular exercise. The proposed ranking model determines the most influential signals/features that can accurately identify the set of labels that are similar to the test repetition. The predicted set of labels is then used to provide feedback on the quality of exercises performed. The proposed models perform significantly better than traditional classifiers. The classification accuracy of identifying the correct set of labels using ranking model is close to 70%.

In Chapter 4, we adapted the general ranking model for speed skating application. The model identified the strokes performed by the skaters along with different phases (micro-activities) using the data from a wearable body suit (with 7 IMUs). The model identifies the most significant signal that can classify a stroke and its micro-activities. This information can be used to reduce the number of IMUs deployed for stroke identification. Unlike previous works, we used only IMUs data from four skaters to identify strokes. The proposed model was able to identify all the strokes across different sections of the lap. The stroke classification has an average length and offset error of each micro-activity of 5.2% and 122 ms respectively for the straight sections for the lap. The average length and offset for the total lap from two skaters is 5.4% and 135 ms respectively. . Information on the number of strokes, length of a stroke and different phases in a stroke can now be provided to the coaches to understand the technique of the speed skaters. This can further be used to analyze the performance and compare techniques with other skaters.

The proposed framework can be applied to other applications such as swimming, basketball, rowing, and other rehabilitation exercises to identify accurately the micro-activities. Furthermore, the proposed models can be run online on an embedded systems to provide near-real time feedback tot he users. We believe that the novel methodology and analysis presented in this thesis will make the rehabilitation and sport coaching simple, faster and accurate by exploiting the advantages of wearables for human augmentation.

6.2 Future work

In this thesis, we analyzed our proposed models for two real-world applications (i) Knee rehabilitation and (ii) Speed skating. We have identified several points that need improvement or that can be further enhanced.

- *Applications and activity recognition:* In Chapter 3, we proposed ASM and RM models to recongize lunge exercise performed by the patients. However, our models can be extracted to other exercises such as squats, jumping jacks, etc. Similarly, for speed skating, the analysis can be extended to identify other kinematic characteristics such as knee angle, double support, etc. Hence, applicability of the ranking models to other applications and activities needs to be investigated.

- *Nano-Activities:* As shown in this thesis, analyzing fine-grained activity information i.e., micro-activities helps to understand user activities and more importantly to provide detailed feedback. Hence, decomposing micro-activities to *Nano-Activities* will give a better description of the activity. These nano-activities can further help to monitor user exercises and actions to provide precise feedback.

- *Bottom-Up model:* In both applications we design the MAR from a Top-down approach, i.e., the labels were partially provided and our models used this information to derive micro-activities. Alternative approach (bottom-up) may be developed completely unsupervised to determine the micro-acitvities and to label them. This approach may indeed identify only those activities which are prominent, consequently eliminating the need of domain experts for labeling.

- *Model parameters:* In the ranking models presented in this thesis, we used different configuration parameters such as type of clustering, number of clusters, and filtering mechanism for each signal. The main objective was to identify the most influential signal for a particular application. These parameters needs to be fine tuned for different applications. Furthermore, our models can be extended to combine two or more signals to improve the classification accuracy or to add reliability in detection of micro-activities.

Bibliography

[1] Sarkar, C., Akshay, A. U., Prasad, R. V., Rahim, A., Neisse, R., & Baldini, G. (2015). DIAT: A scalable distributed architecture for IoT. IEEE Internet of Things Journal, 2(3), 230239. http://doi.org/10.1109/JIOT.2014.2387155

[2] Mann, Steve (2012): Wearable Computing. In: Soegaard, Mads and Dam, Rikke Friis (eds.). "Encyclopedia of Human-Computer Interaction". Aarhus, Denmark: The Interaction-Design.org Foundation.

[3] Activity tracker - Wikipedia, the free encyclopedia. (n.d.). Retrieved February 29, 2016, from https://en.wikipedia.org/wiki/Activity_tracker

[4] Ermes, M., Prkka, J., Mantyjarvi, J., & Korhonen, I. (2008). Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions. IEEE Transactions on Information Technology in Biomedicine : A Publication of the IEEE Engineering in Medicine and Biology Society, 12(1), 206. http://doi.org/10.1109/TITB.2007.899496

[5] What is Human Augmentation? - Definition from Techopedia. (n.d.). Retrieved March 1, 2016, from https://www.techopedia.com/definition/29306/human-augmentation

[6] Fahim, M., Lee, S., & Yoon, Y. (2014). SUPAR: Smartphone as a ubiquitous physical activity recognizer for u-healthcare services. Conference Proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference, 2014, 36669. http://doi.org/10.1109/EMBC.2014.6944418

[7] How machine learning will take wearable data to the next level. (n.d.). Retrieved March 7, 2016, from http://www.wareable.com/wearable-tech/machine-learning-wearable-data-sensors-2015

[8] Trabelsi, D., Mohammed, S., Chamroukhi, F., Oukhellou, L., & Amirat, Y. (2013). An Unsupervised Approach for Automatic Activity Recognition Based on Hidden Markov Model Regression. IEEE Transactions on Automation Science and Engineering, 10(3), 829835. http://doi.org/10.1109/TASE.2013.2256349

[9] Bayati, H., del R Millan, J., & Chavarriaga, R. (2011). Unsupervised Adaptation to On-body Sensor Displacement in Acceleration-Based Activity Recognition (pp. 7178). http://doi.org/10.1109/ISWC.2011.11

[10] Yan, Z., Chakraborty, D., Misra, A., Jeung, H., & Aberer, K. (2012). SAMMPLE: Detecting Semantic Indoor Activities in Practical Settings Using Locomotive Signatures (pp. 3740). http://doi.org/10.1109/ISWC.2012.22

[11] Dillard, W., Narayanan, K., Trent, V., Greene, M., & Redkar, S. (2008). Issues in wearable biomechanical inertial sensor systems. In Record - IEEE PLANS, Position Location and Navigation Symposium (pp. 210216). IEEE. http://doi.org/10.1109/PLANS.2008.4569971

[12] Lymberis, a, & Ieee, I. (2003). Smart wearables for remote health monitoring, from prevention to rehabilitation: Current R&D, future challenges. In Itab 2003: 4th International Ieee Embs Special Topic Conference on Information Technology Applications in Biomedicine, Conference Proceedings: New Solutions for New Challenges (pp. 272275). IEEE. http://doi.org/10.1109/ITAB.2003.1222530

[13] Oppedijk, R., Gonzalez, L., Steginga, D. & Mul, J. (2015) "MyKneeCoach: Wearable knee sleeve for knee injury rehabilitation". http://www.dutch-coast.com/

[14] Real-Time Feedback for Better Speed Skating Performance, STW dossier nr. 12870, in collaboration with TUDelft, V. University Amsterdam and InnoSportLab Thialf Speed Skate Arena

[15] Khan, A. M., Lawo, M., & Homer, P. (2013). Wearable Recognition System for Physical Activities (pp. 245249). http://doi.org/10.1109/IE.2013.50

[16] Rai, A., Yan, Z., Chakraborty, D., Wijaya, T. K., & Aberer, K. (2012). Mining Complex Activities in the Wild via a Single Smartphone Accelerometer (pp. 4351). New York, NY, USA: ACM. http://doi.org/10.1145/2350182.2350187

[17] "Knee replacement - Recovery". Retrieved February 15, 2016, from http://www.nhs.uk/Conditions/Knee-replacement/Pages/Recovery.aspx

[18] "Rehabilitation Guide: Anterior Cruciate Ligament Reconstruction". University of Wisconsin. UW Health Sports Medicine Center.(2013)

[19] Wikipedia contributors. "Goniometer." Wikipedia, The Free Encyclopedia. Wikipedia, The Free Encyclopedia, 22 Feb. 2016. Web. 18 Mar. 2016.

[20] Ahmadi, A., Mitchell, E., Destelle, F., Gowing, M., OConnor, N. E., Richter, C., & Moran, K. (2014). Automatic Activity Classification and Movement Assessment During a Sports Training Session Using Wearable Inertial Sensors (pp. 98103). http://doi.org/10.1109/BSN.2014.29

[21] O. D. Lara and M. A. Labrador,"A Survey on Human Activity Recognition using Wearable Sensors," *in Communications Surveys & Tutorials, IEEE,* vol.15, no.3, pp.1192-1209, 2013.

[22] Fernandez-Cervantes, V., Stroulia, E., Castillo, C., Oliva, L., & Gonzalez, F. (2015). Serious rehabilitation games with Kinect. In 2015 IEEE Games Entertainment Media Conference (GEM) (pp. 11). IEEE. http://doi.org/10.1109/GEM.2015.7377254

[23] Delis, A. L., de Carvalho, J. L. A., da Rocha, A. F., de-Oliveira Nascimento, F. A., Borges, G. A., & Olaya, A. F. R. (2012). Myoelectric Algorithm for Knee Angle Estimation Using Proprioceptive Data and a Compatibility Test (pp. 177180). http://doi.org/10.1109/Andescon.2012.48

[24] Ahmadi, A., Mitchell, E., Richter, C., Destelle, F., Gowing, M., OConnor, N. E., & Moran, K. (2015). Toward Automatic Activity Classification and Movement Assessment During a Sports Training Session. IEEE Internet of Things Journal, 2(1), 2332. http://doi.org/10.1109/JIOT.2014.2377238

[25] Plotz, T., Chen, C., Hammerla, N. Y., & Abowd, G. D. (2012). Automatic Synchronization of Wearable Sensors and Video-Cameras for Ground Truth Annotation A Practical Approach (pp. 100103). http://doi.org/10.1109/ISWC.2012.15

[26] Anjum, A., & Ilyas, M. U. (2013). Activity recognition using smartphone sensors (pp. 914919). http://doi.org/10.1109/CCNC.2013.6488584

[27] Mortazavi, B. J., Pourhomayoun, M., Alsheikh, G., Alshurafa, N., Lee, S. ., & Sarrafzadeh, M. (2014). Determining the Single Best Axis for Exercise Repetition Recognition and Counting on SmartWatches (pp. 3338). http://doi.org/10.1109/BSN.2014.21

[28] Konings, M. J., Elferink-Gemser, M. T., Stoter, I. K., van der Meer, D., Otten, E., & Hettinga, F. J. (2015). Performance Characteristics of Long-Track Speed Skaters: A Literature Review. Sports Medicine, 45(4), 505516. http://doi.org/10.1007/s40279-014-0298-z

[29] B. Ghanem, M. Kreidieh, M. Farra, & T. Zhang. (2012). Pattern Recognition (ICPR), 2012 21st International Conference on.

[30] Allinger, T.L., Bogert, A.J. vd, Skating technique for the straights, based on the optimization of a simulation model, Medicine & Science in Sports & Exercise 29(2), 279-286,1997

[31] International Skating Union, Special Regulations & Technical Rules, Speed Skating and Short Track Speed Skating.2014 http://static.isu.org/

[32] Noordhof, D. A., Foster, C., Hoozemans, M. J. M., & De Koning, J. J. (2013). Changes in speed skating velocity in relation to push-off effectiveness. International Journal of Sports Physiology and Performance, 8(2), 188194.

[33] Houdijk, H., de Koning, J. J., de Groot, G., Bobbert, M. F., And, & van Ingen Schenau, G. J. (2000). Push-off mechanics in speed skating with conventional skates and klapskates. Medicine and Science in Sports and Exercise, 32(3), 63541. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/10731006

[34] van der Kruk, E. (2013). Modelling and Measuring 3D Movements of a Speed Skater. TU Delft.

[35] van der Kruk, E., Veeger, H. E. J., van der Helm, F. C. T., & Schwab, A. L. (2015). Two Body Dynamic Model for Speed Skating Driven by the Skaters Leg Extension. In icSports conference 2015.

[36] van der Kruk, E*, A.L. Schwab, F.C.T. van der Helm & H.E.J. Veeger (2016) Getting the angles straight in speed skating: a validation study on an IMU filter design to measure the lean angle of the skate on the straights. ISEA conference 2016

[37] van der Kruk, E., den Braver, O., Schwab, A. L., van der Helm, F. C. T., & Veeger, H. E. J. (2016). Wireless instrumented klapskates for speed skating. Currently under Review in Journal of Sports Engineering.

[38] van der Kruk, E, F.C.T. van der Helm1 , A.L. Schwab1 and H.E.J. Veeger. Giving the force direction: Analysis of speed skater push off forces with respect to an inertial coordinate system. (2016) ISBS Conference 2016

[39] van Ingen Schenau, G.J, and Bakker, K, (1980). A biomechanical model of speed skating,Journal of Human Movement Studies, 6, 1-18.

[40] De Boer RW, Ettema GJ, Faessen BG, et al. Specific characteristics of speed skating: implications for summer training. Med Sci Sports Exerc. 1987;19(5):504-10.

[41] Boer, R.W. de, Schermerhorn P., Gademan, J., Groot G., de, and Ingen Schenau, G.J. van, Characteristic Stroke Mechanics of Elite and Trained Male Speed Skaters, Int. J. Sport. Biomech. 2, 175-185, 1986

[42] Speed skating rink - Wikipedia, the free encyclopedia. (n.d.). Retrieved February 29, 2016, from https://en.wikipedia.org/wiki/Speed_skating_rink

[43] Nachtmetingen in Thialf Skate & Science. (n.d.). Retrieved March 11, 2016, from http://skatescience.nl/nachtmetingen-thialf/

[44] P. E. Taylor, G. J. M. Almeida, J. K. Hodgins and T. Kanade,"Multi-label classification for the analysis of human motion quality," *in Engineering in Medicine and Biology Society (EMBC) IEEE,* pp.2214-2218, 2012.

[45] S. Ananthanarayan, M. Sheh, A. Chien, H. Profita and K.A. Siek, "Designing wearable interfaces for knee rehabilitation," *in Proceedings of the 8th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth), ICST,* pp.101-108, 2014.

[46] I. M. Albaina, T. Visser, C. A. P. G. van der Mast and M.H. Vastenburg,"Flowie: A persuasive virtual coach to motivate elderly individuals to walk," *in International Conference on Pervasive Computing Technologies for Healthcare, PervasiveHealth,* pp.1-7, 2009.

[47] C. L. Bennett, C. Odom and M. Ben-Asher, "Knee Angle Estimation based on IMU data and Artificial Neural Networks," *in Biomedical Engineering Conference (SBEC),* pp.111-112, 2013.

[48] A. Masdar, B. S. K. K. Ibrahim, D. Hanafi, M. M. A. Jamil and K. A. A. Rahman, "Knee joint angle measurement system using gyroscope and flex-sensors for rehabilitation," *in Biomedical Engineering International Conference (BMEiCON),* pp.1-4, 2013.

[49] K. H. Chen, P. C. Chen, K. C. Liu and C. T. Chan, "Wearable Sensor-Based Rehabilitation Exercise Assessment for Knee Osteoarthritis," *in Sensors 2015,* vol.15, pp.4193-4211, 2015.

[50] WEKA: Waikato Environment for Knowledge Analysis [online] http://www.cs.waikato.ac.nz/ml/weka/

[51] Dejnabadi, H., Jolles, B. M., & Aminian, K. (2005). A new approach to accurate measurement of uniaxial joint angles based on a combination of accelerometers and gyroscopes. IEEE Transactions on Biomedical Engineering, 52(8), 14781484. http://doi.org/10.1109/TBME.2005.851475

[52] Masdar, A., Ibrahim, B. S. K. K., Hanafi, D., Jamil, M. M. A., & Rahman, K. A. A. (2013). Knee joint angle measurement system using gyroscope and flex-sensors for rehabilitation (pp. 14). http://doi.org/10.1109/BMEiCon.2013.6687719

[53] Tomaru, A., Kobashi, S., Tsumori, Y., Yoshiya, S., Kuramoto, K., Imawaki, S., & Hata, Y. (2010). A 3-DOF knee joint angle measurement system with inertial and magnetic sensors (pp. 12611266). http://doi.org/10.1109/ICSMC.2010.5642420

[54] Cheng, T. M., Savkin, A. V., Celler, B. G., Su, S. W., & Wang, N. (2009). Universal algorithm for exercise rate estimation in walking, cycling and rowing using triaxial accelerometry. Electronics Letters, 45(8), 394395. http://doi.org/10.1049/el.2009.3515

[55] E. van der Kruk. Google glass koppelt real-time rondetijden terug. January 30, 2015. Retrieve from http://skatescience.nl/google-glass-koppelt-real-time-rondetijden-terug/

[56] Van der Steen, D. Jansen, A.J. Dekker, M.C. Den Braver, O. Industrial Design Engineering Design for Interaction Master Thesis 2012-06-25 AFThe Vibe of Skating: A Wearable Vibrotactile Speed Skating Coach %(c) 2012 Van der Steen, D.