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Automated detection and classification of movement cycles in cross-country skiing through analysis of inertial sensor data movement patterns

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Problem description

Modern instrumentation allows studies of human movement at an unprecedented level of detail in a vast number of contexts. The long-term aim of this project is to exploit this potential to study, describe and eventually improve techniques and exercise regimens in top-level cross country skiing.

The movement patterns in cross country skiing are characterized by two different classes of techniques - the skating technique and the classical technique. Classical cross country skiing is again divided into four major subtechniques: diagonal stride, double poling, double pole kick and herring bone (steep uphill). For the skating technique mainly four subtechniques are employed; G2 (paddling), G3 (double dance), G4 (single dance) and G5 (skating without poling). The skier must adapt these techniques to changes in terrain topography, skiing velocity and snow conditions. The movement in cross country skiing is cyclic, and each cycle can generally be classified as either one of the subtechniques or a transition between subtechniques.

The objective for the present project is to develop a valid method to (1) identify each cycle, (2) calculate the cycle time for each cycle and (3) classify which cross country skiing technique and sub-technique is being used in each cycle, based on data from a wearable IMU (Inertial Measurement Unit) comprising accelerometers, gyroscopes, magnetometer and altimeter. The identification and classification algorithm should be robust and work for different skiers on different levels without the need for separate calibration for different skiers or for different velocities. The classification technique should be applicable to near real-time classification and have a complexity which makes implementation on a microcontroller possible. It is suggested that the methods to be applied for the identification and classification is based on similarity transforms and cross correlation.

Evaluation of the algorithms should be done by applying the algorithms to calculation of cycle time and classification for three different skiers who each ski for 15 minutes in varying technique and sub-technique according to the following scheme,

- Evaluate the percentage of the cycles for which the algorithms correctly identify the correct sub-technique. If a cycle is correctly identified as a transition cycle between two sub-techniques, this should be taken as a correct identification.

- Evaluate the percentage of the cycles for which the algorithms correctly identify the correct sub-technique when near real-time classification is done (classification delivered less than 3 seconds after a cycle is finished)

The project aims for the algorithms to classify at least 95% of the cycles correctly, including transition cycles. A discussion of how the algorithms should be modified to improve the classification accuracy should be included.

Relevant data material will be provided by NTNU SenTIF. The following type of material will be provided: (1) IMU data for each of the different sub-techniques, for different skiers, on different levels, at different velocities, where each sub-technique is performed for periods of minimum 30-60 seconds by each skier. (2) IMU data along with accompanying video material for different skiers doing approximately 15 minute runs where the skiers change sub-technique based on the terrain and conditions.

The data material will be marked with the correct classification through visual inspection by the student. Marking of data material will be done ahead of the algorithm evaluation.

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Summary

Published technique analysis tools for movement patterns in cross-country skiing have accuracies ranging from 88% up to 98.5%, but reviews of these studies reveals that none have thoroughly addressed classifier robustness across variations in terrain, athlete skill level and movement intensity, in addition to none being proven able to classify both classical and skating technique without technique specific alterations. This thesis has therefore suggested an approach of using a template matching based classifier, with its main goal being identifying and classifying movement cycles of both cross-country skating and classical subtechniques, in addition to providing estimates of cycle times for each cycle.

Investigations found variation in parameters of characteristics and terrain of significant impact to the classifier, whilst variations in movement intensity had less effect. The final template matching implementation was tested on three different athletes, doing full laps of varied terrain and choosing technique freely. Video analysis of these recordings found 649 valid movement cycles, of these 616 were detected correctly. A total of 575 of the correctly detected cycles were classified correctly, resulting in an overall classification rate of 88.6%. Cycle time calculations were implemented and compared against the video annotations, with results showing strong consistency and coherence between them.

Specific challenges were tied to the most prominent misclassifications, and are believed solvable through further investigations. If these issues were solved properly overall classifier performance for the current implementation would elevate to 94.3%. Common challenges within the field regarding turns and transitioning were also seen for this method. Real-time implications have been evaluated, conclusions being that conversion into real-time functionality is possible through simple alterations to the sequential execution of the algorithm.

These results are considered promising in developing a classifier capable of handling movement patterns of both classical and skating techniques, as the first method within the field to handle both classical and skating without technique specific alterations. The method is based solely on general templates representing movements, thus utilizing this algorithm on other fields of cyclic movement should only require an alteration of the template base used.

Sammendrag

Publiserte verktøy for teknikkanalyse av bevegelsesmønstre i langrenn har vist ytelse i klassifiseringsrate fra 88% opp mot 98.5%, men vurderinger av disste studiene har vist at ingen så langt har undersøkt påvirkning som følge av variasjon i terreng, ferdighetsnivå og bevegelsesintensitet, samt har ingen blitt vist til å kunne håndtere både klassisk- og skøyteteknikk uten endring av implementasjonen. Gjennom denne studien er det derfor foreslått en ny tilnærming med å bruke en "template matching"-klassifikator, med formål å kunne håndtere både identifisering og klassifisering av bevegelsessykluser innen både klassisk- og skøyteteknikk, i tillegg til å gjøre estimering av syklustid for hver identifiserte syklus.

Gjennom arbeidet har variasjon av terreng og bevegelseskarakteristikk blitt påvist å gi betydelig påvirkning i forhold til klassifikatorytelse, mens variasjoner i bevegelsesintensitet gav mindre grad av påvirkning. Den endelige klassifikatorimplementasjonen ble testet på tre forskjellige utøvere, som tilsammen gjorde tre fulle runder med fritt valg av teknikk. Videoanalyse av opptak fant 649 gyldige bevegelsessykluser, og av disse ble 616 korrekt detektert av algoritmen. I alt 575 av disse riktig detekterte syklusene ble klassifisert riktig, som resulterte i en overordnet klassifiseringsrate på 88.6%. Syklustidberegninger fra algoritmen ble sammenlignet opp mot resultater fra videoanalyse og indikerte konsist samsvarende resultater.

Det ble funnet konkrete utfordringer relatert til de mest fremtredende feilklassifiseringene, og disse er antatt løsbare gjennom videre arbeid med implementasjonen. Dersom disse utfordringene blir løst vil ytelsen på den nåværende implementasjonen bli løftet til 94.3%, som kan sies å være på høyde med bransjestandarden. Det ble også for denne metoden observert utfordringer relatert til sving og transisjoner, som er generelle alle publiserte metoder. Santidsaspekter for impementasjonen ble vurdert, med konklusjon om at konvertering til santidsfunksjonalitet er mulig gjennom enkle endringer i kjørestrukturen, uten endring av kjernefunksjonalitet.

Resultatene som er presentert er ansett for å være lovende i å utvikle en generell klassifikator kapabel til å håndtere både klassisk- og skøyteteknikk, og er den første metoden innenfor feltet som har gjort dette uten konkrete teknikk-relaterte endringer i implementasjonen. Siden metoden er utelukkende er basert på "templates" representativ for bevegelsene som klassifiseres er det anledning til å tro at implementasjonen enkelt kan benyttes innenfor alle felt for klassifisering av sykliske bevegelse gjennom å endre template-basen.

Acronyms

G2 Single time ski subtechnique

G3 Double time ski subtechnique

G4 Padle ski subtechnique

G5 Free skate ski subtechnique

DS Diagonal stride subtechnique

DP Double poling ski subtechnique

DPK Double pole kick ski subtechnique

HB Herringbone ski subtechnique

IMU Inertial Measurement Unit

Contents

Chapter 1

Introduction

Analysing human movement patterns is a large field in sports biomechanics, with its research trying to aid athletes in performing and preparing better for their activities Bartlett (2007). Analysing the execution and choice of movement patterns can reveal useful knowledge related to athlete skill, capacity and strategies, as one can study how such parameters affects performance and results which later can be used in planning of training regimes, race strategies, equipment choices, and other relevant aspects for the sport.

Cross-country skiing is a complex locomotion that requires both high physical capacity and good technical skills. Movement patterns in cross country skiing are characterized by two different classes of techniques - the skating technique and the classical technique, with both techniques being divided into several underlying subtechniques. The movement in cross country skiing is cyclic, and each cycle can generally be classified as either one of the subtechniques or a transition between subtechniques. A large amount of studies have been published regarding movement analysis of cross-country skiing technique, and amongst other aspects technique execution and distribution has been shown to have an effect on performance (see for example Smith (2003); Bolger et al. (2015); Øyvind Nøstdahl Gløersen (2014); Håvard Myklebust (2013); Losnegard et al. (2016); Myklebust (2016)). With technique distribution and execution showing relevance to performance, along with possibilities for studies of athlete skill, capacity and strategies, being beneficial for planning of training regimes, race strategies, equipment choices,and other relevant aspects, it is clear that development of tools made for technique analysis, able to quantify and classify the specific cross-country skiing movement patterns, is of both high value and in demand.

There are already several methods presented for identifying and classifying cross-country movement cycles, with accuracies ranging from 88% up to 98.5%. Constraints made to the classification problem, in terms of which techniques and subtechniques are being classified, in addition to variations in parameters such as terrain, athlete levels, number of sensors, sensor placements, and number of athletes used in the studies have direct implications on the premises for success. This makes direct comparisons between these studies difficult, however, a general review of the methods and their implementations reveal certain common drawbacks.

In general all published methods of the field handle steady-state classification within a subtechnique well, with problematic areas reported being classifying activity not cohering to well-defined subtechniques, such as turning and transitioning between subtechniques. Other areas not thoroughly addressed previously are classifier robustness and performance across variations in terrain, athlete skill level and movement intensity, along with classification of both classical and skating technique done by the same classifier. This leaves highly relevant aspects in terms of creating an easy-to-use classifier meant for practical use and assessing the possibilities of for utilization on a broad user group where these variations are present unanswered.

Because of these aspects, the objective for the present project is to develop a valid method to identify and classify each movement cycle in an IMU generated series of cross-country skiing data. The method will also do calculations of cycle times for each cycle, as this is a parameter relevant for athlete evaluation in cross-country skiing. The identification and classification algorithm aim to be robust and work for different skiers on different levels, without the need for separate calibration for different skiers or for different velocities.

1.1 Guidelines for the reader

This report is written both for readers with a background in engineering sciences and readers with a background in movement sciences. The report is structured as follows: **Chapter 2** documents background material to better prepare the reader for the theory presented later in the report, along with a literature survey of relevant published studies in the field of classifying cross-country skiing techniques. The details and implementations of the methods used is explained in **Chapter 3**, and the results of experiments with these are further presented and analysed in **Chapter 4**. **Chapter 5** contains a final discussion and conclusions of work within in the report.

1.2 Contributions

The following contributions have been made through this thesis:

- **Litterature review** of published methods for detecting and classifying subtechnique movement cycles of cross-country skiing
- **Development, implementation and evaluation of a template matching algorithm** for detecting and classifying individual cycles of movement patterns in cross-country skiing, along with calculating the cycle time for each cycle.

Chapter 2

Background

Throughout this chapter relevant topics of background material for this thesis are presented.

2.1 Movement patterns in sports

Analysing human movement patterns is large field in sports biomechanics, with its research trying to aid athletes in performing and preparing better for their activities Bartlett (2007). Analysing the execution and choice of movement patterns can reveal useful knowledge related to athlete skill, capacity and strategies, as one can study how such parameters affects performance and results which later can be used in planning of training regimes, race strategies, equipment choices, and other relevant aspects for the sport. Throughout recent years there has been a great number of studies related to pattern recognition in movement, and techniques of pattern recognition have been applied to a great number sports, swim style classification Ohgi (2002), hockey and soccer movements Mitchell et al. (2013), interdisciplinary activity recognition Jenny Margarito and Bonomi (2016), and cross-country skiing techniques (table overview in appendix) to name a few.

Technique analysis and pattern recognition methods used define opportunities and limitations. Historical methods range from 2D video analysis to combining whole-body 3D kinematics, kinetics, and muscle activation. For cross-country skiing main drawbacks have been limited capture volume, interference with the skier's natural movement pattern, and the increased demands of in-field recordings compared to laboratory measurements Myklebust (2016). Today the use of low-cost inertial measurement units (IMU) have been introduced as a new tool for technique analysis in sports. These sensors have possibilities for providing high accuracy movement data in large quantities, with the added benefit of being easy to setup and configure. This combined with high sampling frequencies and ambulatory capabilities makes them excellent for outdoor on-body data collection and monitoring Aminian and Najafi (2004); Kavanagh and Menz (2008).

2.2 Movement patterns and technique in cross-country skiing

Cross-country skiing is a complex cyclical locomotion that requires both high physical capacity and good technical skills. Movement patterns in cross country skiing are characterized by two different classes of techniques - the skating technique and the classical technique, with both techniques being divided into several underlying subtechniques. The movement in cross country skiing is cyclic, and each cycle can generally be classified as either one of the subtechniques or a transition between subtechniques. A large amount of studies have been published regarding movement analysis of cross-country skiing technique, and amongst other aspects technique execution and distribution has been shown to have an effect on performance (see for example Smith (2003); Bolger et al. (2015); Øyvind Nøstdahl Gløersen (2014); Håvard Myklebust (2013); Losnegard et al. (2016); Myklebust (2016)). With technique distribution and execution showing relevance to the cross-country skiing field of research it is clear that development of tools made for technique analysis, able to quantify and classify these specific types of movement patterns, is of high value and demand.

As mentioned, advances in sensor technology has allowed the use of inertial measurement units in movement analysis, with Van Den Bogert et al. (1999) being the first to apply this in cross-country skiing through its study of hip joint loading in various activities. IMUs in cross-country skiing have also been used to identify and define separable characteristics for the various subtechniques utilized in both skating and classical techniques, and to develop algorithms for classifying movement data into corresponding subtechniques utilized by the athlete.

The first study to utilize IMUs in technique analysis in cross-country skiing was Myklebust et al. (2011) in its temporal pattern analysis and classification of subtechniques in ski skating. The study used temporal parameters of ski pole hits to do transition classification, and achieved a classification rate of 88%. The following year Finn Marsland and Chapman (2012), through visual analysis of IMU acceleration data from the athlete's upper back, identified separable subtechnique characteristics, indicating the possibilities of developing algorithms for classification of subtechniques. Subtechnique movement pattern characteristics have in general been shown to be both inter- and intra-athlete reproducible (Finn Marsland and Chapman (2012); Håvard Myklebust (2013); Øyvind Nøstdahl Gløersen (2014)), whilst detailed characteristics within subtechnique movement patterns also have been shown to vary between athletes Øyvind Nøstdahl Gløersen (2014).

Following the article of Myklebust et al. (2011) several studies have been made to research the field of movement analysis and classification in cross-country skiing through the use of IMUs, and a complete list of all studies utilizing IMUs in cross-country research is presented and summarized in table 2.1. The studies regarding technique classification are presented through a table in the appendix, and are further discussed in the next sub-chapter.

2.3 Classification of cross-country skiing

Generally, classification techniques used in movement pattern recognition are highly varied, with heuristic, time-domain, frequency-domain and time-frequency being the most prominent Preece et al. (2009). A review performed by Preece et al. (2009) comparing the performance of different classifiers found indications of decision trees or artificial neural networks being the methods which provides the highest classification accuracy, but differences were small, which in turn might suggest that implementation and training is of higher importance than the choice of classifier technology. Technique classification methods used in studies of cross-country skiing have been temporal parameters Myklebust et al. (2011), decision trees Yoshihisa Sakurai and Ishige (2014); Finn Marsland and Chapman (2015); Yoshihisa Sakurai and Ishige (2016), markov-chain Holst and Jonasson (2013); Thomas Stöggl and Holmberg (2014); Meland (2016), unsupervised learning Thomas Stöggl and Holmberg (2014); Garsjø (2016), and similarity transform template matching Meland (2016). Details of these studies are presented in a table presented in the appendix.

The accuracy of the methods made for classifying cross-country subtechniques vary from 88% up to 98.5%. Constraints made to the classification problem in terms of which techniques and subtechniques are being classified varies greatly, which in turn impacts the resulting classification accuracy. All the publications are also varied both in terms of sensor placements, numbers, and technology, and also in classifier technique, terrain, athlete level, and number of athletes used for testing and training. These aspects make direct comparisons between studies difficult, as they might have varying premises for success. However, a general review of the methods and their implementations is beneficial in considering aspects which remain unanswered or is handled poorly and needs more research to give conclusive results.

In general all published methods handle steady-state classification within a subtechnique well, with problem areas reported being classifying activity not cohering to the well defined subtechniques, with turning Yoshihisa Sakurai and Ishige (2014); Finn Marsland and Chapman (2015); Yoshihisa Sakurai and Ishige (2016) and transitions between subtechniques Myklebust et al. (2011); Holst and Jonasson (2013); Yoshihisa Sakurai and Ishige (2014); Thomas Stöggl and Holmberg (2014); Yoshihisa Sakurai and Ishige (2016); Meland (2016); Garsjø (2016) being the most prominent. As indicated in Preece et al. (2009), this further supports that the choice of technique classification method might not be the most crucial factor in providing a high accuracy, but rather the implementation and training of this method. If the classification methods of these published studies were trained for or made able to handle turns and transitions the accuracy is likely to have been higher across all studies.

Although the various studies use athletes of different skill levels between them, none of the studies have so far done any comparison of accuracy between athlete skill levels within the studied classification method. This leaves the question of performance across athlete levels unanswered, which is relevant for a classification algorithm meant to hit a commercial consumer market with athletes of all levels. In addition, none of the studies investigate classification accuracy across varying intensities of techniques, which is highly relevant as a range of different intensities is used in both training and competition environments. Similarly, the terrain used for recording movement data ranges from asphalt roller-skiing to treadmill roller-skiing and on-snow skiing, but there are no studies which have verified any portability between these terrains in terms of classification. In Myklebust (2016) it is shown that subtechnique movement patterns are different for on-snow skiing and roller-skiing, by means of distinct alterations in hip rotation patterns, whilst roller-skiing on treadmill and asphalt have inter-athlete similarities. This indicates that portability of a high accuracy classifier between different terrain might be difficult, which in turn might restrict the area of application for certain methods or demand more extensive training and even alterations in implementation to be able to handle variations in terrain.

The study of Jenny Margarito and Bonomi (2016) looks into classification across a variation of activities, not including cross-country skiing, through the use of a template matching classifier. The results were promising and found template matching to be a simple and robust classifier which handled these variations well. In addition the classifier proved to be robust on data generated from previously unseen subjects with different biometric characteristics and motor skills, with the conclusion that template matching is well suited for recognition of sporting activities of periodic nature. These advantages play well into current difficulties in the field of pattern recognition in cross-country skiing, and a preliminary study by Meland (2016) have already shown promising results of utilizing template matching for this problem. In its study Meland (2016) also states that already available classifiers lacks properties of simplicity and generality, this as a result of all studies either specializing on either classical or skating, with none having a focus on creating an general algorithm for the field as a whole, and suggests template matching to be of interest in trying to solve these issues.

Conclusions and findings relatable to this study

From the general review of the existing methods of classification in cross-country skiing it is apparent that consistency for reasonably high accuracies is already achieved, with most classifiers having a performance of >90% classification rate. This does however also indicate that a classifier performance of 90-95% might not be dependant on the choice of classifier, but might be just as much a result of how well the chosen method is trained and implemented. Another point worth considering is that since current classifiers all struggle with similar issues in achieving even higher accuracies, efforts looking into solving these should benefit the field as a whole. Along with the specific difficulties of achieving accuracies higher than 95% there are also unanswered aspects regarding these method's robustness in terms of being able to classify through variations in terrain, athlete skill level, movement intensity and technique, which should be considered highly relevant for any implementation meant for a broad group of users. Such an implementation will most likely benefit from a classifier with properties of simplicity and generality, in terms of being easy to implement and train for these variations. As technique analysis tools which are precise and easy to use are of high value and demand a focus on performing well across these variations, along with providing high accuracy performance, should be central for further development in the field.

As the combined results of Jenny Margarito and Bonomi (2016) and Meland (2016) have indicated promising results for the template matching classifier regarding these issues, this method is chosen as the classifier used throughout this study.

2.4 Classification

In many practical problems classification is an important part, or even the main goal, of the task. Classification is a term which is used for the process of deciding what something is or which category to label something into. The process is based on identifying and evaluating different characteristics of the object being classified, and then assigning the object to a certain class based on this evaluation. The algorithms doing these evaluations and classifications are named classifiers. Discriminative characteristics of the objects are most often identified by examining a big set of representative sample objects, referred to as training the classifier. This process helps identify the characteristics separating the classes from each other, which the classifier then later uses to classify new and unknown data. A classification system is mainly built

Year	Author(s)	Technique(s) / Activity	Classificator	Sensor placement	no. of athletes	size test set	size training set	Athlete level	Terrain	Accuracy	Difficulties
2011	Myklebust et al.	Skating	temporal analysis	poles, ski boots and hip	3	3	0	elite	on-snow	88 %	Transitions
2013	Holst	G2, G3, G4	Markov-chain with unsupervised learning	chest, centrally above breastbone	14	7	7	elite	outdoor roller skiing	98 %	Transitions
2014	Sakurai	DP, KDP, DS	Decision tree	wrists and roller skiis	11	1	10	elite	roller ski tread mill	98.5 %	Turns, Transitions
2014	Stöggl	G2left, G2right, G3, G4left, G4right	Markov-chain with unsupervised learning	chest, centrally above breastbone	11	5	6	regional-to-inter national	outdoor roller skiing	90.3%	Transitions
2015	Marsland	DP, DS, KDP	Decision tree	upper back	7	7	0	national	on-snow	83.8 %	Direction changing techniques
2016	Meland	G2, G3, G4	Markov chain & similarity transform	lower back	9	3	6	upper secondary school	on-snow	95.5 %	Transitions
2016	Garsjø	standstill, DP, DPK and DS	Unsupervised learning	lower back	6	1	5	upper secondary school	on-snow	95.7 %	Transitions, standstill
2016	Sakurai Y, Fujita Z, Ishige Y.	Cross-country ski skating	Decision tree	wrists and roller skiis	16	15	1	college	outdoor roller skiing	94.8 %	Turns, Transitions

Figure 2.1: Table showing key points of previous research on classification of cross-country skiing.

up by feature extraction and classification, for a physical system one also needs some kind of sensor(s) to create data for the feature extraction. A typical configuration of a classification system is depicted in figure 2.2, taken from Johnsen (2016).

For the problem at hand the sensor will be an IMU gathering acceleration and rotational data from the movement of a cross-country skier. The feature extraction will be the data processing done to the raw signal from the sensor(s), identifying and enhancing the discriminative features. These features will then be evaluated by the classifier to classify the unknown data into classes corresponding to sub-techniques. Training of the classifier will be done utilizing a separate and known data set. The classifier chosen for this study, reasoning explained in previous subchapter, is based on the simple and robust principles of template matching, and the details and theory behind template matching and its classifier is presented and discussed in the following subchapters.

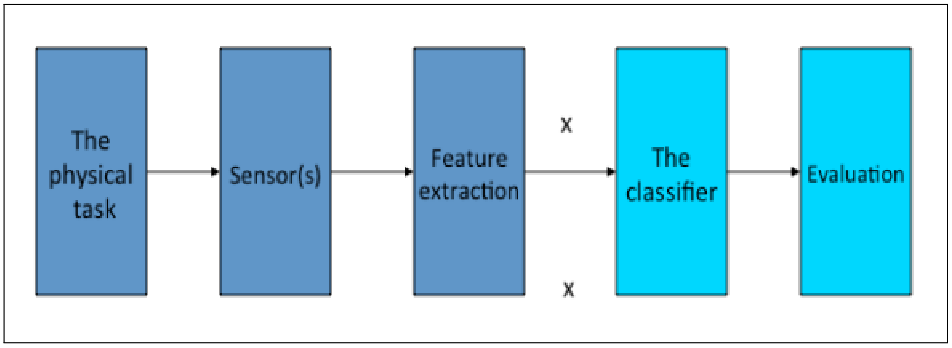

Figure 2.2: A flowchart describing a typical classification algorithm, taken from Johnsen (2016).

2.5 Template matching

In doing classification and developing of classifiers there are an abundance of different methods available, each with drawbacks and advantages which might apply to the specific problem at hand. An underlying problem in automated analysis of cross-country skiing IMU data is detecting and classifying periodically repeating movement pattern cycles. In the study of Jenny Margarito and Bonomi (2016) template matching was shown to be a simple and robust way of classifying a variety of activities, and found that template matching performs robustly on data generated by previously unseen subjects with different biometric characteristics and motor skills. Their conclusion was being that template matching is well suited for the recognition of sporting activities with inherent periodic properties. The main idea behind template matching consists of two major steps: generating templates for each target class using entities with particular patterns, and then comparing each new entity to this set of generated templates in order to find the best fitting one. Thus, the unknown entities can be classified to the target class represented by the selected template Jenny Margarito and Bonomi (2016).

Template matching has previously been successfully applied to great extent in several domains, such as computer vision Brunelli (2009), speech recognition Deng et al. (2007), and gait analysis Zhang et al. (2011), but has seldom been applied for physical activity Jenny Margarito and Bonomi (2016). There have been some studies utilizing template matching as a classifier for motion patterns, e.g. identifying sport activities Jenny Margarito and Bonomi (2016) and human gait Vaaga (2008), and Meland (2016) even showed some preliminary promising results on using the classifier from Vaaga (2008) on cross-country skiing data. The results of Meland (2016)

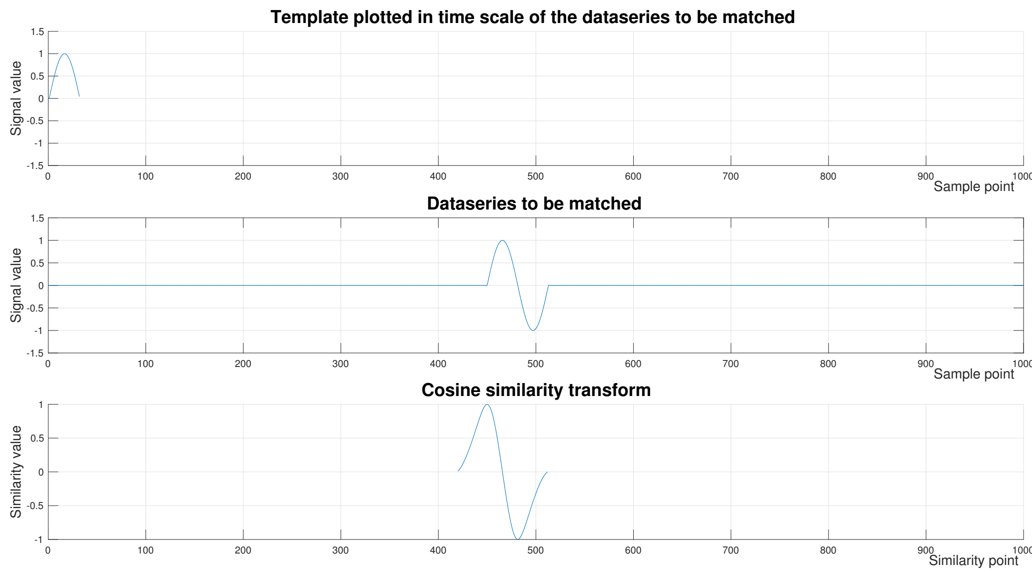

Figure 2.3: Illustration of template matching.

suggested that the simplistic and versatile properties of template matching could prove beneficial for some of the difficulties present in the field of classifying cross-country skiing, with the possibilities of creating a single classifier for handling both classical and skating techniques being the most important.

2.5.1 Template matching in cross-country skiing

The general principle of template matching classification is quite simple; compare a segment of unknown data with previously generated templates and classify according to highest similarity.

In the field of cross-country skiing the classifier is most often not only used to classify a timeline of data, but is in addition used to detect and segment each individual movement cycle of the skier, which also is a predefined requirement for the classifier being developed in this study. This additional requirement to the classifier algorithm further complicates the problem at hand, and is usually solved by creating a way for the algorithm to segment the incoming data into corresponding movement cycles before doing classification of each individual cycle. The ways of segmenting this data are solved in a varied number of ways, but generally these solutions either work for the classical or skating techniques specifically, and a general method able to handle both techniques has yet to be presented.

The inherent nature of template matching will in cyclic data create peaks and troughs when the template and data series gradually goes in and out of phase with each other. For cyclic movement patterns such as in cross-country skiing the highest peaks and lowest troughs should represent the same frequency as the cycle rate of the skier, as long as the templates sufficiently incorporate the characteristics of a full cycle of the subtechnique in question. Utilizing this to do a similarity transformation on unknown data from cross-country skiing, with different templates representing different subtechniques, the resulting information should be enough to both identify movement cycles and classify the subtechnique for the data in question in a single operation. This solution effectively removes the need for a separate cycle identification algorithm, and in turn should make the method general enough to be able to handle both classical and skating techniques, as long as it incorporates all necessary subtechniques in its training process.

2.5.2 Cosine Similarity Transform

A template matching method compares two segments of data, providing a measure of similarity between them later utilized by the classifier. The methods for creating such a similarity measure are many and, similar to the many possibilities in classifiers, these all contain properties which can be seen as advantages or drawbacks to the problem at hand. In the study of Jenny Margarito and Bonomi (2016) a comparison between five different similarity measures utilized for template matching is made, specifically *Euclidean distance*, *dynamic time warping* (DTW), *derivative dynamic time warping* (DDTW), *correlation*, and their own index combining distance and correlation metrics named *Rce*, with their results suggesting that correlation-based mathing techniques generally outperformed the Euclidian, DTW and DDTW similarity measures Jenny Margarito and Bonomi (2016). The study of Vaaga (2008) utilized the simplistic correlation based similarity measure of the Cosine Similarity Transform on human gait detection with great results. This similarity measure was later also utilized in the study of Meland (2016) on cross-country skiing data, which stated that the method was promising both in terms of performance accuracy and its ease of implementation, with indications that such a simplistic method could prove beneficial in solving difficulties in creating a general classifier able to handle both classical and skating techniques for cross-country skiing. Because of these aspects, the usage of the Cosine Similarity Transformation will be continued throughout this study, with the most prominent advantages being the methods combination of simplicity in implementation and previous promisingly results on similar classification problems.

Chapter 3

Methods

In this chapter the experimental approach and details of the methods used and developed throughout the work of this thesis are described. The first subchapter contains details of the data recording process in creating the data sets used in this study, followed by a description of the instruments and materials used, and a description of the video analysis process performed. The last subchapters relates to the development process of the template matching method.

3.1 Data sets

When developing a template matching classifier for cross-country skiing the first step is to gather representative training data which can be used for template creation. This data has to cover all relevant movements which are to be classified, techniques and subtechniques of cross country skiing in this case, and needs to be as representative as possible if one is to separate between the similar movements of these different subtechniques. The gathered data for this study consisted of information recorded from an inertial measurement unit (IMU), which included a 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer and a barometer. The IMU sensor used when collecting data was mounted centrally on the subjects lower back.

These data sets were collected in Granåsen ski-center in Trondheim, Norway, during the spring and winter seasons of 2016. All protocols and procedures were explained verbally to each skier. The course, terrain, and snow quality were not controlled factors. All data collection was super-

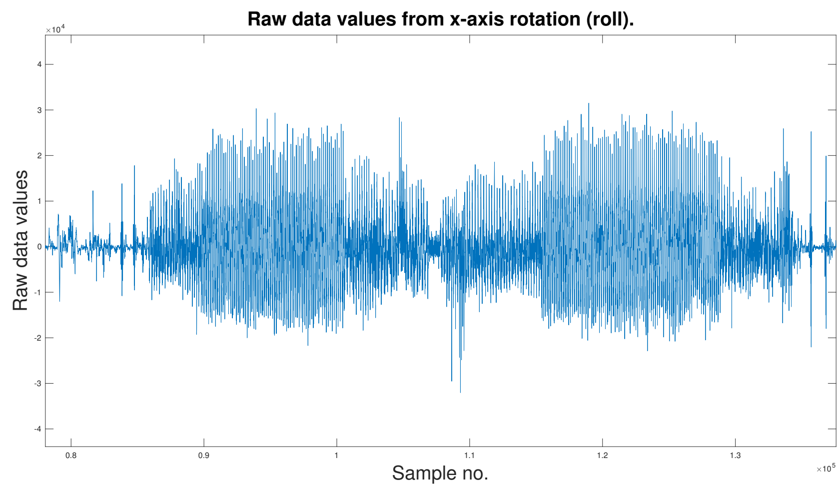

Figure 3.1: Example single axis data from an athlete recorded during cross country skiing.

vised by either one or more video cameras (Garmin VIRB Ultra 30) placed on the athlete's own torso and/or operated by an additional athlete following the subject with a head-mounted camera pointing at the subject at all times. These video recordings were used to verify classification by visually identifying cycle count and sub techniques utilized by the skier, and to investigate any discrepancies in the classification results.

When collecting data for template creation the subjects were told to ski using the designated sub-technique in a straight line, with G4 and herringbone recorded in uphill segments. The collection of data used in classification tests was done in a non-specified course which varied in terrain features (uphills, downhills, turns etc.). In the first round of recording a total of 3 athletes, 2 female and 1 male, of former active elite level participated. For the second round of recording a total of 8 male skiers volunteered for participating, with 5 being of elite skill level and 3 of amateur skill level. The elite skiers were between national and international skill level, the amateurs were recreational skiers.

In order to research possibilities for classification across variations in terrain a preliminary study comparing templates from treadmill and on-snow recorded data was done. A study done by Myklebust (2016) have already shown alterations in hip movement patterns between on-snow and treadmill skiing, and this was expected to be reflected in templates. The results of this study are described further in chapter 4. The treadmill data was also used for investigating the implications of varying intensity for template characteristics, results discussed in chapter 4, as the recodrings included runs of low, medium and high intensities. The roller-skiing was performed on a 5 × 3-m motor-driven treadmill (Forcelink B.V., Culemborg, The Netherlands). The inclination and speed were calibrated using the Qualisys Pro Reflex system and Qualisys Track Manager software (Qualisys AB, Gothenburg, Sweden). The non-slip rubber surface of the treadmill belt allowed the subjects to use poles (Madshus UHM 100, Biri, Norway) with special carbide tips. Poles were available in five-centimeters intervals and the subjects chose the preferred length. A safety harness secured the skiers during the treadmill testing. In order to minimize variations in rolling resistance, all of the skiers used the same pair of IDT roller skating skis with standard resistance category 2 wheels (IDT Sports, Lena, Norway).

3.2 Instruments and materials

The sensor unit used in this study is a single 9-axis Apertus IMU (Apertus Skiing Sensor, Apertus AS, Asker, Norway) with integrated barometry, built up by an accelerometer, a gyroscope and a magnetometer. To reduce confounding factors of classification the barometer and magnetometer were not used in this study, as they are affected by external factors (human made magnetic fields, altitude) not related to ski technique. The Apertus IMU was placed centrally above the lower spine of the skier. Data was transmitted in real-time by Bluetooth, using a mobile phone (Sony Xperia Z3 compact, Sony Inc., Tokyo, Japan), which received and stored the collected data for post processing in Matlab R2016a (The MathWorks Inc., Natick, MA). All participants used their own skis, boots and poles.

Axis	**Figure**
Accelerometer x-axis	FwdA
Accelerometer y-axis	SideA
Accelerometer z-axis	Up
Gyroscope x-axis	Roll
Gyroscope y-axis	Pitch
Gyroscope z-axis	Yaw

Table 3.1: Table describing axes orientation in accordance with figure 3.2.

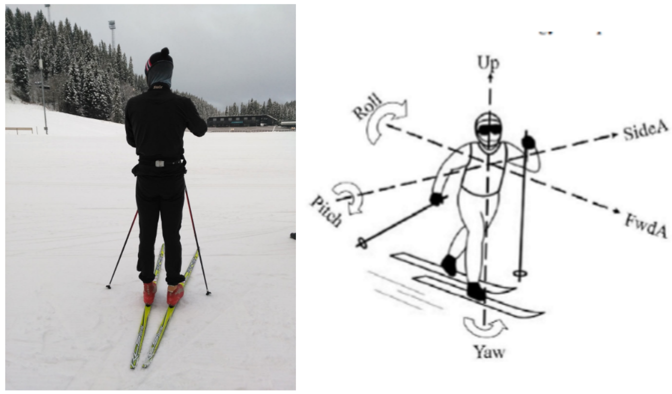

Figure 3.2: Illustration of IMU placement (white square on athletes lower spine, left picture,) and axis orientation, right picture, taken from Finn Marsland and Chapman (2012).

3.3 Video analysis

For verification of the template matching algorithm video analysis is utilized by manually identifying true cycle detections and classifications. This process is done by revising the recorded videos of the test subjects and manually marking starting and end points for each movement cycle, along with assigning it to its representative subtechnique. This video analysis is done through usage of the ANVIL video annotation tool, which offers multi-layered annotation based on user-defined coding schemes. This coding scheme is made representative to the subtechniques in question, with separate annotation layers for manual marked cycles and the cycles resultant from the template matching method. In addition, layers for reviewing the performance of the algorithm is included, with possibilities for separately annotating correctly detected cycles, correctly classified cycles, undetected cycles and erroneously detected and classified cycles. This process is exemplified in figure 3.3. The outputs from the template matching method are converted into a format compatible with this ANVIL coding scheme, and can because of this easily be imported into ANVIL for comparison with the manually marked cycles. For rough alignment of the video marked cycles and the template matching cycles a manual offset is added to the template matching data.

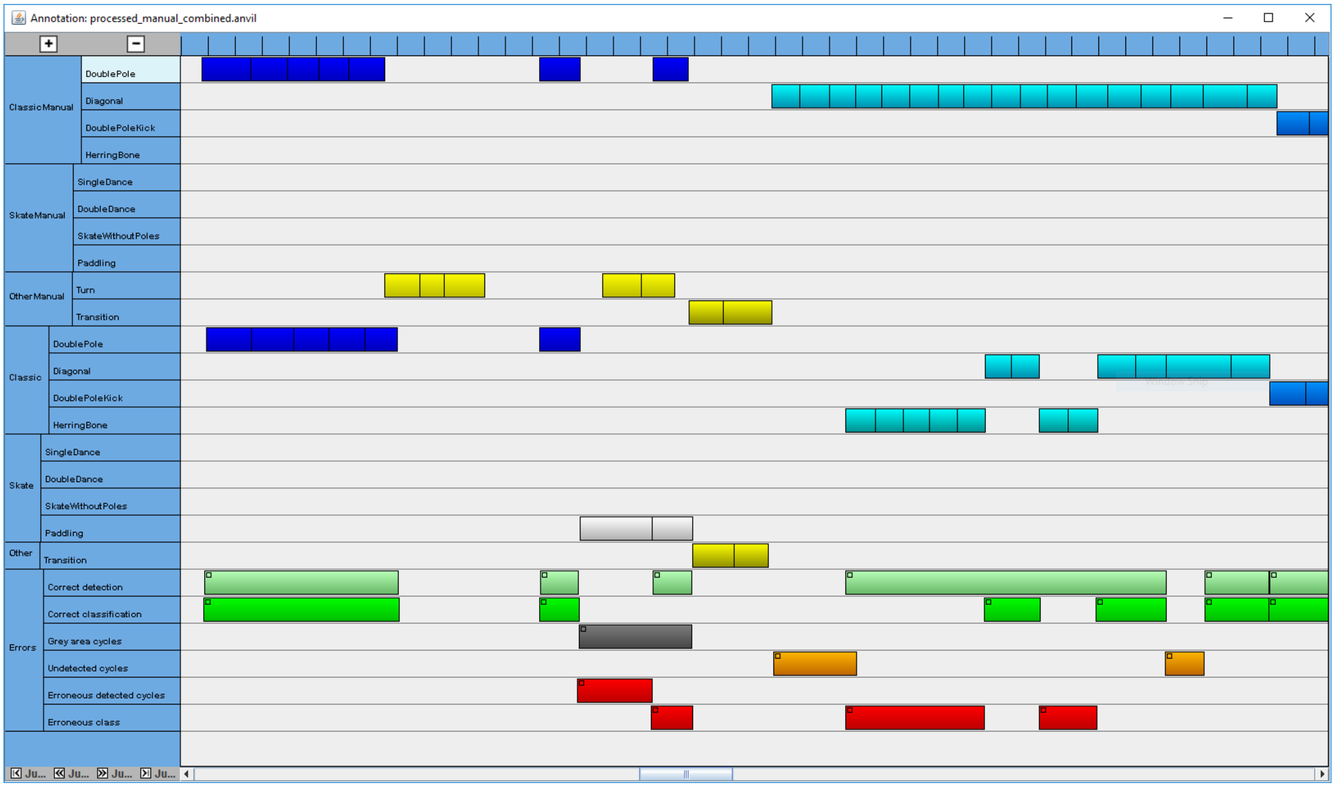

Figure 3.3: Example of video analysis annotation comparisons.

3.4 Template creation

As mentioned earlier the performance of a template matching method is highly dependent on accurate templates representing each specific pattern to be classified, and because of this the template creation process is a crucial part of the development process. The templates needs to be carefully selected in order to be as representative as possible, and in some cases there might be a need for several templates to cover variations within a subtechnique.

To ensure a repeatable and accurate template creation process, a semi-automated algorithm was developed. This developed script lets the user choose a segment of raw data through start and end points for a single subtechnique, which the algorithm then processes into templates for that subtechnique. The result of the process is shown visually for ease of inspection, with the most critical aspect being proper cycle detection. The flow diagram for the developed template creation algorithm is shown in figure 3.4, with its details explained in the following subchapters.

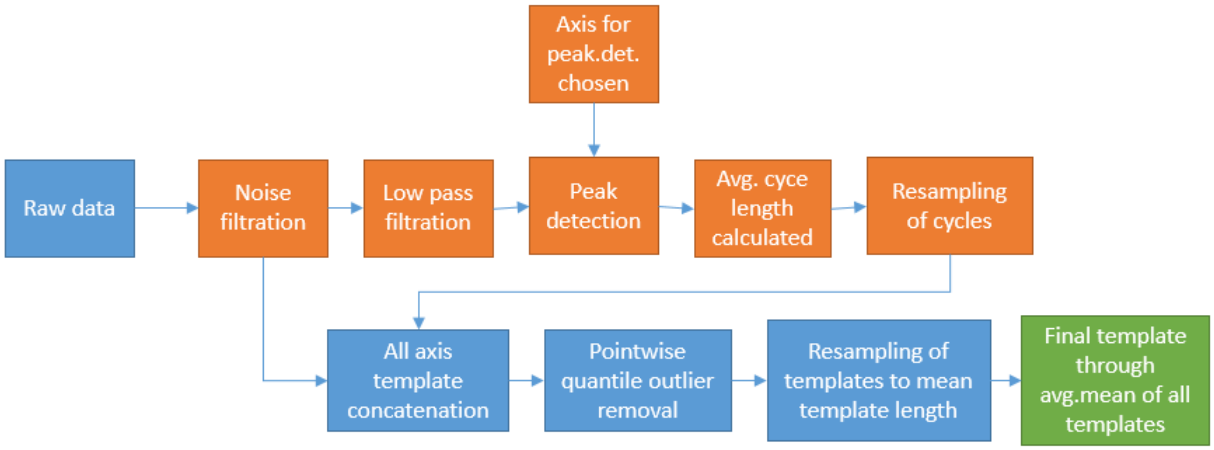

Figure 3.4: Flowdiagram illustrating the template creation algorithm.

3.4.1 Data processing

The method of cycle detection in the template creation process utilizes low-pass filtering of raw data to enhance the harmonic frequency of the movement. This low-pass filtering removes noise and higher frequency movements, so that the signal resembles a pure sinusoidal with the extremal points corresponding to the cycle rate of the subject. For cycle detection a single axis from the 6-axis raw data available is chosen. This chosen axis is crucial for the resultant template constructed, as not all axes will have an harmonic frequency corresponding to the cycle rate of the subject. The process of choosing an axis for cycle detection was done through spectral analysis for each axis using a Welch PSD estimate together with evaluating the performance of the different possible axes through cycle detection. An example PSD is shown in figure 3.7, and the resulting axes used for each subtechnique are presented in table 3.2. The Welch PSD was also used when doing filter design for the sinusoidal enhancement. From the example figure 3.7 one can see that the harmonic frequency is < 2Hz, which was true for all subtechniques in this study. To reduce the impact of data processing lag, resulting in skewed extremal points, a zero-phase filter was used. The filter design was done by using built-in functionality in Matlab. If the filter did not perform optimally in removing all movements except for the sinusoidal, the filtering process was simply repeated, effectively increasing the filter order. This can be done as the filter is zero-phase, with no lag affecting the processed data, and the effects on amplitude does not matter in terms of cycle detection. The initial filter order was chosen through experimentation.

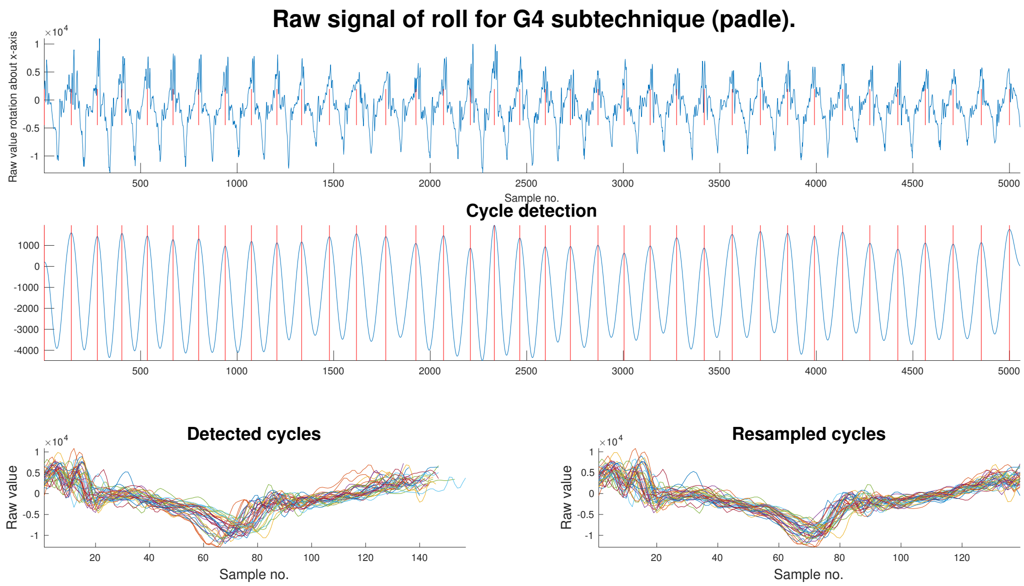

Figure 3.5: Plot illustrating raw data, low pass filtered data with cycle detection, and cycle re-sampling.

Table 3.2: Overview of axes used for peak detection in template creation.

Class	**DS**	**DP**	**DPK**	**HB**
Axis	gyro-x	gyro-y	gyro-y	gyro-z
Class	**G2**	**G3**	**G4**	**G5**
Axis	gyro-z	gyro-z	gyro-z	gyro-z

3.4.2 Peak detection and cycle segmentation

The base harmony after low-pass filtering the signal corresponds to the base harmony of the movement, and thus the peaks of this signal indicates the cycles of the motion pattern. These peaks are used to segment the signal up in cycles, and after the segmentation each segment represent a cycle of raw data. When segmentations have been, processed each cycle will naturally vary in length (time) corresponding to the variations in cycle time from the subject movements. The template creation is based on finding representative templates for each subtechnique based on the many cycles collected from a long segment of raw data. The variations in cycle length will then cause irregularities in timing of the different characteristics within a cycle, which might result in a degradation template quality if not countered. To counter this the mean cycle length from the collected segments is calculated and each cycle is resampled in length correspondingly, causing the templates to be of equal length, and the characteristics within a cycle to be coherent.

The re-sampling is done through Matlab's built-in function $resample(X, P, Q)$, which resamples the values, X, of a uniformly sampled signal at P/Q times the original sample rate Mathworks (2016). When re-sampling a cycle to fixed length the P corresponds to the desired number of points and the Q corresponds to the length of the original cycle being re-sampled. For further details of this function the reader is referred to Matlabs documentation at Mathworks (2016). As the templates and unknown data are results of concatenation of six-axis sensor data series their lengths has to be multiplums of six, because each axis of the unknown has to represent a sixth of the template. This always has to be considered when creating and resampling templates, and is because of this handled automatically by both the template creation and resampling algorithm.

3.4.3 Template post-processing

The cycle detection algorithm will sometimes detect a false or erroneous cycle, with characteristics differing significantly from the mean of the subtechnique characteristic. To counter this, outlier removal is implemented to remove data points which is far from the mean distribution for each point. This is done through moving points outside the .25 and .75 quantiles of the individual point normal distribution to the .5 quantile (mean) for each point. This ensures that

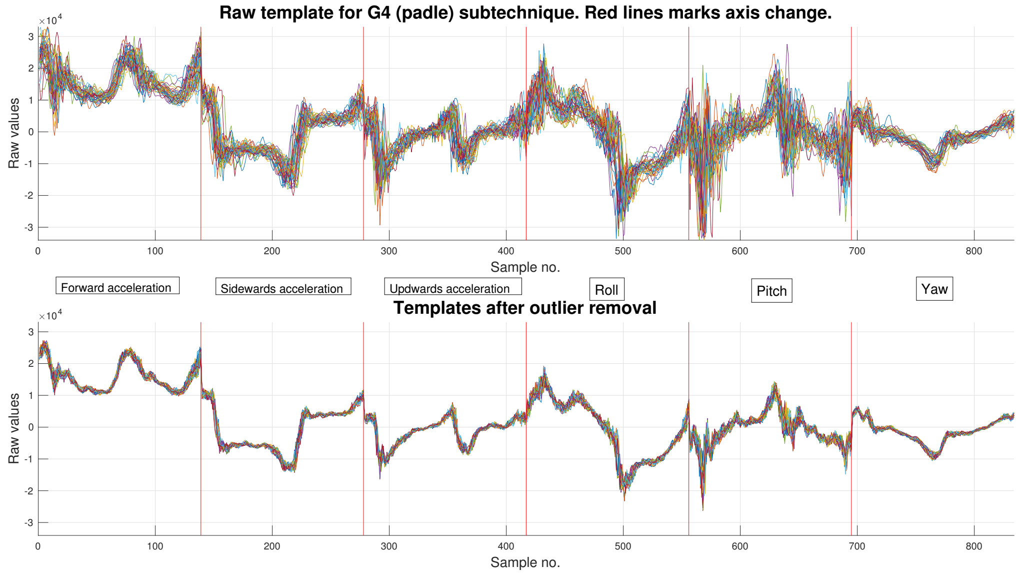

Figure 3.6: Plot illustrating segmented cycles, from the G4 (padle) subtechnique, compiled into overlapping templates. The second subplot illustrate results from outlier removal.

there is no outlier point greatly affecting the resultant template characteristics. Results of outlier removal is illustrated the lower subplot of figure 3.6.

The final template from each creation process is created from the mean of all individual, outlier corrected, templates found in the segment of raw data chosen.

Normalised template set

In order to reduce complexity and computational load of the algorithm, a goal is to create a reduced template set by processing all available templates into a minimalistic yet representative template set. To make analysis of subtechnique templates across athletes possible, all templates are grouped into sets corresponding to their representative subtechnique. For such a grouping to be possible the templates has to correspond in terms of template length, and this is ensured by normalising the template lengths within subtechniques by resampling all templates of a subtechnique to the mean template length of that specific subtechnique. The resulting groups are then analysed by doing clustering of their contained templates in an attempt to reveal any characteristical subsets within each subtechnique. If such subsets are identified the groups are divided accordingly in order to preserve unique characteristics, as these are crucial to the classifier performance. All final template groups are then reduced to single templates by creating a representative mean template for each group. These resulting templates are then representative of their subtechnique both in terms of their unique subtechnique characteristics and their normalised template length.

3.5 Template matching

This chapter outlines and describe the details of the template matching model developed during the work of this thesis. A flow diagram for the template matching algorithm developed is illustrated in figure 3.9.

3.5.1 Data processing

To ensure the best conditions possible for the template matching method it is desireable to remove unwanted frequency components from the raw sensor data. For this classification algorithm one wants to remove high frequency components which are unrelated to the movements of the skier. Most signals of real-world implementations have a component of high frequency Gaussian white noise, but high frequency noise could also be from external sources such as the electrical components of the sensor or uncontrolled high frequent movement from the imperfections of the skiing surface.

Filtration of data actually has two purposes in this study, high frequency noise removal and enhancement of the lowest harmonic frequency component. The lowest harmonic frequency component will for certain axes represent the cycle rate of the athlete. Through removing all other frequencies, leaving only the frequency corresponding to cycle rate, will allow automatic detection of cycles in the dataseries, which is utilized in the template creation process for the template matching method.

In doing filtration of unwanted components, an analysis of the frequency components of the raw signal must be done to create a basis for filter design. The frequency distribution of the raw signal is revealed through calculating the power spectral density. This can be done in several different ways, and for this study Welch's method has been chosen. The calculated Welch's PSD is shown in figure 3.7. Peaks in a PSD represents frequencies which are dominantly present in the raw signal. From the PSD plot one can see harmonic frequency components in the lower regions of the spectrum, and one finds that above 5-10Hz there are no prominent peaks and that the lowest harmonic frequency is below 2Hz, meaning that 2Hz and 10Hz are suitable cut-off frequencies for this application.

Since both cases of filtration aims to remove frequencies higher than the ones enhanced, a low-pass filter is suitable. The low-pass filter design is done through utilizing Matlabs built in functionality, which simply requires the filtertype, cut-off frequency, desired filter order and normalized sampling rate of the signal as inputs. Filtertype and cut-off frequencies are chosen as described above, whilst the filter order is chosen by experimentation. The normalized sampling rate is calculated from the true sampling rate of the sensor.

The resulting filters used are shown in figures 3.8, and the effects of these filters on raw data are shown in figure 3.7.

3.5.2 Algorithm implementation details

The algorithm developed for this thesis is specifically aimed at being able to identify and classify movement cycles and cycle rates in cross country skiing. The model operates through comparing known templates of representative subtechnique movement cycles with unknown data series of continuous skiing. The similarity between each template and the unknown data series is calculated through iteratively using the cosine similarity transform on segments of the unknown data, with equal length to the template being used.

This comparison results in n new data series containing similarity values for each point of unknown data for each template, with n being the number of templates. These similarity value data series will have peaks and troughs representing the template going in and out of phase with the unknown data movement cycles, which are used for cycle detection and classification.

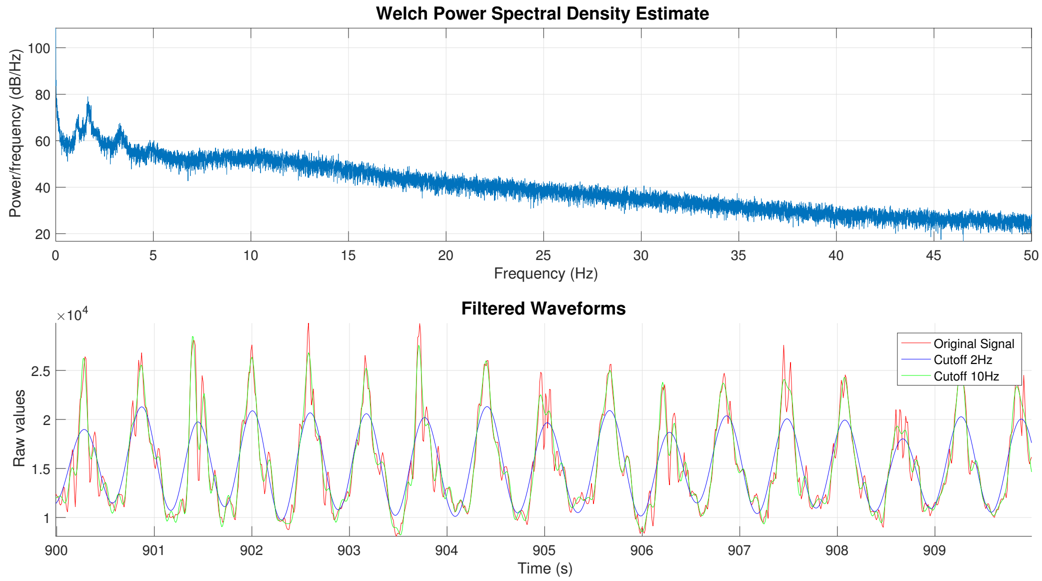

Figure 3.7: Plot illustrating the power spectral density of raw IMU cross-country data and the effects of filtering. The PSD is calculated using Welch's method.

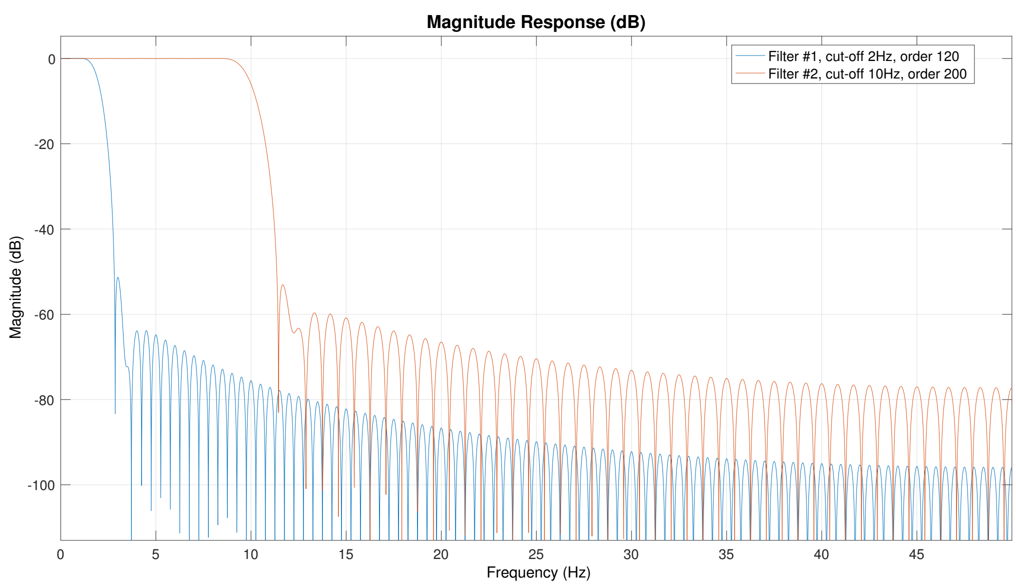

Figure 3.8: Frequency response of the low-pass filters designed and used in this study.

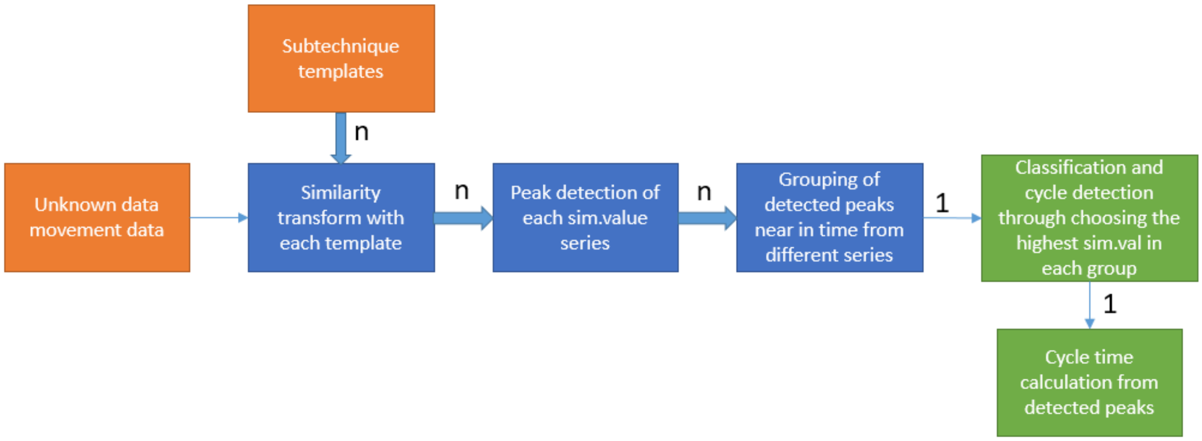

Figure 3.9: Flowdiagram illustrating the template matching algorithm. *'n'* equals number of templates.

The process of cycle detection is is done by isolating and detecting all similarity peaks above a certain threshold, and grouping the peaks from different templates together. These groups of similarity points will then contain a value from each template having a high enough similarity with the unknown data. The cycle detection index and class is then assigned according to the point in the group having the highest similarity score, using the original index and template class tied to that specific similarity point. Further details of this implementation is described in the following subchapters.

Cosine similarity transform

A cosine similarity transform uses the geometrical relation of the dot product, length, and angle between two vectors as a measure of similarity. The cosine of two vectors can be derived by using the Euclidean dot product formula shown in equation 3.1. It is common to use similarity and not $cos(\theta)$ as the annotation for this transformation, and the equation can thus be rewritten to equation 3.2 Vaaga (2008).

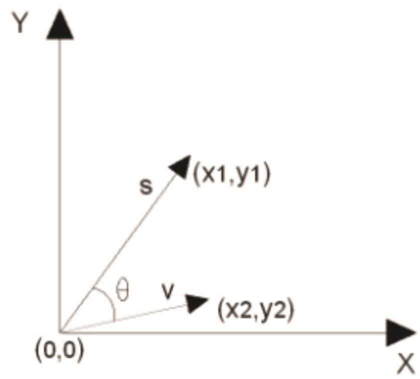

Figure 3.10: Illustration of the cosine similarity transform, with θ being the measure of similarity between the vectors V and S.

$$a \cdot b = \|a\| \|b\| cos(\theta) \tag{3.1}$$

$$sim = cos(\theta) = \frac{\underline{v} \cdot \underline{s}}{\|\underline{v}\| \cdot \|\underline{s}\|} \tag{3.2}$$

With a known vector S, used as a template, one can do a cosine similarity transform on a data set. For each sample point of the data set one extracts a vector, V, of same length as the known vector S. The cosine of the angle between them is calculated using equation 3.2, and represents a measure of how similar they are. When this is done throughout the whole data set one gets a measure of where and how much the data segment represented by S is present throughout the series of unknown data. This new data series of similarity values will have extremal points where the known vector, template, fits the uknown data set Vaaga (2008). The values represent the similarity value between the template and data series, ranging from -1 to 1, with 1 being an exact match, 0 giving no similarity at all, and -1 an exact inverse relationship between the template and data.

Calculating a similarity value for a segment of unknown data is done through comparing this segment with the template. The length of the segment being investigated thus has to be the same length as the template, and you get a single value of similarity for this specific segment. This process is run iteratively through the whole length of the unknown data series, resulting

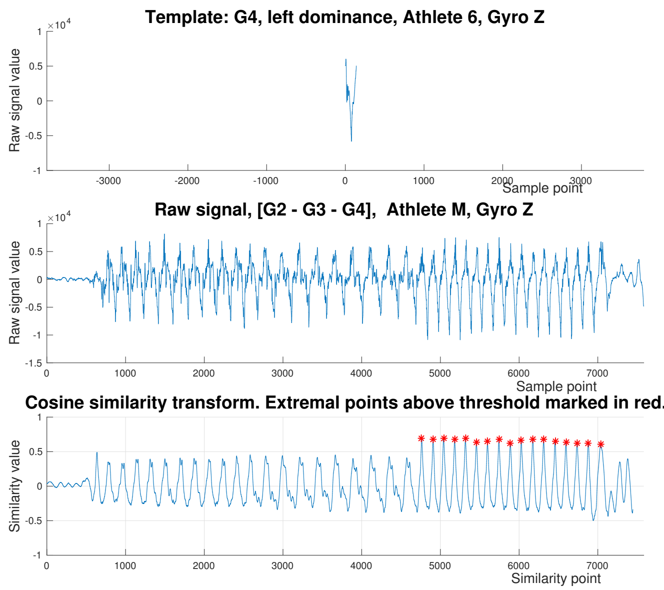

Figure 3.11: Plot illustrating the cosine similarity transform on cross-country skiing data. The upper plot shows the gyro-z axis segment of the template, plotted in the scale of the data for context illustration. The lower data shows the results of the similarity transform, with peaks above threshold marked in red.

in "N - n" similarity points, where N is the length of the data series and "n" the length of the template. The method used on cross-country skiing data with a single template is illustrated in figure 3.11.

Resolution of similarity transform calculations

A parameter related to computational load and accuracy for the similarity transform is the incrementation step used. As the similarity between the template and movement data gradually goes in and out of phase one can linearly reduce the computational load by incrementing the segment of movement data evaluated by steps greater than 1, e.g. incrementing the data segment by 4 data points instead of 1 will result in a x4 reduction in calculations. This reduction in computational load does however at the same time impact the resolution of the cycle detection. With an incrementation step of 1 the similarity transform has a resolution corresponding to the sample frequency, and in this study a sample frequency of 100Hz is used. Increasing the incrementation from 1 to 4 this sample frequency is effectively reduced to 25Hz, which in turn is a reduction in accuracy by altering the cycle detection resolution from 10ms to 40ms. In the experiments of this study several incrementation steps were tested and a step of 4 was found to be accurate, stable, and providing decent reductions of computation time.

Peak detection of similarity values

The similarity comparison results in n data series of similarity values for each point of unknown data for each template, with n being the number of templates. These similarity value data series will have peaks and troughs representing the template going in and out of phase with the unknown data movement cycles. These peaks and troughs are the basis used for cycle detection and classification. The main challenge of using these extremal points is that the values of similarity will naturally fluctuate when the template and sections of the unknown data has partially similar characteristics, resulting in a data series almost solely consisting of a fluctuation between extremal points. However, the out-of-sync partial hits in similarity will have a much lower similarity value than the in-sync peaks, and the problem of isolating the peaks is solved by assigning the values below a certain threshold to zero - leaving only the peaks of interest in the similarity data series followed by running a peak detection of these smaller above-threshold segments detecting the single highest value representing the true original peak of the similarity data. This process is illustrated in figure 3.12. When the peaks in similarity values for each template has been detected, the peak index, template class and similarity value is stored for further use in the cycle detection and classification process.

Peak detection threshold

The threshold chosen for the peak detection in similarity value series is an important performance parameter. If this threshold is chosen too high there is an increased chance of cycles being undetected by simply having a similarity value below the threshold, and if the threshold is too low the chances of saturation in the peak detection increases. The dysfunction caused by a low threshold is a result of detecting too many low-value peaks in between the high valued peaks, causing a saturation in the centroid detection of the binning process of cycle detection, effectively masking the high valued peaks also resulting in undetected cycles.

From this it is apparent that the choice of the similarity peak value threshold is crucial in expect-

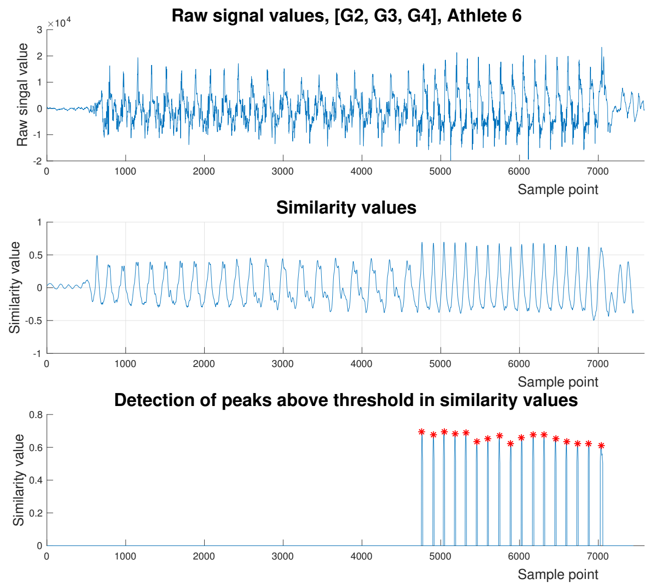

Figure 3.12: Plot illustrating peak detection in similarity values.

ing a well-performing algorithm. Through testing a threshold of 0.65 is chosen and used on all final results of this study. Utilizing a dynamic threshold was considered but not implemented, later studies might benefit from looking into this for improving the accuracy of the template matching method.

Grouping of similarity values

A challenge still remaining when all peaks of similarity have been identified and stored, is that the peak values from different templates will not necessarily have the same index, meaning that one cannot simply chose the highest value for all indexes and classify accordingly. A seemingly easy solution to this is to always choose the highest value within a certain index range, i.e. within the length of a template, but this is non-trivial as the template lengths are highly variable in representing different athletes individual subtechnique execution and also in representing different frequencies of execution within the same subtechnique. To overcome this problem a method of grouping the peaks from different templates have been developed. A flow diagram for this algorithm is shown in figure 3.13.

The technique utilizes a method of histogram bin counts with dynamical adjustment of each

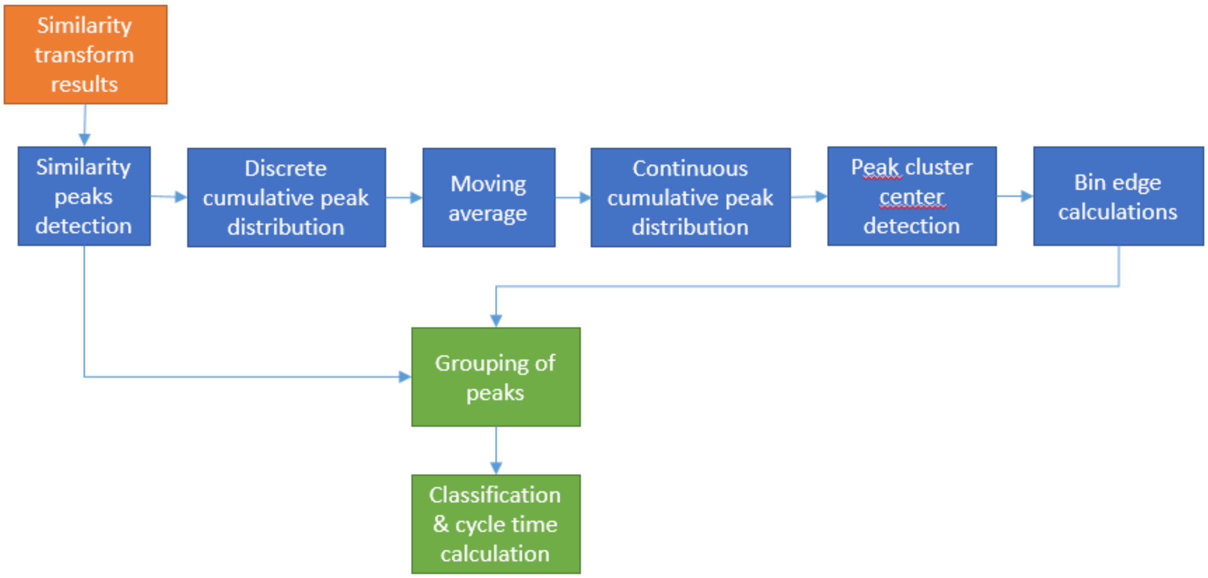

Figure 3.13: Flow diagram illustrating the grouping algorithm.

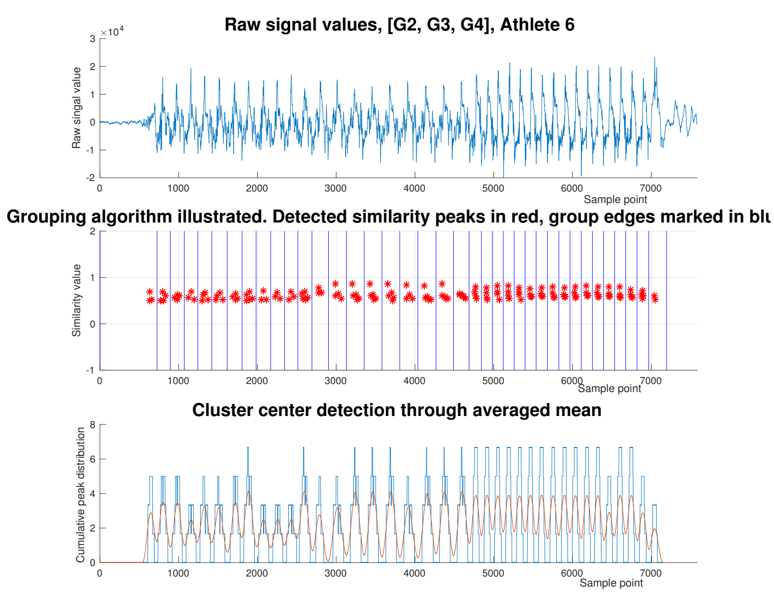

Figure 3.14: Plot illustrating the grouping algorithm.

edge based on all peaks detected in the similarity data. The dynamical calculation of bin edges is initialized by creating a new zero-initialized vector and adding in a fixed value for each detected similarity peak at the original index of this peak. This results in a discrete cumulative distribution of the peaks detected. The distribution is then converted into a continuous cumulative distribution by running a moving average across this dataseries. The peaks of the continuous distribution is then roughly representative of the center for each cluster of similarity peaks across all templates. These central peaks can then be used to create dynamical edges for bins used to group the similarity peaks, by calculating the middle value between the center points. The grouping process is simply done by assigning the similarity peaks into its corresponding bin by using the original similarity point indexes. This is done by utilizing Matlab's built in histogram bin count method, *histcounts*, which groups a vector of specified points into bins with the bin edges specified by a separate vector given to the function. An example of the grouping process is shown in figure 3.14.

Classification and cycle detection

These groups of peak points will then contain a single value from each template having a high enough similarity value within reasonable distance from each other. The cycle identification and cycle class is then assigned according to the point in the group having the highest similarity score, using the original index and template class tied to that certain similarity point.

Template resampling

The templates from the template creation process have lengths corresponding to the cycle rate of the subjects at the time of recording. When utilizing the method of similarity transform, the timing of characteristics between the template and the unknown data has to match in order to produce a high similarity value.

If the cycle rate represented in a template and true cycle rate of movement in the unknown data does not match, the similar characteristics of the template and data has no way of fully aligning. This results in similarity values being lower than had a full alignment occurred. This shows that the length of the templates is an important factor in generating good results from template matching.

In preparation for data collection, a study was made to investigate differences between characteristics of same-subtechnique templates of different execution intensities. The results of this study was that the differences in amplitudinal characteristics were small and the differences in template lengths were substantial, which is not unexpected as a higher intensity corresponds to a higher cycle rate and shorter cycle time. The details of this study are presented in chapter 4. This further substantiates that the template lengths are of great importance. It does also imply that if one has a template representing a certain intensity of a subtechnique, and have ways of modifying it in length, it should be possible to use this template in classifying a variation of intensities for that specific subtechnique. This not only reduces complexity in reducing the number of unique templates needed, but also reduces the amount of data collection that has to be made when training the classifier.

A way of changing template length without altering the amplitudinal characteristics is to perform a resampling of the template. A resampling will either stretch or compress the templates in time according to a new sampling rate, by either decimating or interpolating the original template. The decimating and interpolation are respectively mainly used for compressing and stretching. The process of resampling is however delicate, as one has to make sure that the new sampling rate is uniform and that the process does not add any form of noise, in the form of unwanted components. If the decimating and/or interpolation methods do not account for this, the template characteristics might be unevenly affected, resulting in corrupt templates. Because of this both decimating and interpolation might be used interchangeably in the resampling process. In this study the complex task of resampling is performed by utilizing the built in functionality of Matlab, to ensure consistently good results. The Matlab function $resample(x, p, q)$ resamples the input sequence, x, at p/q times the original sample rate, and applies an antialiasing FIR lowpass filter to x to compensate for the delay introduced by the filter Mathworks (2016).

3.5.3 Cycle time calculations

For detection of cycle time there are several methods which can be applied. In a template matching method the most obvious approach is to utilize the peaks within the similarity data,

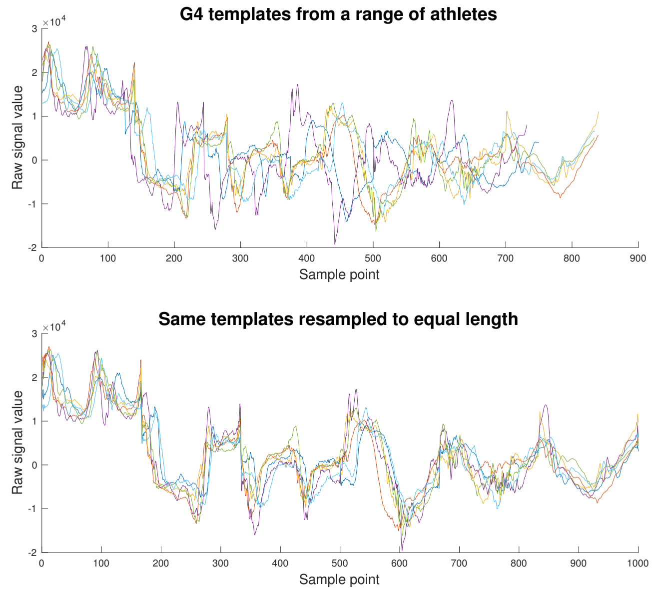

Figure 3.15: Plot showing the effects of resampling templates of the same subtechnique from different athletes to equal length.

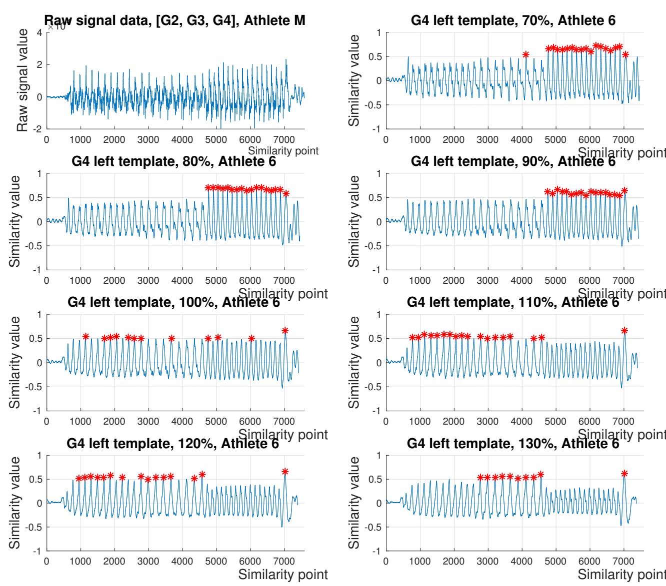

Figure 3.16: Plot showing the effects of using resampled versions of the same template in the similarity transform.

more specifically the peaks chosen in the cycle detection and classification algorithm. These peaks correspond to the end of the template which produced it, and thus the end of the cycle is detected. These can further be used to calculate the corresponding cycle lengths, if the starting point of each cycle is found.

Different approaches are possible for finding the starting point corresponding to each detected cycle end point. A first approach is using the previous end point as a starting point for the next cycle, and another approach is using the corresponding template length of the template used in detecting the cycle. Each of these approaches does however have drawbacks in regards to accuracy of the cycle time calculation. A drawback for the approach of solely using similarity peaks to define cycle times is that cycle times will be stretched in length for sporadic cycles, an example being if the athlete pauses in between cycles, ex. downhill tuck, the cycle time for the next cycle has its starting point at the end of the last cycle which makes this cycle time include both the cycle itself and the period of downhill tuck. Drawbacks with the approach of solely using template lengths is the resulting predefined resolution, with cycle times not being able to differ from the predefined template lengths used in cycle detection, along with the possibility of overlapping cycles if the template lengths are longer than the interval between the similarity peaks. An advantage of using template lengths is that each cycle has the ability to be isolated from others, countering the drawback of only using similarity peaks for calculating starting points. What is apparent when reviewing these advantages and drawbacks is how they counter each other when combined, with the similarity peaks advantage of non-overlapping and ability of variable cycle times working well together with the properties of non-stretching of cycle times through template lengths. A third approach is thus to use this through having template lengths as a starting point for cycle times, along with adjusting these starting points to the previous similarity peak in cases of overlapping cycle times.

Chapter 4

Results

In this chapter results produced and found throughout the work of this thesis are presented. The first subchapters contains various analytical results relevant to the development and implementation of the template matching method, followed by the results of performance for the template implementation algorithm. The results presented are discussed further in chapter 5.

4.1 Differences in template characteristics

A premis for the work of creating a well-performing template matching method is having the characteristical differences between subtechniques reflected in the templates made. To ensure this, a study of the differences in characteristics of different subtechnique was made, described in detail here.

One of the most differentiating characteristic entity of the G3 technique in comparison to G2 and G4 is the variation in template length (shown in figure 4.2). The template length for G3 is significantly longer than that of the other skating techniques, across all intensity levels (LIT, MIT, HIT). Because of this one might want to avoid stretching and compressing templates too much during the resampling process of the template matching algorithm, as this might reduce the differences between the templates and as a result making the process of separating these subtechniques more difficult for the classifier.

In figure 4.1 templates of different subtechniques are shown together. From figure 4.1 one can observe that characteristics for templates within the skating techniques are similar when represented in a form of equal length, but with differences in the gyro-X axis (at approx. sample points 670-850 in figure 4.1) separating them.

For the classical techniques, differences between templates are more distinct. Figure 4.1 shows double poling being the most divergent from the others, whilst the diagonal stride technique has some similarities with the skating techniques, whilst still containing some significant differences in certain axes, predominantly in the acc-Y axis (at approx. sample points 170-340 in figure 4.1). The double pole kick technique is not illustrated in figure 4.1, but has shown to have separable characteristics from double poling in the gyro-Y axis.

These results show that templates of different subtechniques generally show similarities between them, but also inhibit distinctive differences in characteristics, indicating that a template matching classifier should be able to separate subtechniques from each other.

4.2 Intensity related differences for subtechniques

For development and classifier performance it is relevant to investigate if it is possible to do classification across varying intensities with a single intensity template, or if a variation in athlete movement intensities also requires templates representative of these intensities.

Differences are most prominent in terms of template lengths (cycle time), and the templates of different intensities show increased similarity when resampled to an equal amount of sample points. From the resampled templates one can observe that there are minor differences in both timing and amplitude between the intensities, but these are less significant than the differences in cycle time. These findings are true across all subtechniques and mainly reveal two things, first; for classifying a subtechnique across intensities with a single template there is most likely a need for stretching and compression in regards to length of the template, second; compressing and stretching in regards to amplitude might have an effect in terms of accuracy, but this is

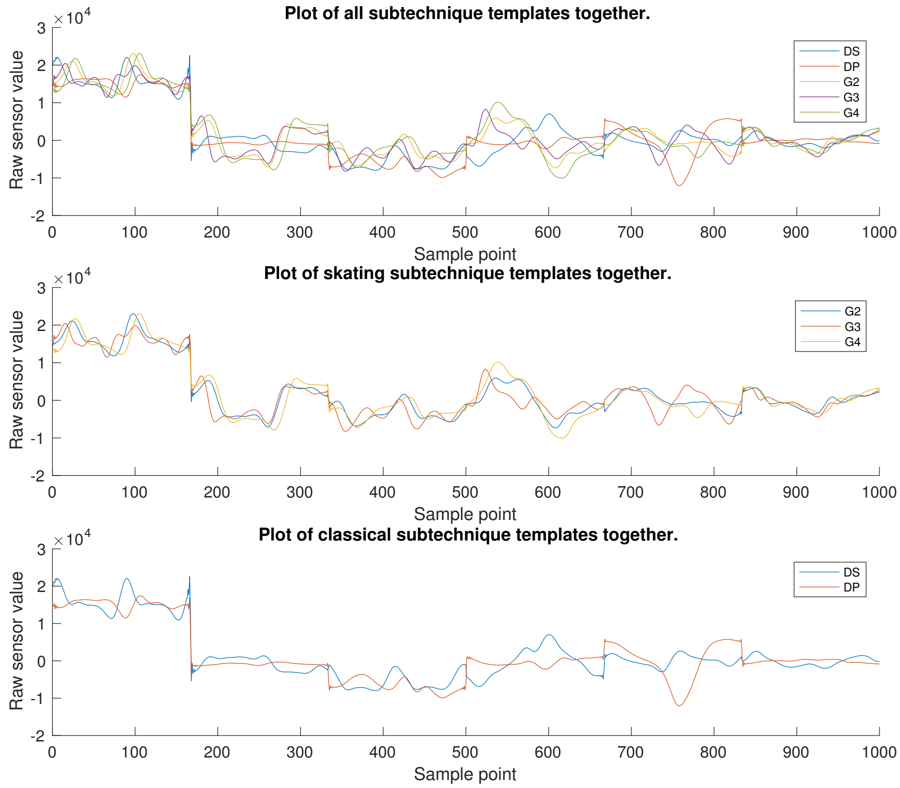

Figure 4.1: Comparison of templates from different subtechniques

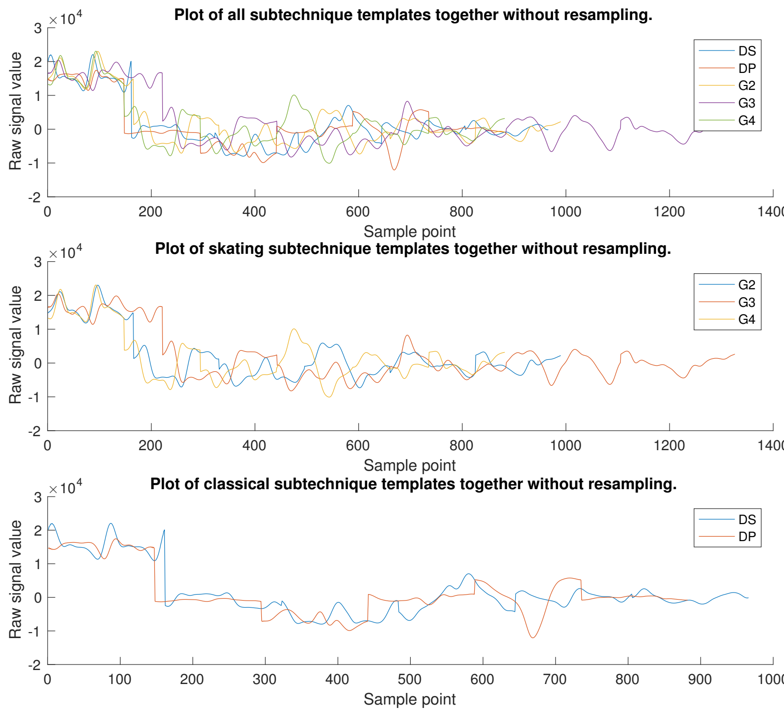

Figure 4.2: Illustration of differing template lengths for templates from different subtechniques

likely to be of much less significance than resampling in length. Figure 4.3 illustrates differences in characteristics within subtechnique templates of different intensities for the double poling subtechnique.

The variations in length according to variations in intensity are likely to be different between different athletes. Creating a template base through resampling a representative normalised template through compression and stretching should be a good approach in avoiding having a large athlete-count template base covering the various possible template lengths, and through this reducing the computational loads of the algorithm as each template adds an iteration of computation in the method.

The variation in amplitudes varies between athletes, but this is much less significant than the variations in template length. The variation in amplitude of raw versus mean templates of an athlete could also be less than the variation within a single intensity. Because of this, stretching

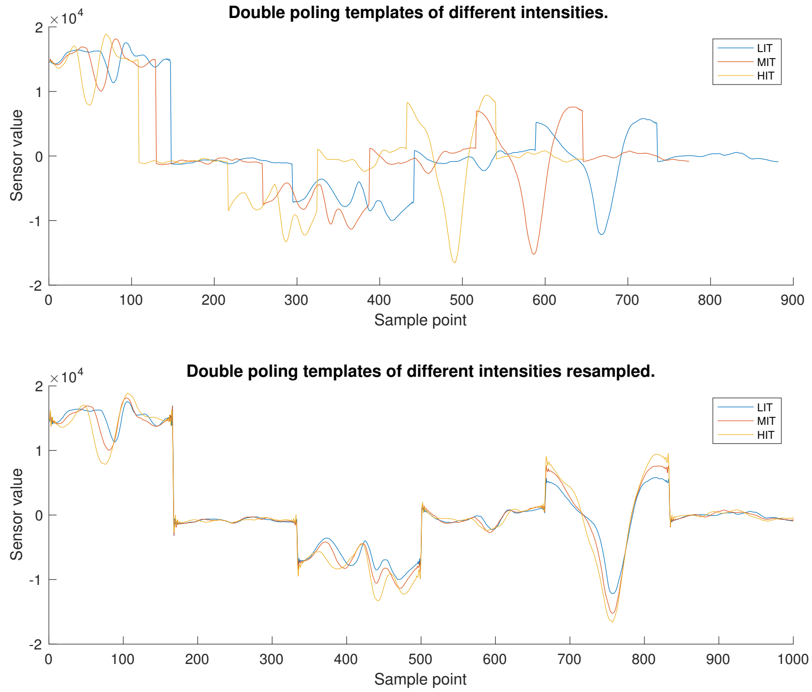

Figure 4.3: Illustration of differing characteristics between different intensities for templates within the same subtechnique

and compressing in terms of amplitude is expected to have less of an impact on classifying accuracy, albeit it might have a reasonable effect and further studies could prove this to be beneficial. The most significant difference in amplitude characteristics is observed between MIT and HIT intensity, which indicates that both MIT and HIT might be useful in template matching, whilst LIT and MIT are more similar and MIT should suffice in covering these.

4.3 Preliminary assessment of cross-terrain classification

To assess the possibility of a general algorithm with possibilities for cross-terrain classification between on-snow, treadmill and roller skiing, characteristic differences of movement cycles recorded for these variations were looked into and tested in terms of classification performance. A study done by Myklebust (2016) show clear variations in hip movement between on-snow and treadmill movement patterns for the skating technique, which indicated that there should be differences in template characteristics created on different terrain.

To a certain degree the results of Myklebust (2016) were also seen in this study, with G2 showing the most significant differences. The G4 templates showed a higher degree of similarity, with only the gyro-Y axis showing significant differences. For G3 templates no significant differences were found, with templates being similar throughout all axes. Preliminary cross-terrain classification tests, using templates of treadmill skiing to classify on-snow data and vice versa, gave poor results in both classification and cycle detection rate, predominantly for the G2 subtechnique.

It should be emphasized that these results only indicate cross-terrain classification possibilities to be non-trivial, and further in-depth investigations might find ways of processing templates into being cross-terrain compatible. As the tools for classification were in need of further development at the time of this analysis the matter was not pursued further. Classical templates were not a part of this analysis, but are believed to be more compatible with cross-terrain classification.

4.4 Effects of characteristics and resampling

To investigate the effects of different templates and the effects of resampling, several test were run on test data from a straight line recording. The straight line course was chosen for these initial tests to reduce the amount of cycles containing turns and transitions, as these are known problem areas in classifying cross country subtechniques, discussed in chapter 2. The tests were done in a systematic manner in first using a single-athlete template base for classification, followed by using an all-athlete template base, and lastly using the normalised template set (described in chapter 2).

In analysing the impact of resampling, the first two tests were done both with and without resampling of template length. As resampling was found beneficial all later tests were done solely with inclusion of resampled templates. The test subjects were not part of the training set for any test performed. The results from all tests are presented in table 4.1.

Table 4.1: Straight line course classification

Template set	**Test subject**	**Technique**	**Classification rate No resampling**	**Classification rate Resampling, 70%-130%**
A1	Athlete M	Skating	75.0%	80.6%
A3	Athlete M	Skating	66.7%	66.7%
A4	Athlete M	Skating	97.2%	94.4%
A6	Athlete M	Skating	100%	97.2%
A7	Athlete M	Skating	86.1%	88.9%
A8	Athlete M	Skating	75.0%	88.9%
All athletes	Athlete M	Skating	97.2%	97.2%
All athletes	Athlete T	Skating	92.9%	95.2%
All athletes	Athlete C	Skating	87.8%	97.6%
Normalised	Athlete M	Skating	-	**97.2%**
Normalised	Athlete T	Skating	-	**95.2%**
Normalised	Athlete C	Skating	-	**100%**
Normalised	Athlete M	Classical	-	**95%**
Normalised	Athlete T	Classical	-	**64.3%**

The initial straight line tests were done on a single subject, Athlete M, skating run with a variation of single-athlete template bases. Large fluctuations in successful cycle classification rate was shown, ranging from 67.7% to 100% for different athlete template bases, with an overall mean classification rate of 83.3%. Utilizing resampling of template lengths gave a slight increase (2.8% percentage points) in overall classification, with approximately the same variation. The tests gave a cycle detection rate of 100%. The large variation in classification rate for different template bases indicates differences in characteristics to be significant in terms of performance.

The following straight line course study utilized the complete template base, including all athletes used in training, and were tested on three different subjects utilizing skating subtechniques. The complete template set without resampling showed a variation of 87.8% to 97.2%, with an overall mean classification rate of 92.6%. The same test redone with resampling gave a variation of 95.2% up to 97.2%, with an overall classification rate of 96.7% (4.1% percentage points increase). The tests gave a cycle detection rate of 100%.

As a next step the normalised mean template set was tested on the same three skating straight

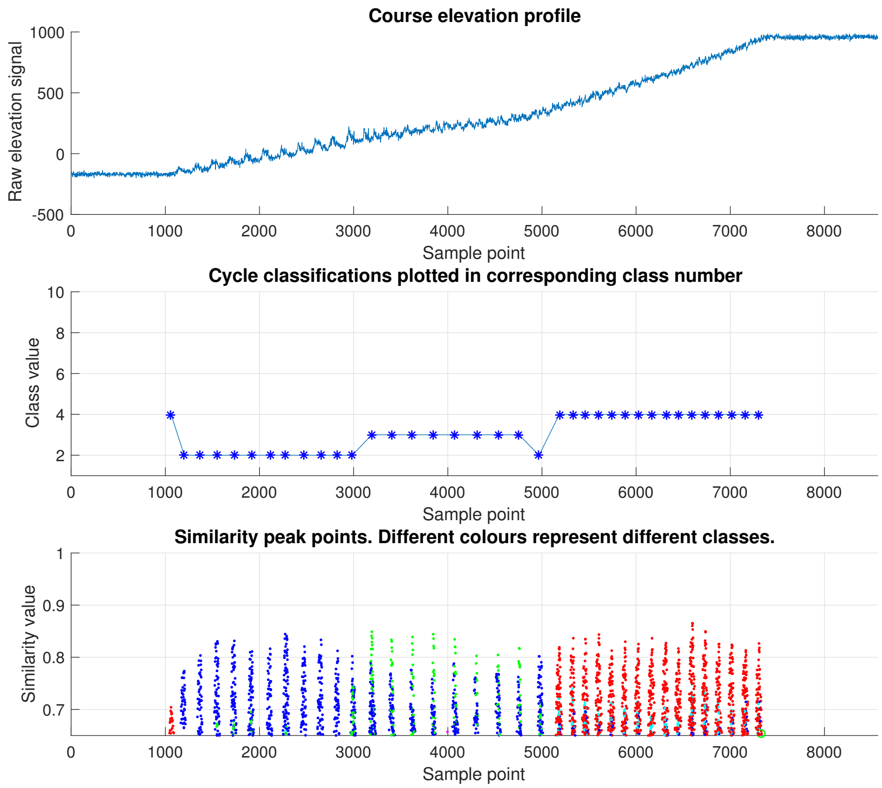

Figure 4.4: Example of straight course classification results

line runs in addition to two classical straight line runs, with results being classification rates 95.2%, 97.2% and 100% for skating, and 64.3% and 95.0% for classical, overall mean classification rates being 97.6% and 79.6% respectively. A cycle detection rate of 100% for skating and 95% and 64.3% for classical was observed.

For all straight line skating studies misclassifications for the high-classification rate results were related to either transition cycles or cycles with movement intensity differing greatly from the intensity of the movements recorded for template creation. In the classical technique study all misclassifications and missed cycle detections were related to diagonal stride performed in uphill terrain.

Recorded	Athlete	Training data Classical	Training data Skating	Test data Skating	Test data Classical	Experience level
Spring 2016	M	not recorded	not recorded	used	used	Mid-level
	T	not recorded	not recorded	used	used	Mid-level
	C	not recorded	not recorded	used	not recorded	Mid-level
Fall 2016	1	used	used	available	available	Elite
	2	corrupted	corrupted	corrupted	corrupted	Elite
	3	not recorded	used	available	not recorded	Amateur
	4	used	used	available	no video	Elite
	5	corrupted	corrupted	corrupted	corrupted	Amateur
	6	not recorded	not used	used	not recorded	Elite
	7	not used	not used	available	used	Elite
	8	used	used	available	not recorded	Amateur

Figure 4.5: Dataset overview

4.5 Full lap classification

For the final study, classifications were done on data recorded through full laps of varied terrain and subjects choosing technique freely. There were two different courses used for the two rounds of data collections. Two sets (one skating, one classical) of the first round, and one set (skating) of the second were used as test data, with the remaining four data sets of the first round used as training data. The training set used were the processed normalised template base, described in chapter 2. Only one set of the available first round recordings was used as test data, as these sets had little variation in terrain with a dominantly large portion of uphill segments, and using several might have produced biased results. Prior to classification, video analysis of the recordings were done to create true cycle counts and classifications which the results of the template matching were compared against. From this the classification rate, overall classification rate and cycle detection rate were calculated. These parameters, along with the number of undetected and erroneously detected cycles are presented in figure 4.6.

Overall performance

Three laps were used in testing, with a total of 649 true cycles predetermined from the video analysis process, 249 of classical and 400 of skating technique. Of these 616 (94.9%) were detected correctly, with a total of 23 undetected cycles. In addition there was a total of 40 erro-

Athlete / Technique	Description	Total detected cycles	Correctly detected cycles	Erroneous detected cycles	Undetected cycles	Correctly classified cycles	Erroneous classified cycles	Video cycle count	Classification of correctly detected cycles	Overall classification rate	Cycle detection rate
7 Classical	Normalised mean template set	236	231	5	18	210	21	249	90,9%	84,3%	92,8%
	Misclassifications due to DS uphill (16) ignored.	220	215	5	5	210	5	220	97,7%	95,5%	97,7%
M Skating	Normalised mean template set	214	207	7	2	199	8	209	96,1%	95,2%	99,0%
	Without classical templates	213	207	6	2	199	8	209	96,1%	95,2%	99,0%
6 Skating	Normalised mean template set	196	178	18	3	166	12	191	93,3%	86,9%	93,2%
	Without classical templates	192	188	4	3	176	12	191	93,6%	92,1%	98,4%

Figure 4.6: Table showing results from full lap template matching

Table 4.2: Confusion matrix for correctly detected cycles

	G2	G3	G4	G5	DS	DP	DPK	HB	Total
G2	36		1						37
G3	12	64		1		14			91
G4			250						250
G5		1		16					17
DS					74			15	89
DP			1			77			78
DPK						5	59		64
HB								0	0

neously detected cycles, 10 of which were also labeled as misclassifications. A total of 575 of the correctly detected cycles were classified correctly, giving a classification rate of 93.3% for the correctly detected cycles, and an overall classification rate of 88.6% related to the video cycle count. A confusion matrix for the correctly detected cycles is shown in table 4.2.

Classical technique specific observations

Misclassifications and undetected cycles from the classical technique results were mostly related to the digonal stride subtechnique performed in uphill terrain. Reasons for this was investigated in detail, with the results being that the uphill diagonal stride differs significantly from diagonal stride performed on flat terrain. This implicates that the uphill diagonal stride is not well reflected in the training set utilized by the template matching method. For analytic purposes an evaluation of the classical results with these cycles ignored was made. Ignoring the errors related to diagonal stride uphill gave a cycle detection rate of 97.7% and an overall classification rate of 95.5%, with a 76% decrease in erroneously detected cycles and 72% decrease in undetected cycles. This indicates that the difficulty regarding diagonal stride performed in

Athlete / Technique	Description	Total detected cycles	Correctly detected cycles	Erroneous detected cycles	Undetected cycles	Correctly classified cycles	Erroneous classified cycles	Video cycle count	Classification of correctly detected cycles	Overall classification rate	Cycle detection rate
7 Classical	Ambiguous (5) cycles and misclassifications due to DS uphill ignored.	220	215	5	0	210	5	215	97,7%	97,7%	100,0%
M Skating	Ambiguous cycles ignored	209	206	3	1	199	7	207	96,6%	96,1%	99,5%
6 Skating	Ambiguous cycles ignored	186	183	3	1	176	7	184	96,2%	95,7%	99,5%

Figure 4.7: Table showing results with ambiguous cycles ignored

uphill terrain should be solvable through proper and representative training of this movement pattern.

Skating technique specific observations

For the skating data a significant number of erroneously detected cycles were related to double poling being detected within the G3 subtechnique. To assess the performance of the classifier without these errors, classification was done with a template base consisting solely of skating subtechniques on the run containing these problems. This resulted in a 61% decrease in erroneously detected cycles, with the classification rate increasing from 86.9% up to 92.1% and the cycle detection rate increasing from 93.2% up to 98.4%.

Analytical overall performance

Looking at overall results with errors related to uphill diagonal stride and double poling within the G3 subtechnique ignored, most remaining anomalies are related to ambiguous cycles of movement. Ambiguous cycles are cycles where a true classification is hard to define, as the cycle might not be a full movement cycle of the specified subtechnique or the movement it self might differ greatly from the normal movement of that subtechnique. Ambiguous cycles are predominantly related to direction altering movements and transitions between subtechniques. When disregarding these ambiguous cycles, along with the alterations for skating and classical technique considered above, an overall classification rate of >95% and a cycle detection rate of 99% is observed. These results are of analytical interest in later discussions of the method. This analysis is illustrated in figure 4.7.

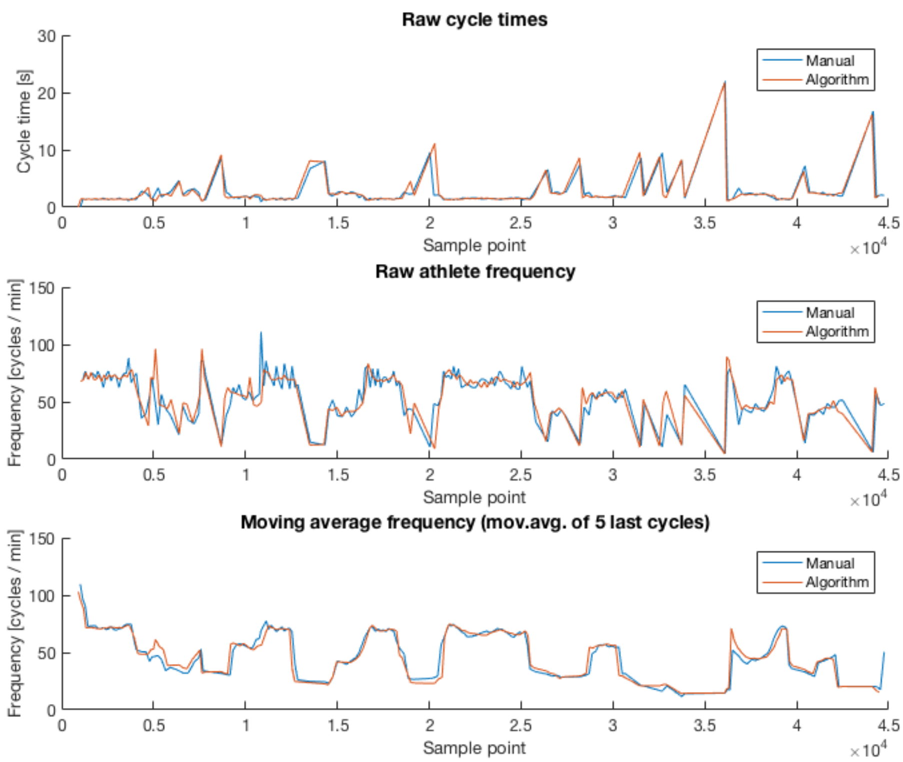

Figure 4.8: Results of cycle time and frequency comparison between manually marked and algorithm produced cycles.

4.6 Cycle time evaluations

As high precision evaluation of the cycle time calculations proved challenging, due to shaking and movement of video recordings and a slight drift in IMU sampling rate, the first apporach described in chapter 3 of solely using detected cycle end points was utilized. These calculations were compared to the manual markings made through video analysis, which both were converted into cycle times and athlete frequency. The comparison was done on the results of the skating run performed by athlete 6, with classical templates removed from the template matching method. From the overlaid results shown in the figure a clear coherence between the manual and algorithm produced data is shown, which indicates that even this simplified version is capable of producing consistent results. Utilizing the third apporach described in chapter 3 could provide even more accurate results, and should be tested through utilizing a more controlled environment for recordings. The described results are illustrated in figure 4.8.

Chapter 5

Discussion

In this chapter the results presented in chapter 4 and its implications are discussed.

Cycle detection

Cycle detection is found to be stable and consistent, with some specific problematic areas related to false cycles of double poling detected within G3 cycles and difficulties in detecting cycles of diagonal stride in uphill terrain. For analytical purposes a study of results with these problem areas ignored was done, and revealed possible cycle detection rates of >99%, indicating that if these two specific difficulties are solved properly the outlook for the template matching algorithm is very promising.

Solutions to these difficulties requires further investigations. For double pole false detections, utilizing the lower similarity values of the falsely detected peaks to detect and disregard these or implementing a utilization of cycle times to avoid within-cycle detections might be possible. Another approach could be doing a second classification run with classical templates removed from the template base. This was tested during this study and gave promising results as it removed all false detections of double poling within the G3 subtechnique. In a real-time implementation one could utilize this by first doing initial rough calculations for determining the main technique utilized by the athlete followed by adjusting the template base to reflect this accordingly.

Difficulties related to uphill diagonal stride should prove solvable by simply doing specific training through template creation of representative segments for this movement, as this was not done in the training process for this study.

Cycle classification

From the confusion matrix presented in table 4.2 one can see most misclassifications are due to diagonal stride being classified as herringbone, and G3 being classified as G2. The diagonal stride misclassifications suffers from templates being unrepresentative for the uphill variation of this technique, and is likely reduced or removed by proper training. The G3 misclassifications into G2 are predominantly related to transitions between subtechniques, either into or from G3. This is likely to be caused by the G3 template start body position being different from the cycle start body position of the transition made by the athlete. As an example, the template could represent a cycle start body position with the right foot being fully engaged in the skating motion whilst the transition into G3 for the subject being initiated with a left foot skating motion. This causes the template matching similarity peak not to occur before the subsequent right-foot started cycle has been completed, one and a half cycle later than the actual transition. This leaves half a cycle not covered by the G3 template during the transition, which in turn to some degree will be covered by the G2 templates, resulting in a source of misclassification into G2. The difficulty of transitions not being sufficiently covered by the G3 templates could be solvable through having templates representing both initiation and endings of G3 segments of both right and left start body positions. This in turn might create a need for some added functionality to avoid false detection of double frequency, as these templates will be opposite in phase and together will provide a doubled frequency in similarity data. The problem might also be solvable by dividing the G3 templates into halves, and through this detecting half-cycles instead of complete cycles.

The overall classification rate for the classifier of the current implementation has shown to be 88.6% across three separate runs, with individual rates at 84.3%, 95.2%, and 86.9%. Compared to other classifiers of the field the implementation of this study places itself somewhere in the middle, with classifier performance rates varying from 88% up to 98.5%, as presented in figure 2.1. However, these results should be considered promising, as this method is the first one in the field to incorporate both classical and skating classifications without technique specific alterations, with its problematic areas being well-defined and solveable. With these areas resolved, analysis indicates that the method will be on-par with the top-performaing classifiers within the field. The implementation does also have the challenges common for all classifiers classifying cross-country subtechnique, more specifically difficulties regarding undefinable and ambiguous cycles, related to turns and transitioning between subtechniques. There probably several ways of countering these common challenges in an improved manner, and investigations and development of those should prove beneficial for the field as a whole.

That being stated, there is also an aspect of these challenges which should not be ignored, in that the ambiguous cycles makes the classification problem in itself not completely definable, and thus an optimal classification accuracy of 100% should not be expected as it is likely not possible. Explained more in detail, as this problem come as a result of cycles which can be multiply defined as several subtechniques they cannot be completely defined nor classified even by human interpretation, and thus an automated method have no way of reaching classification rates of 100% if the human interpretations can not. As these ambiguous cycles are present there will always be an undefined element of uncertainty within the problem of classifying movement cycles in cross-country skiing.

Advantages and drawbacks of the template matching implementation

In summary, this study has successfully implemented a template matching algorithm which tackles the classification problem of identifying and classifying subtechnique movement cycles of cross country skiing, and in this the template matching method has shown both advantages and drawbacks compared to other methods in solving this problem.

One of the most profound advantages of the template matching method is its generality and mathematical simplicity, with generality being the ability to detect and classify across ranges of skill level and both classical and skating main techniques of cross-country skiing, along with being a method which easily can be altered into classifying other fields of cyclical data. Another advantage is its ability to detect and identify cycles and do classification simultaneously, removing the need for a separate cycle detection algorithm.

As for drawbacks the most protruding ones specific to this method are the difficulties described earlier, in regards to false detections within the G3 subtechnique and the poor cycle detection rate and misclassifications related to uphill diagonal stride. These problems are however specific, and should be solvable through continued investigations and efforts in development. The template matching approach also suffers from the same difficulties which are common across the field for all methods trying to solve this particular classification problem, more specifically transitions and direction altering movements, and solutions to these difficulties should prove beneficial for all methods of the field.

Cycle time calculations

For cycle time calculation several methods were proposed and implemented, with a combination of using similarity peaks and template lengths being indicated as the most promising one. However, as accurate assessment of cycle time calculations proved difficult, caused by shaking and movement in camera recordings and a slight drift in the IMU sampling rate, along with challenges in converting cycle times from the manually marked data, the simplified approach of only utilizing similarity peaks (corresponding to cycle end points) for cycle time calculations was pursued, as this method could also be directly used on the manually marked data. The assessment of the algorithm and manually made cycle times gave promising results through strong coherence, indicating consistency between the video analysis and template matching method.

Real-time considerations

A real time version of the template matching algorithm, doing cycle detection and classification within a 3 second time limit for each cycle, can easily be realized by doing simple alterations to the offline-implementation. The offline-implementation does all its calculations and decision making on a time horizon shorter than 3 seconds, and by segmenting the data instead of doing calculations on the whole data series a real-time model is achieved. More specifically, the data series can be segmented into three-second-segments, with an incrementation step of one second for each batch of data. Using the offline-template-matching mechanics on this segment will provide duplicate cycle detections, which are reduced into single points by simply merging nearby duplicates. With these simple alterations the offline implementation is converted into a real-time implementation, with all the same principles in mechanics. As the method functionality stays the same, the same results found for the offline-implementation is expected.

5.1 Conclusions

With an overall cycle detection rate of 94.9% and an overall classification rate of 88.6%, the results of the template matching algorithm of this thesis are considered promising in developing a classifier capable of handling both movement patterns of classical and skating techniques in cross-country skiing. This method is the first in the field to handle both classical and skating without technique specific alterations, and should provide a good foundation for further development.

The current implementation does have specific challenges in terms of misclassifications related to diagonal stride performed on uphill terrain and double poling being erroneously detected within G3 skating cycles. However, these challenges are well-defined, and remedies such as extended training of templates to include uphill diagonal stride and algorithm alterations to detect technique and adjusting the template base accordingly have already been suggested, and should elevate the performance of the template matching method to be on-par with the highest performing in the field.

In addition, as the method is based solely on general templates for each movement, utilizing this technique on other fields of cyclic movement should only require an alteration of the template base used, increasing its value in terms of versatility and field of general use even more.

5.2 Recommendations for Further Work

- Investigations into finding solutions for the specific problems described revolving misclassifications regarding double pole detections within G3 subtechnique and uphill diagonal stride. A redone template creation process with representative segments for uphill diagonal stride are believed to suffice in handling misclassifications within G3.

- Assessment of cycle time calculations through utilization of a more controlled environment in terms of video recrodings.

- Studies related to solving challenges related to ambiguous cycles.

Works and published articles with IMU usage in study of cross-country skiing. Based on similar table from [Myklebust 2016].

Title	Author (Year)	Technique	Aim	Findings	Subtechnique classification	Subtechnique characteristics	Number of IMUs	IMU position	Instrumentation
An analysis of hip joint loading during walking, running, and skiing.	Bogert et al. (1999)	Classical, skate	To compare loading of the hip joint in alpine skiing, cross-country skiing, walking and running.	Hip joint loading was higher for both classic and skating techniques compared to walking, but from a rehabilitation perspective, skiing was found safer than running.	-	-	4	upper body	Four 3D accelerometers in a semi-rigid frame on the upper body. 300 Hz (EGAXT, Onset Computer Corporation, Bourne, MA).
Morphological analysis of acceleration signals in crosscountry skiing	Myklebust et al. (2011)	Skate	Temporal pattern analysis and subtechnique classification while skating on snow.	Pole hits and leaves, and ski leaves were detected 99% correctly; ski hits were only 77% correct during stable technique; technique transitions were 88% correct. From hits and leaves, cycle time, poling time, pole reposition time, and asymmetry were successfully calculated, and individual differences illustrated.	x	x	5	Poles, ski boots, hip	Accelerometer data from poles, ski boots and hip. 125-1000 Hz (PLUX Wireless Biosignals SA, Portugal).
Identification of Cross-Country Skiing Movement Patterns Using Micro Sensors	Marsland et al. (2012)	Classical, skate	Classic and skating subtechnique classification on snow.	General patterns for all subtechniques in both classic and skating were visually identified across all skiers.	In part (identification)	-	1	back	3D accelerometer 3D gyroscope data from upper back. 100 Hz. (MinimaxX S4, Catapult Innovations, Australia).
Classification of movement patterns in skiing	Holst & Jonasson (2013)	Skate, roller ski	To develop and test an algorithm for skating subtechnique classification.	100% classification on a training set of data from 7 skiers, and 98% classification on a test set of data from 7 different skiers.	x	-	1	chest	3D accelerometer data from Android phones or Zephyr bioharness mounted to the chest. 50 or 80 Hz
Automated Identification and Evaluation of Subtechniques in Classical-style Roller Skiing	Sakurai et al. (2014)	Classical, roller ski	Classic subtechnique classification, examining relationships between speed, inclination and the subtechniques used.	Out of 9444 cycles, 98.5% were automatically identified correctly. Some indications for sub-technique transitionthreshold intensities were discussed, but no conclusions were presented.	x	-	4	wrist, skis	3D gyroscope data from wrists and skis. 100 Hz, GNSS position data at 5 Hz. (LPWS0901, Logical Product Corp., Japan).
Differences in V1 and V2 ski skating techniques described by accelerometers	Myklebust et al. (2014)	Skate	**To describe the differences between the ski skating techniques V1 and V2 and evaluate reproducibility in complex cyclic hip movements measured by accelerometers.**	Identified characteristic differences between V2 and V1 subtechniques. Elite skiers reproduce their own individual patterns. One triaxial accelerometer on the lower back can distinguish techniques and might be useful in field research as well as in providing individual feedback on daily technique training.	-	x	5	Poles, ski boots, hip	Five triaxial accelerometers were attached to the subject's hip (os sacrum), poles, and ski boots.
Automatic Classification of the Sub-Techniques Used in Cross-Country Ski Skating Employing a Mobile Phone	Stöggl et al. (2014)	Skate, roller ski mill	Skating subtechnique classification using Smartphone accelerometer data.	Accelerometer data from a Smartphone is sufficient for classification. For fixed techniques, classification was 100% correct. Machine learning on individual data increased correct classification from 86% to 90% of data including subtechnique transitions.	x	-	1	chest	3D accelerometer data from a Sony Ericsson Xperia ST17i mounted to the front of the chest. 80 Hz.
Quantitative technique analysis in XC-skiing	Gløersen Ø (2014)	Skate	**To assess whether a single accelerometer and gyroscope (both 3 axis) positioned at the athletes sacrum could record interesting differences between athletes.**	Method proved able to identify differences in skiing technique, even in a group consisting solely of elite skiers. Some of the differences appeared to relate to the FISpoint ranking of the athletes, which suggested that these features could be important for performance	-	x	1	hip	accelerometer and a gyroscope (both 3 axis) positioned at the athletes sacrum.
Validity of Ski Skating Center-of-Mass Displacement Measured by a Single Inertial Measurement Unit	Myklebust et al. (2015)	Skate	(1) How accurately can a single IMU estimate displacement of os sacrum (S1) on a person during ski skating? (2) Does incorporating gyroscope and accelerometer data increase accuracy and precision? (3) Moreover, how accurately does S1 determine COM displacement?	**IMU-Acc provided an accurate and precise estimate of vertical S1 displacement, but IMU-Gyro was required to attain accuracy and precision of < 8 mm in all directions and with both subtechniques. S1 displacement was valid for estimating sideways COM displacement, .**	-	In part (COM)	1	hip	An IMU including accelerometers alone (IMU-A) or in combination with gyroscopes (IMU-G) were mounted on the S1. A reflective marker at S1, and COM calculated from 3D full-body optical analysis, were used to provide reference values
An inertial sensor-based system for spatiotemporal analysis in classic cross-country skiing diagonal technique.	Fasel et al. (2015)	Classical, roller ski mill	To automatically compute spatio-temporal parameters in diagonal stride.	The system was sensitive enough to detect differences previously found for different terrains and fatigue. Accuracy and precision for cycle time and ski-push time were below 6 milliseconds, and below 35 milliseconds for poling time. Cycle speed and length precisions were < 0.1 m/s and < 0.15 m, respectively.	-	x	2	one pole, one ski	3D accelerometer 3D gyroscope at left pole and left roller ski. 500 Hz (Physiolog III, GaitUp, CH).
Using Micro-Sensor Data to Quantify Macro Kinematics of Classical Cross-Country Skiing During On-Snow Training	Marsland et al. (2015)	Classical	To validate classic subtechnique classification in terms of total time, cycle frequency, and cycle counts.	78%, 74%, 88% correctly classified cycles in double poling, kick-double poling, and diagonal stride, respectively. Good reliability between IMU and video-calculated cycle frequency. Incorrect turn detection was a major factor in technique cycle misclassification.	x	-	1	back	3D accelerometer 3D gyroscope data from the upper back. 100 Hz, GNSS at 10 Hz (MinimaxX S4, Catapult Innovations, Australia).
Automatic Identification of Subtechniques in Skating-Style Roller Skiing Using Inertial Sensors	Sakurai et al. (2016)	Skate, roller ski	Develop and validate automatic skating subtechnique classification	Accuracy: 94.8% out of 6768 cycles automatically identified correctly. Precision: 87% – 98%. Most incorrect classifications related to turns (95%) and subtechnique transitions (5%).	x	-	4	wrist, skis	3D accelerometer 3D gyroscope data from wrists and skis. 100 Hz (LP-WS0901, Logical Product Corp., Japan).
Kinematical analysis of the V2 ski skating technique: A longitudinal study	Losnegard et al. (2016)	Skate, roller ski mill	To characterise timing of movements and evaluate performance effects of technique alterations in V2 ski skating.	Mixed-model analysis, adjusting for systematic time-point effects, identified that both reduced vertical hip acceleration and increased cycle time gave a small likely reduction in oxygen cost and 1000-m time. In conclusion, well-developed hip movement is a key characteristic of the V2 technique for elite-standard skiers' long-term performance development.	-	x	5	Poles, ski boots, hip	
Quantification of movement patterns in cross-country skiing using inertial measurement units	Myklebust (2016)	Skate	To assess how, and to what extent, IMUs can contribute to technique analysis in cross-country skiing.	Hip movement patterns captured by IMUs differed systematically between the V1 and V2 subtechniques. V2 showed a similarity to double poling in terms of hip lowering during poling. Further, there were distinct differences between skiers using the same subtechnique, but movement patterns were consistent for individual skiers. When directly comparing on-snow skiing and roller skiing, altered hip rotation patterns, greater lateral displacement, longer poling times, and a tendency to smoother hip movements were found for on-snow skiing.	x	x	4 / 1	Poles, ski boots, hip / hip	3D accelerometer 3D gyroscope at sacrum. Five triaxial accelerometers were attached to the subject's hip (os sacrum), poles, and ski boots.

Bibliography

Aminian, K. and Najafi, B. (2004). Capturing human motion using body-fixed sensors: outdoor measurement and clinical applications. *Computer animation and virtual worlds*, 15(2):79–94.

Bartlett, R. (2007). *Introduction to sports biomechanics: Analysing human movement patterns*. Routledge.

Bolger, C. M., Kocbach, J., Hegge, A. M., and Sandbakk, Ø. (2015). Speed and heart-rate profiles in skating and classical cross-country-skiing competitions. *International journal of sports physiology and performance*, 10(7):873–880.

Brunelli, R. (2009). *Template matching techniques in computer vision: theory and practice*. John Wiley & Sons.

Deng, L., Strik, H., et al. (2007). Structure-based and template-based automatic speech recognition-comparing parametric and non-parametric approaches. In *Interspeech*, pages 898–901.

Finn Marsland, Keith Lyons, J. A. G. W. C. M. and Chapman, D. (2012). Identification of Cross-Country Skiing Movement Patterns Using Micro-Sensors. *sensors*, 12:5047–5066.

Finn Marsland, Colin Mackintosh, J. A. K. L. G. W. and Chapman, D. W. (2015). Using micro-sensor data to quantify macro kinematics of classical cross-country skiing during on-snow training. *Journal of Sports Science and Medicine*, 14(4):435–447.

Garsjø, L.-K. (2016). Automated movement based classification of techniques in classic cross-country skiing. Specialization Project, Norwegian School of Sport Sciences.

Holst, A. and Jonasson, A. (2013). Classification of movement patterns in skiing. *Twelfth Scandinavian Conference on Artificial Intelligence*, 12:115–124.

Håvard Myklebust, Thomas Losnegard, J. H. (2013). Differences in V1 and V2 ski skating techniques described by accelerometers. *Scandinavian Journal of Medicine & Science in Sports*, 24(6):882–893.

Jenny Margarito, Rim Helaoui, A. M. B. F. S. and Bonomi, A. G. (2016). User-Independent Recognition of Sports Activities From a Single Wrist-Worn Accelerometer: A Template-Matching-Based Approach. *TRANSACTIONS ON BIOMEDICAL ENGINEERING*, 63(4):788–796.

Johnsen, M. H. (2016). Klassifisering. Lecture notes from TTT4225 Anvendt Signalbehandling 2016.

Kavanagh, J. J. and Menz, H. B. (2008). Accelerometry: a technique for quantifying movement patterns during walking. *Gait & posture*, 28(1):1–15.

Losnegard, T., Myklebust, H., Ehrhardt, A., and Hallén, J. (2016). Kinematical analysis of the V2 ski skating technique: A longitudinal study. *Journal of Sports Sciences*, 24(6):1–9.

Mathworks (2016). Resample.

Meland, H. J. (2016). A study of published methods, and implementation and critique of a markov-chain classifier, for classification of cross-country skiing techniques. Specialization Project, Norwegian School of Sport Sciences.

Mitchell, E., Monaghan, D., and O'Connor, N. E. (2013). Classification of sporting activities using smartphone accelerometers. *Sensors*, 13(4):5317–5337.

Myklebust, H. (2016). Quantification of movement patterns in cross-country skiing using inertial measurement units. PhD, Norwegian School of Sport Sciences.

Myklebust, H., Nunes, N., Hallén, J., and Gamboa, H. (2011). Morphological analysis of acceleration signals in cross-country skiing-information extraction and technique transitions detection. In *BIOSIGNALS*, pages 510–517.

Ohgi, Y. (2002). Microcomputer-based acceleration sensor device for sports biomechanics - stroke evaluation by using swimmer's wrist acceleration. In *Proceedings of IEEE Sensors*, volume 1, pages 699–704 vol.1.

Preece, S. J., Goulermas, J. Y., Kenney, L. P., Howard, D., Meijer, K., and Crompton, R. (2009). Activity identification using body-mounted sensors—a review of classification techniques. *Physiological measurement*, 30(4):R1.

Smith, G. A. (2003). Biomechanics of cross country skiing. *Handbook of Sports Medicine and Science: Cross Country Skiing*. Blackwell Science Ltd, Oxford, UK.

Thomas Stöggl, Anders Holst, A. J. E. A. T. W. C. N. and Holmberg, H.-C. (2014)). Automatic Classification of the Sub-Techniques (Gears) Used in Cross-Country Ski Skating Employing a Mobile Phone. *sensors*, 14:20589–20601.

Vaaga, S. (2008). Identifikasjon av menneskelig aktivitet basert på kroppsmonterte sensorer. Norwegian University of Science and Technology.

Van Den Bogert, A. J., Read, L., and Nigg, B. M. (1999). An analysis of hip joint loading during walking, running, and skiing. *Medicine and science in sports and exercise*, 31(1):131–142.

Yoshihisa Sakurai, Z. F. and Ishige, Y. (2014)). Automated Identification and Evaluation of Subtechniques in Classical-Style Roller Skiing. *Journal of Sports Science and Medicine*, 13:651–657.

Yoshihisa Sakurai, Z. F. and Ishige, Y. (2016)). Automatic Identification of Subtechniques in Skating-Style Roller Skiing Using Inertial Sensors. *sensors*, 16(4).

Zhang, H., Liu, Z., and Zhao, H. (2011). Gait modeling and identifying based on dynamic template matching. *Journal of Computational Information Systems*, 7(4):1155–1162.

Øyvind Nøstdahl Gløersen (2014). Quantitative technique analysis in XC-skiing. Master thesis, University of Oslo.