Quantitative and qualitative assessment of human movement during exercising using inertial and magnetic sensors

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Supervisor:
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DOMINIK DŽAJA

KVANTITATIVNA I KVALITATIVNA PROCJENA LJUDSKOGA POKRETA TIJEKOM TJELOVJEŽBE UPORABOM INERCIJSKIH I MAGNETSKIH SENZORA

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ABOUT THE SUPERVISOR

Ratko Magjarević was born in 1959 in Zagreb. He graduated Electrical Engineering in 1982 and in 1988 he received his master's degree. In 1994 he received his Ph.D. in the field of Electrical Engineering from the University of Zagreb. He spent his Academic career at the University of Zagreb, where he was elected to the position of full professor with tenure in the field of Electrical Engineering in 2011. Apart from Zagreb, he has been teaching at the universities of Trieste, Ljubljana and Bogota, Colombia, for many years. During 2005-06, he resides at the Institute for Biomedical Engineering, University of Stuttgart, Germany. In 2002-04 he was already one of the experts on the European Commission project "Chartography of Medical and Biological Engineering in Europe" and later in the European projects FP6, FP7, Horizon 2020, TEMPUS and COST projects. He has been the leader of bilateral scientific projects with partners in Slovenia, Italy, the United Kingdom, Macedonia, Hungary, France and Colombia. He has led an R&D project under IRI1 and a number of other research and professional projects. He has published more than 80 papers in journals and conference proceedings, several editorial books, several book chapters, and encyclopedia citations, and has delivered more than twenty invited lectures at major international conferences. Professor Magjarević is an official and a member of several international and national scientific and professional organizations. In the International Federation of Medical and Biological Engineering (IFMBE), he was elected for two three-year terms of office as President: 2012-15 term and 2021-24. In 2014, he received the FER Golden Plaque "Josip Lončar" for his contribution to the teaching and development of biomedical engineering, as well as the recognition of the Senate of the Republic of Colombia for his global contribution to the development of biomedical engineering. In 2013, he was elected Honorary Senator of the University of Ljubljana.

O MENTORU

Ratko Magjarević rođen je u Zagrebu 1959. godine. Diplomirao je elektrotehniku, smjer Industrijska elektronika 1982., magistrirao 1988. i doktorirao 1994. godine u polju elektrotehnike na Sveučilištu u Zagrebu Fakultetu elektrotehnike i računarstva. Akademsku karijeru proveo je na Sveučilištu u Zagrebu gdje je 2011. godine izabran u zvanje redoviti profesor u trajnom zvanju u polju elektrotehnike. Osim u Zagrebu, predaje već niz godina na sveučilištima u Trstu, Ljubljani i Bogoti, Kolumbija. Tijekom 2005./2006. boravi na Institute for Biomedical Engineering Sveučilišta u Stuttgartu, Njemačka. Godine 2002.-2004. jedan je od eksperata na projektu Europske komisije „Chartography of Medical and Biological Engineering in Europe", a kasnije na europskim projektima FP6, FP7, Obzor 2020 te TEMPUS i COST projektima. Bio je voditelj bilateralnih znanstvenih projekata sklopljenih s partnerima u Sloveniji, Italiji, Ujedinjenom Kraljevstvu, Makedoniji, Mađarskoj, Francuskoj i Kolumbiji. Vodio je istraživačko razvojni projekt u okviru IRI1 i niz drugih znanstvenoistraživačkih i stručnih projekata. Objavio je više od 80 radova u časopisima i zbornicima konferencija, nekoliko uredničkih knjiga, više poglavlja u knjigama i navoda u enciklopedijama te održao više od dvadeset pozvanih predavanja na značajnim međunarodnim konferencijama. Dr. sc. Magjarević je aktivni dužnosnik i član više međunarodnih i nacionalnih znanstvenih te strukovnih organizacija. U Međunarodnoj federaciji medicinskog i biološkog inženjerstva (International Federation for Medical and Biological Engineering – IFMBE), izabran je u dva trogodišnja mandata za Predsjednika u mandatnom razdoblju 2012.-2015. i 2021.–2024. godine. 2014. primio je zlatnu plaketu "Josip Lončar" FER-a za doprinos nastavi i razvoju biomedicinskog inženjerstva kao i priznanja Senata Republike Kolumbije za globalni doprinos razvoju biomedicinskog inženjerstva. 2013. godine izabran je za počasnog Senatora Sveučilišta u Ljubljani.

SUMMARY

Monitoring a person's physical activity has a wide range of applications in both sports and medicine. With the advancement of technology for measuring human movement, it is possible to monitor the performed activity without a need for an expert to directly overlook the trainee. Due to the low price, sufficiently accurate measurements, portability, and availability, the work of many research groups is especially directed towards wearable systems, i.e. wearable devices with inertial and magnetic sensors. While the initial interest was mainly in aerobic exercises, research has recently begun to focus on strength exercises as well. To independently monitor and evaluate repetitive human movements through this type of exercise, a proper form is to classify them into quantitative and qualitative manner. Quantitative information will provide an overview of how many movements (i.e. repetitions) are done, and qualitative will show whether repetition is being performed correctly. For successful counting and assessment of repetition quality it is necessary to first detect and separate the repetitions (segmentation), and then determine which exercise they belong to (classification). Only after the segmentation and classification of repetitions have been done, it is possible to start the quality assessment. The goal is to achieve the highest possible accuracy in tracking movement while maintaining low cost and energy autonomy of the monitoring system.

The challenges researchers are facing with are primarily related to the minimization of the number and position of wearable devices on individual human body segments and the development of algorithms that will provide appropriate assessment and feedback. Taking into consideration existing solutions and their limitations, as well as the desire to fulfill the requirements of simplicity, generalizability, and reliability a new procedure for quantitative and qualitative monitoring of exercise performance is proposed. The procedure is designed so that it can be easily applied not only to exercises aimed at activating individual body segments, but also to activation of the whole body. For the procedure to meet the set goals, a measurement method of human movement variability and movement execution metrics were developed along with it.

Successful implementation and validation of the procedure, method, and metrics were first done in controlled conditions and on a reduced number of subjects (no. 6), afterward in real conditions on a larger scale of subjects (no. 40). Each subject performed one workout session which consisted of 9 strength exercises while wearing 3 wearable devices (wrist, chest, and thigh).

Keywords: wearable devices, strength exercises, repetition segmentation, repetition classification, quantitative assessment, qualitative assessment, human movement monitoring

KVANTITATIVNA I KVALITATIVNA PROCJENA LJUDSKOG POKRETA TIJEKOM TJELOVJEŽBE UPORABOM INERCIJSKIH I MAGNETSKIH SENZORA

Praćenje fizičke aktivnosti osobe ima širok raspon primjena u sportu i medicini. Zahvaljujući napretku tehnologije za praćenje ljudskog pokreta, moguće je pratiti izvedenu aktivnost bez potrebe za stručnjakom koji izravno nadgleda polaznika. Zbog niske cijene, dovoljno preciznih mjerenja, prenosivosti i dostupnosti, rad mnogih istraživačkih grupa usmjeren je posebno prema nosivim sustavima, odnosno nosivim uređajima s inercijskim i magnetskim senzorima. Iako je početni interes istraživačkih grupa uglavnom bio usmjeren na aerobne vježbe, istraživanja su se nedavno počela usmjeravati i na vježbe snage. Kako bi se neovisno pratili i procjenjivali ponavljajući ljudski pokreti kroz ovu vrstu vježbi, prikladno ih je klasificirati na kvantitativan i kvalitativan način. Kvantitativne informacije pružaju pregled o broju pokreta (odnosno ponavljanja) koji se izvode, a kvalitativne pokazuju jesu li ponavljanja izvedena ispravno. Za uspješno brojanje i procjenu kvalitete ponavljanja, potrebno je prvo detektirati i odvojiti ponavljanja (segmentacija), a zatim odrediti kojoj vježbi pripadaju (klasifikacija). Tek nakon što su segmentacija i klasifikacija ponavljanja odrađene, moguće je započeti s procjenom kvalitete. Cilj je postići što veću moguću točnost u praćenju pokreta uz održavanje niske cijene i energetske autonomije sustava za praćenje.

Izazovi s kojima se istraživači suočavaju primarno su vezani uz minimiziranje broja i pozicije nosivih uređaja na pojedinačnim dijelovima ljudskog tijela i razvoj algoritama koji će pružati odgovarajuću procjenu i povratne informacije. Uzimajući u obzir postojeća rješenja i njihova ograničenja, kao i želju za ispunjavanjem zahtjeva jednostavnosti, generaliziranosti i pouzdanosti, predlaže se nova procedura za kvantitativno i kvalitativno praćenje izvedbe vježbi. Procedura je osmišljena tako da se može lako primijeniti, ne samo na vježbe usmjerene na aktivaciju pojedinačnih dijelova tijela, već i na aktivaciju cijelog tijela. Kako bi procedura ispunila postavljene ciljeve, uz nju je razvijena metoda za mjerenja varijabilnosti ljudskog pokreta i metrika izvođenja pokreta.

Uspješna primjena i validacija procedure, metode i metrika prvo su izvršene u kontroliranim uvjetima i na smanjenom broju ispitanika (br. 6), a potom u stvarnim uvjetima na većem broju ispitanika (br. 40). Svaki ispitanik je izveo jednu tjelovježbu koja se sastojala od 9 vježbi snage noseći tri nosiva uređaja, na zapešću, prsima i bedru.

U prvom, uvodnom poglavlju opisuje se kontekst i ciljevi istraživanja. Redovita i umjerena fizička aktivnost ima pozitivan učinak na zdravlje ljudi, smanjuje rizik od bolesti i smrti, te se često koristi kao dio rehabilitacije tijekom oporavka od operacije ili ozbiljne bolesti. Ova vrsta aktivnosti može se provoditi u teretanama, kod kuće ili na otvorenom, a kako bi se maksimizirao pozitivan učinak, preporučuje se provoditi ju uz određeno znanje ili u prisutnosti stručnjaka. Najčešće zbog financijske nemoći, ali i ovisnosti o unaprijed planiranom rasporedu treninga, ljudi sa nedostatnim znanjem pristupaju vježbanju na vlastitu ruku, što često dovodi do gubitka motivacije i odustajanja, neefikasnog treninga ili, u najgorem slučaju, do ozljeda. Ako osoba ipak odluči primijeniti neku vrstu nadziranog vježbanja, često se odvija u skupinama, umjesto personalizirano, što predstavlja izazov za trenere da sistematski nadgledaju pojedinca. Osim toga, postojeći mjerni instrumenti (testovi, upitnici, skale procjene) koji se koriste u procjeni vježbanja mogu se poboljšati u smislu automatizacije, objektivnosti i pouzdanosti. Brzi razvoj tehnologije u posljednjem desetljeću znatno je omogućio i olakšao proces digitalnog snimanja ljudskog pokreta, stoga može predstavljati moguće rješenje za razvoj inteligentnih podražavajućih uređaja ili sustava koji bi dodatno pomogli stručnjaku ili ih čak mogli zamijeniti u određenim situacijama. S obzirom na opremu i tehnologiju potrebnu za snimanje, može se grubo podijeliti u dvije grupe: a) optičke sustave i b) nosive sustave. Odabir grupe primarno ovisi o području primjene, vrsti aktivnosti i prostoru gdje se aktivnost odvija. Optički sustavi se primarno koriste u zatvorenim prostorima i s izuzetno visokom preciznošću (s više kamera i specijaliziranim markerima), dok se nosivi sustavi koriste kada sustav treba pružiti veću fleksibilnost bez prostornih ograničenja. U sklopu ove doktorske disertacije naglasak je na nosivim sustavima temeljenim na inercijskim i magnetskim senzorima koji se postavljaju na određene tjelesne segmente, a sastoje se od dva glavna dijela: senzora i pratećeg hardvera za mjerenje akceleracije, kutne brzine i magnetskog polja te algoritma za segmentaciju i klasifikaciju pojedinog ljudskog pokreta.

Poglavlje 2 govori o pretraženoj literaturi relevantnoj za praćenje ljudskog pokreta tijekom fizičke aktivnosti pomoću nosivih sustava te njihovim nedostatcima. Različite vrste fizičke aktivnosti analiziraju se i vrednuju, ali je naglašeno kako je njihov primarni fokus orijentiran upravo na aerobne vježbe i na jednostavnije pokrete unutar rehabilitacije dok su vježbe snage zapostavljene. Nadalje, opisana je struktura sustava za vrednovanje repetitivnih vježbi snage temeljena na inercijskim i magnetskim senzorima. Glavni dijelovi strukture sastoje se od: načina prikupljanja podataka, broja i položaja senzorskih čvorova na ljudskom tijelu, segmentacije, klasifikacije i evaluacije pokreta.

Poglavlje 3 predstavlja i istražuje metode za mjerenje varijabilnosti ljudskog pokreta. U kontroliranim laboratorijskim uvjetima i uz smanjeni broj ispitanika, provedena su mjerenja prilikom izvođenja niza vježbi snage. Mjerenja pokreta tijekom vježbanja izvedena su pomoću tri senzorska čvora, a snimljeni i obrađeni podaci poslužili su kao referenca za odabir osjetljivosti senzora, odabir broja i položaja senzora, definiranje modela te odabir podataka koji se prate i pohranjuju kroz izvođenje vježbe. Zaključeno je da dostupni podaci iz mjerenja akceleracije i kutne brzine daju najznačajniju povratnu informaciju o kretanju. Nakon analize podataka prikupljenih senzorskim čvorovima, razvijene su i dvije različite tehnike za brojanje i segmentiranje ponavljanja, pri čemu jedna koristi prethodno znanje o specifičnoj vježbi, a druga ne. Osim toga, određena je učinkovitost različitih klasifikatora za točno prepoznavanje vrste vježbe koja se izvodi, kao i utjecaj pojedinačnih značajki senzora i položaja senzorskih čvorova na točnost klasifikacije.

Poglavlje 4 opisuje kako određenu vježbu odnosno pojedino ponavljanje možemo numerički opisati koristeći parametre izvođenja ekstrahirane iz prethodno odabranih veličina. Uzimajući u obzir dosadašnja istraživačka dostignuća, osmišljena je i predložena metrika s kojom je moguće krenuti u vrednovanje pokreta. Predložena metrika primjenjiva je na većoj skupini ispitanika (poglavlje 5), bilo s istim ili različitim obilježjima, podjednako kao i u slučaju pojedinca. Metriku izvođenja pokreta tijekom tjelovježbe moguće je podijeliti u dvije kategorije, baziranu na pravilima ili baziranu na predlošku. U pristupu temeljenom na pravilima, potrebno je definirati neke određene parametre (kao npr. kutovi, brzina, položaj zglobova i slično) koji definiraju uzorak. Njihova prednost je mala kompjuterska zahtjevnost izvođenja, a mana nedostatak generalizacije i ponovne upotrebljivosti za različite vježbe, što može dovesti do velikog skupa podataka pravila. Osim toga, kada se složenost pokreta povećava, mapiranje pravila postaje potencijalno narušeno, a samim time i određivanje točne procjene pokreta. Nasuprot tome, pristup temeljen na predlošku uključuje snimanje jednog pokreta kao reference za usporedbu s naknadnim ponavljanjima. Iako ovaj pristup nudi prednost bržeg vremena definiranja, ograničen je potrebom za unaprijed snimljenim predloškom pokreta i možda neće uzeti u obzir individualne razlike u obrascima kretanja. Kako bi se riješila ograničenja ovih pristupa i postigla veća generalizacija, u ovom poglavlju predložen je novi pristup. Ova metoda uključuje generiranje novostvorenih veličina na temelju početne orijentacije pojedinca, a koje se zatim mogu usporediti pomoću nove bodovne funkcije. Predloženi pristup omogućuje procjenu pojedinačnih ponavljanja pomoću univerzalne metrike, neovisno o orijentaciji IMU na tjelesnom segmentu ili položaju pojedinca. Nadalje, predložena metrika može se koristiti ili s osobnim načinom ili općim predloškom za usporedbu.

U 5. poglavlju detaljno je razložen postupak kvantitativnog i kvalitativnog praćenja uspješnosti vježbanja. Objašnjeni su pojmovi kvantitete i kvalitete pokreta te je predstavljen razvijeni algoritam koji to omogućava. Struktura algoritma sastoji se od: segmentacije aktivnosti, segmentacije zasebnog ponavljanja, ekstrakcije značajki, prepoznavanju vježbe i ocjene. Ocjena je krajnjem korisniku najzanimljivija informacija koju je moguće promatrati na nižoj (pojedina vježba) ili višoj (cjelokupna tjelovježba) razini kroz vrijeme te eventualno pravovremeno reagirati kako bi se spriječila loša izvedba, a samim time i mogućnost ozljede. U istraživanje je bilo uključeno 40 ispitanika (28 muškaraca i 12 žena). Podaci su prikupljeni na isti način i s istom osjetljivošću senzora i položajima kao što je opisano u poglavlju 3. Uzimajući u obzir istražene i razvijene metode mjerenja varijabilnosti ljudskog pokreta (poglavlje 3) i metrike izvođenja pokreta tijekom tjelovježbe (poglavlje 4) osmišljen je i predložen postupak za praćenje uspješnosti vježbanja. Postupak je moguće podijeliti u 3 načina rada, a odabir rada ovisi direktno o tome gdje se postupak koristi i kakvu povratnu informaciju od njega korisnik očekuje. Prvi način rada je najosnovniji, i korisniku pruža povratnu informaciju samo o kvantiteti pokreta odnosno koliko ponavljanja je odrađeno. Ovakav način rada pogodan je tijekom samostalnog treniranja iskusnijih vježbača za praćenje broja odrađenih pokreta tijekom tjelovježbe, neovisno o tome koje vježbe se izvode. Drugi način rada osim kvantitete izvedenih pokreta pruža i informaciju o kvaliteti pokreta. Ovakav način rada zamišljen je kao virtualni trener za vježbače koji osim broja ponavljanja žele i dodatnu informaciju o tome kako izvode pojedinu vježbu. U posljednjem načinu rada pretpostavka je da sustav unaprijed zna kojim redoslijedom vježbač izvodi tjelovježbu, poput rehabilitacije. Zbog dodatnog prethodnog znanja, sustav korisniku u stvarnom vremenu može pružiti informaciju o izvedenom pokretu što korisniku omogućuje da odmah prilagodi tehniku vježbanja.

Posljednje poglavlje disertacije (6. Zaključak) daje raspravu o postignutim rezultatima i sažima zaključke koji proizlaze iz provedenog doktorskog istraživanja i potencijalne buduće smjerove daljnjeg istraživanja.

Ključne riječi: nosivi uređaji, vježbe snage, segmentacija ponavljanja, klasifikacija ponavljanja, kvantitativna procjena, kvalitativna procjena, praćenje ljudskog pokreta

CONTENTS

1 INTRODUCTION

1.1 Background and Motivation

Regular and moderate physical activity has a positive effect on human health, reduces the risk of illness and death, and is often used as part of rehabilitation during recovery from surgery or serious illness [1]. It is defined as the movement of the body that increases energy expenditure above the level of rest, and can occur spontaneously (leisure, work or transport) or organized (sports, physical training or exercise). Recommendations and strategies for physical activity can be found in the publicly available literature [2][3], and it can be briefly concluded that a person, in addition to their daily responsibilities (spontaneous activities) during the week, should also strive for a balanced organized program of activities or exercise to improve aerobic working capacity and muscle strength. This form of activity can be carried out in gymnasiums, at home or outdoors, and to maximize the positive effect, it is recommended to perform it with some knowledge or in the presence of a professional expert.

Most often due to financial incapacity, but also dependence on a pre-planned training schedule, people with inadequate knowledge approach exercise on their own, which often leads to loss of motivation and giving up, ineffective training or, in the worst case, even to injuries [4][5][6]. If a person still decides to apply some form of supervised exercise, it is often in a group, rather than individualized, which is a challenge for trainers to systematically monitor an individual [7]. In addition, the existing measurement instruments (tests, questionnaires, assessment scales) used in the evaluation of the exercise [8] can be improved in terms of automation, objectivity and reliability [9][10].

The rapid development of technology in the last decade has greatly enabled and facilitated the process of digital recording of human movement [11]; therefore, it can present a possible solution for the development of intelligent supporting devices or systems that would additionally help a professional expert or could even replace them in certain situations. Considering the equipment and technology needed for recording, it can be roughly divided into two groups: a) optical systems and b) wearable systems. The choice of the group primarily depends on the field of application, the type of activity, and the space where the activity takes place [12]. Optical systems are primarily used in closed spaces and with extremely high accuracy (with multiple cameras and specialized markers), while wearable ones are used when the system needs to provide greater flexibility without spatial constrains.

Different types of physical activity can be monitored with the help of such systems. While in the initial research emphasis was mainly on aerobic physical activity [13][14], more recently attention has also begun to focus on muscle-strengthening physical activity. Muscle-strengthening physical activity is referred to as strength training or resistance training and most often consists of performing several different exercises that are composed of a series of repetitive movements. The existing systems usually deal with automatic counting of these repetitions and exercise recognition, but they rarely provide additional information about the quality of the performance of these movements or the entire exercise [4][15][16][17].

Considering existing research and gaps, throughout this doctoral thesis are presented the procedure, method and metrics with which it is possible to realize a closed-loop system for human movement monitoring and assessment using wearable devices during exercising. The problem of the number and position of wearable devices, the selection of measurable quantities, the definition of the model, segmentation, classification, and assessment of the performance of individual movements and the entire exercise are defined. The proposed procedure was tested on a group of 40 subjects during a workout session consisting of 9 strength exercises.

1.2 Thesis Overview

The thesis is organized as follows:

Chapter 1 (*Introduction*) provides a brief overview of the topic of this doctoral thesis and the structure of the work.

Chapter 2 (*Literature review*) discusses the literature relevant for human movement monitoring and assessment during physical activity and highlights existing research gaps. The emphasis is more on wearable systems, i.e. wearable devices with inertial and magnetic sensors, during the performance of strength exercises.

Chapter 3 (*Measurement method of human movement variability during exercise using sensor nodes with inertial and magnetic sensors*) presents and investigates methods for measuring the variability of human movement. Through controlled conditions and a reduced number of subjects, measurements were performed and served as a reference for the selection, number and position of sensors, model definition and selection of data that are monitored through the performance of the exercise.

Chapter 4 (*Movement execution metrics during exercise based on measurements using sensor nodes with inertial and magnetic sensors*) describes how a particular exercise or individual repetition can be described numerically using performance parameters extracted from previously selected data. Considering the previous research achievements, a metric was designed and proposed. The proposed metric is applicable to a larger group of subjects, either with the same or different characteristics, as well as in the case of an individual.

Chapter 5 (*Procedure for quantitative and qualitative monitoring of exercise performance using sensor nodes with inertial and magnetic sensors and measurement of heart rate*) explains in detail the procedure for quantitative and qualitative monitoring of exercise performance. The concepts of quantity and quality of motion are explained, and a developed algorithm that enables this is presented. The structure of the algorithm consists of: activity segmentation, repetition segmentation, feature extraction, exercise recognition, and assessment. Assessment is the most interesting information for the end user, which can be observed at a lower (individual exercise) or higher (entire workout) level over time and possibly react on time to prevent poor performance and thus the possibility of injury.

Chapter 6 (*Conclusion*) provides a discussion on the achieved results and summarizes conclusions resulting from the conducted doctoral research.

1.3 Summary of Contributions

Main contributions of this thesis include:

- Measurement method of human movement variability during exercise using sensor nodes with inertial and magnetic sensors. The method is described in Chapter 3.
- Movement execution metrics during exercise based on measurements using sensor nodes with inertial and magnetic sensors. The metrics are described in Chapter 4.
- Procedure for quantitative and qualitative monitoring of exercise performance using sensor nodes with inertial and magnetic sensors and measurement of heart rate. The procedure is shown in Chapter 5.

2 LITERATURE REVIEW

This chapter provides a review of the literature intending to provide background information and practice in the field of monitoring and assessment of human movement during physical activity. The first part explains terms related to physical activity, its benefits, and presents statistics related to activity with strategies for increasing it. Following, the technologies that can be used to monitor physical activity are explained, and the chapter ends with the currently existing solutions and gaps for monitoring and assessment of human movements using wearable systems with an emphasis on muscle-strengthening physical activity.

2.1 Physical Activity

Regular physical activity is widely recognized as a protective factor for the prevention and management of noncommunicable diseases, such as cardiovascular disease, type-2 diabetes, as well as breast and colon cancer. Furthermore, physical activity has been shown to have benefits for mental health, delay the onset of dementia, and contribute to the maintenance of healthy weight and general well-being [18].

In addition to the multiple health benefits of physical activity, more active societies can generate additional returns on investment, including reduced use of fossil fuels, cleaner air, and less congested and safer roads. These outcomes are interconnected with achieving the shared goals, political priorities, and ambitions of the Sustainable Development Agenda 2030 [19].

According to estimates, the global cost of physical inactivity in 2013 was INT$ 54 billion per year in direct health care, with an additional INT$ 14 billion attributable to lost productivity. Inactivity accounts for 1-3% of national health care costs, although this excludes costs associated with mental health and musculoskeletal conditions [19].

2.1.1 Physical Activity and the Related Terminology

Physical activity is a term used to describe any movement of the body that requires energy expenditure and is produced by the contraction of skeletal muscles. This encompasses a broad range of activities, including, but not limited to, walking, cycling, sports, and various forms of recreation such as dance, yoga, and tai chi. Physical activity can also be integrated into work tasks or domestic duties such as cleaning, carrying, or care duties. While some physical activities may be performed for enjoyment or leisure, others may be mandatory or necessary for work or domestic purposes and may not offer the same mental or social health benefits as recreational activities. However, regular physical activity, regardless of its nature, has been shown to provide numerous health benefits, as long it is of sufficient duration and intensity. In 2010, the World Health Organization (WHO) released recommendations on the optimal type and frequency of physical activity for various age groups, including youth, adults, and elderly [2][19][20].

The measurement of exercise intensity can be expressed in absolute or relative terms. Absolute intensity refers to the actual physical work performed, which can be measured in units such as Watts (W), kilograms (kg), or metabolic equivalents (MET). Relative intensity, on the other hand, is measured relative to the individual's maximum capacity or physiological factors such as percentage of maximum heart rate (%HR), rate of perceived exertion (RPE), watts per kilogram of body weight (W/kg), or relative oxygen uptake in liters per minute per kilogram of body weight (VO_2).

Sedentary behavior is defined as any waking behavior characterized by an energy expenditure $\leq$ 1.5 metabolic equivalents, such as sitting, reclining or lying down. Recent evidence indicates that high levels of continuous sedentary behavior (such as sitting for long periods) are associated with abnormal glucose metabolism and cardiometabolic morbidity, as well as overall mortality. Reducing sedentary behavior through the promotion of incidental physical activity (for example, standing, climbing stairs, short walks) can support individuals to increase incrementally their levels of physical activity towards achieving the recommended levels for optimal health [19][21].

According to Malm et al. [3], physical activity can be classified into two categories: aerobic physical activity and muscle-strengthening physical activity. The majority of energy production during aerobic physical activity occurs via oxygen-dependent pathways, making it the type of activity typically associated with stamina, fitness, and the greatest health benefits.

Muscle-strengthening physical activity, on the other hand, is often referred to as "strength training" and is primarily intended to maintain or improve various forms of muscle strength and increase or maintain muscle mass. In addition, a third category, muscle-enhancing physical activity, is sometimes defined, which is important for the maintenance or improvement of coordination and balance, especially in the elderly.

2.1.2 Health Effects of Physical Activity

Human biology necessitates a certain level of physical activity to maintain good health and well-being. It would take several generations for humans to biologically adapt to a life with reduced physical activity. Therefore, the physical activity requirements of people today are more or less the same as they were 40,000 years ago. For example, an average man weighing 70 kg would need to walk about 19 km every day in addition to everyday physical activity. However, daily physical activity has decreased for most people while planned, deliberate exercise and training have increased. Unfortunately, the average daily energy intake has increased more than the daily energy output, leading to an energy surplus. This is one of the reasons for the growing number of overweight individuals, which is a strong contributor to many health issues. Insufficient physical activity combined with increased energy intake (sedentary living) adversely affects both physical and mental abilities, increasing the risk of illness [3][22][23][24].

2.1.2.1 Effects on Physical Health

The health effects of physical activity and exercise can be both acute (during and immediately after) and long-lasting. The latter has far-reaching consequences for health and is crucial for good health. To achieve the desired long-term effects, physical activity should be performed with both progression and continuity. Most physical exercise/training consists of a combination of aerobic and muscle-strengthening exercises, and it can be challenging to distinguish between their health effects (Table 1).

Significant improvements in health are observed when individuals transition from a completely sedentary lifestyle to engaging in moderate physical activity, even before noticeable enhancements in physical performance. While past studies have primarily focused on aerobic exercise, there is growing evidence suggesting that strength training can also offer valuable mental and physical health benefits, as well as help prevent certain diseases.

Table 1 Physiological effects of aerobic and muscle-strengthening physical activity on health. Number 3 indicates that the activity contributes with an effect, whereas a number 1 indicates that the activity has no proven effect. Number 2 indicates that the activity may in some cases be effective [3]

Effects on the body	**Health effects**	**Aerobic**	**Strength**
Larger proportion slow-twitch fibers	Lower risk for metabolic syndrome with increased exchange of gases and nutrition	3	1
Larger proportion slow-twitch	Increased strength, coordination and balance in elderly and in sickness, lower risk for fall	1	3
Formation of new capillaries	Increased aerobic capacity	3	2
Improved endothelial function	Lower risk for cardiovascular disease, improved function in heart disease	3	2
Increased mitochondrial volume	Increased aerobic capacity	3	2
Improved glucose transport	Lower risk or metabolic syndrome/Type-2 diabetes	3	3
Improved insulin sensitivity	Improved health in people with Type-2 diabetes, prevention of Type-2 diabetes	3	3
Increased heart capacity	Lower risk for cardiovascular disease, fewer depressions, also in children	3	3
Increased skeletal volume and mineral content	Improved skeletal health	2	3
Improved body composition	Lower risk for metabolic syndrome	3	3
Improved blood pressure regulation	Lower risk for cardiopulmonary disease	3	3
Improved blood lipid profile	Lower risk for cardiopulmonary disease in elderly and Alzheimer’s. No effect on blood lipid profiles in children and adolescents	3	3
Improved peripheral nerve function	Better coordination, balance and reaction, especially in children and elderly	3	3
Enhanced release of signaling substances	Better sleep, less anxiety, treatment of depression	3	3
Improved hippocampus function	Improved cognition and memory, less medication	3	2
Positive effects on mental capacity	Counteract brain degeneration by disease, anti-inflammatory effects	3	2
Improved immune function	Decreased overall risk for disease, anti-inflammatory effects	3	2
Strengthening the connection between brain, metabolism and immune function	Decreased risk for disease, improved metabolism, decreased risk for depression	3	2
Improved intestinal function	Improved health, mitigated metabolic syndrome, obesity, liver disease and some cancers	3	2

Aerobic physical activity has been demonstrated to promote weight maintenance following weight loss, decrease the risk of metabolic syndrome, improve blood lipid levels, and alleviate cancer and cancer-related side effects (Table 1). However, the effects of aerobic exercise on chronic pain remain inconclusive.

In contrast, muscle-strengthening physical activity has been shown to prevent muscle atrophy, reduce the risk of falling, and mitigate osteoporosis in the elderly. Both men and women in the elderly population respond positively to strength training, and it can also prevent obesity, improve cognitive performance when combined with aerobic exercise, counteract the development of neurodegenerative diseases, reduce the risk of metabolic syndrome, alleviate cancer and cancer-related side effects, reduce pain and disability in joint diseases, and increase bone density. As the risk of falling increases substantially with age, partly due to decreased muscle mass and impaired coordination and balance, there is a strong correlation between physical performance, reduced risk of falls, and improved quality of life in older individuals. Also, deterioration in muscle strength, but not muscle mass, increases the risk of premature death, but this can be counteracted through exercise, with a dose-response relationship between strength improvement and age. To enhance overall health, it is advised to incorporate muscle strengthening exercises alongside aerobic physical activity. According to established guidelines, engaging in high-intensity strength training, specifically performing 6-8 repetitions at 80% of an individual's one-repetition maximum, is considered the most efficacious approach. [3][25].

2.1.2.2 Effects on Mental Health

Mental health is a significant global concern, impacting millions of individuals worldwide. Measures of mental ill health include headache, stress, insomnia, fatigue, and anxiety, among others, with varying levels of severity. The term "ill health" encompasses several mental health issues and symptoms. Recent research has compared the expected health benefits of regular physical activity to other treatments, such as medication, for improving mental health. Studies have shown that physical activity and exercise, when used as primary or secondary interventions, have significant positive effects in preventing or alleviating depressive symptoms and have an antidepressant effect in people with neurological diseases. Additionally, training and exercise have been found to enhance quality of life, coping mechanisms for stress, and self-esteem and social skills. They can also reduce anxiety in individuals diagnosed with anxiety- or stress-related conditions, improve creative thinking, vocabulary learning and memory [3][26].

2.1.3 Current Levels of Physical Activity

Physical inactivity is defined as not meeting the 2010 Global recommendations on physical activity for health and is a leading contributor to global mortality. It is estimated that between four and five million deaths per year could be averted if the global population was more active [18]. Global progress to increase physical activity has been slow, largely due to a lack of awareness and investment duration and intensity. Worldwide, 1 in 4 adults, and 3 in 4 adolescents (aged 11–17 years), do not currently meet the global recommendations for physical activity set by WHO [19]. The data also highlights that women are less active than men in most countries and that there are significant differences in levels of physical activity within and between countries and regions. These differences can be explained by inequities in access to opportunities to be physically active, further amplifying inequalities in health [18]. As countries develop economically, levels of inactivity increase. In some countries, levels of inactivity can be as high as 70%, due to changing patterns of transportation, increased use of technology and urbanization [19].

The country physical activity factsheets summarize specific areas of focus in terms of monitoring and surveillance based on several core indicators, as well as policies and action in the area of health-enhancing physical activity (HEPA) promotion for the European Union Member States of the WHO European Region including physical activity levels for adults, adolescents and children. As the data for the countries differ, below are presented the statistics only for Croatia (Figure 1 Figure 2 Figure 3) [27]. The level of sufficient physical activity covered children, adolescents and adults, while the statistics for aerobic and muscle-strengthening activity, sedentary behavior, and Body Mass Index (BMI) are related exclusively to adults. We can see that in the adult population, only 20% of subjects meet a sufficient level of physical activity, sedentary behavior is accepted (64%) and more than 65% are overweight.

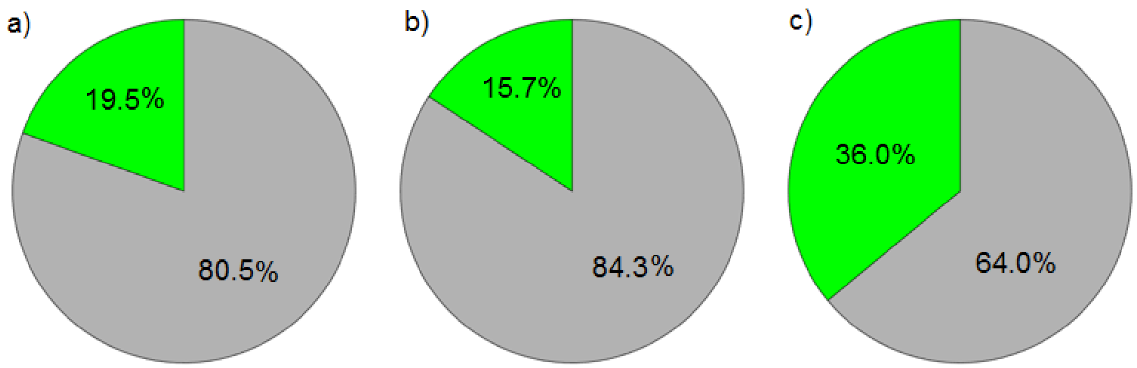


Figure 1 The proportion of the adult population: a) engaged in aerobic physical activity for at least 150 minutes per week, b) engaged in muscle-strengthening physical activity at least 2 times a week and c) that spends too much time sitting or lying down (not including sleeping) [28]

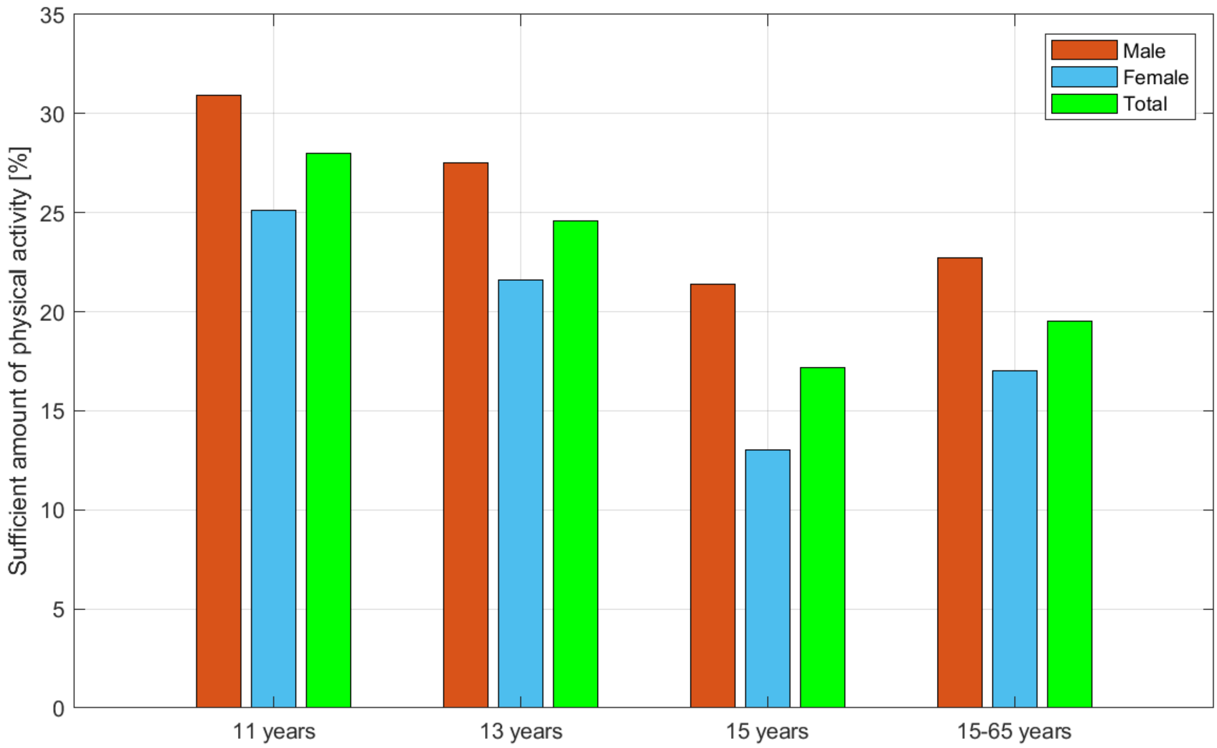


Figure 2 Estimated prevalence of sufficient physical activity levels [27]

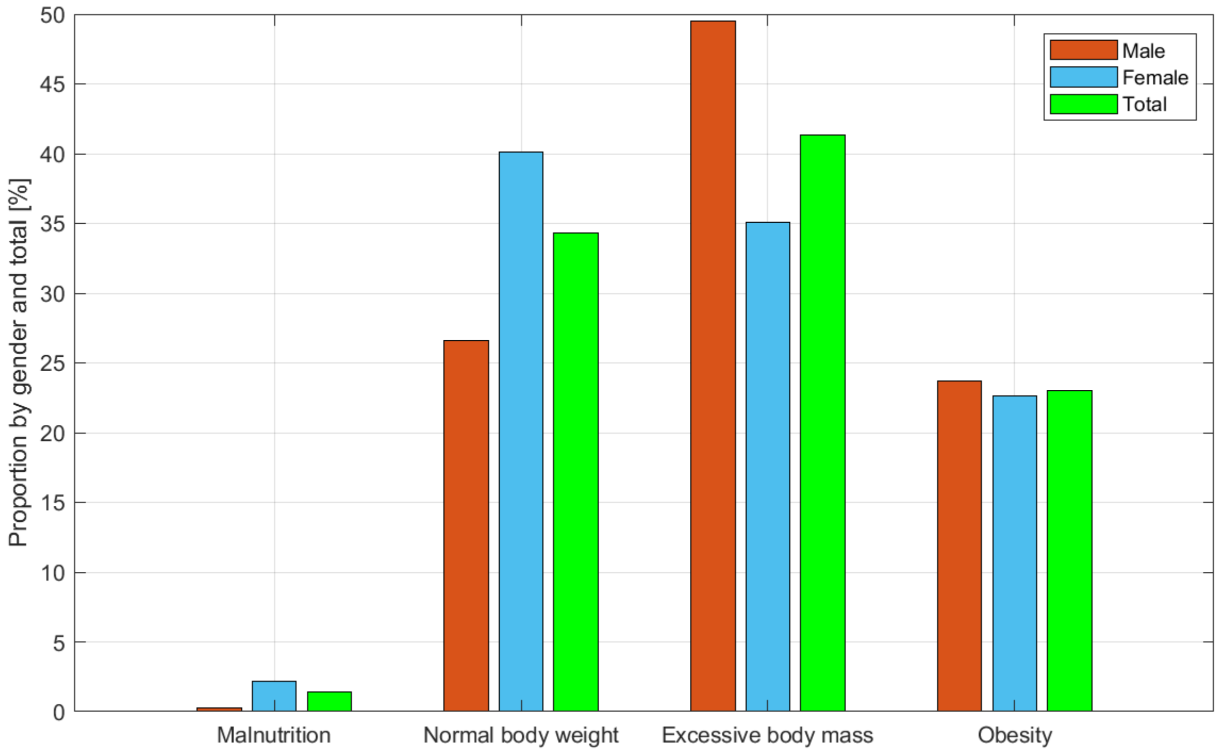


Figure 3 BMI for the adult population– the proportion by gender and total [28]

2.1.4 Recommendations and Strategies

Table 2 provides general recommendations for physical activity, which do not include everyday activities. However, it is important to note that meeting the daily physical activity recommendations by engaging in brief, high-intensity exercise and remaining physically inactive for the remainder of the day may result in a polarization of physical activity. This approach involves a high dose of conscious physical training but a low energy expenditure during normal daily activities due to high volumes of sedentary time. Such polarization may increase the risk of poor health outcomes despite meeting the recommendations for physical activity. In most cases, energy expenditure is greater during normal daily activities than during sports, physical training, and exercise, except for children and the elderly, for whom planned physical activity is especially important. In terms of recommendations to the public, Table 2 often describes intensity in subjective terms, such as "making you breathe harder" for moderate intensity and "making you puff and pant" for vigorous intensity. In [3], low intensity is defined as 1.5–2.9 METs, < 40 %HR and 20% – 39% of VO_2max; moderate intensity as 3.0–5.9 METs, 60–74 %HR and 40% – 59% of VO_2max; and vigorous intensity as 6.0–8.9 METs, 75 – 94 %HR and 60% – 89% of VO_2max. It is important to note that absolute intensity can vary greatly between individuals, with a patient with heart disease having a maximal capacity of < 3 METs, and an elite athlete > 20 METs.

Table 2 Physical activity guidelines for different target groups [3]

Target Group	Recommendations	Purpose
Age 6-17 years Children and youth	For children and adolescents, it is recommended to engage in at least 60 minutes of daily physical activity, with longer durations being even better. The physical activity should be primarily aerobic in nature, with moderate (easy/medium pulse increase) to high (marked pulse increase) intensity levels. High-intensity aerobic physical activity should be performed at least 3 times per week, in addition to engaging in muscle-strengthening physical activity 3 times per week. Weight-bearing activities such as running and jumping are beneficial for bone mineral density. It is important to gradually adjust the physical activity level to the individual's biological and psychosocial maturation.	Development of muscles and skeletal and nervous system. Maintain a healthy weight and a good mental health. Social development, integration, good self-esteem, and self-confidence. Enhanced learning ability. Recommendations are universal, but for individuals with illness, there may be special recommendations.
Age 18-64 Adults	For adults aged 18 years and above, it is recommended to engage in at least 150 minutes of moderate-intensity aerobic physical activity (with a medium pulse increase) or at least 75 minutes of vigorous-intensity aerobic physical activity (with a marked pulse increase) per week. These activities should be distributed over at least three separate days. Additionally, it is recommended to engage in muscle-strengthening physical activity at least twice a week.	Improvements in aerobic work capacity and muscle strength. Recommendations are universal, but for individuals with illness, there may be special recommendations. Profits from carrying out the activity are lower risk of disease, such as disturbed metabolism and certain cancers and bone fractures.
Age > 64 Elderly	The same physical activity recommendations as those for adults should be followed for elderly. It is recommended that muscle-strengthening exercises be performed at a high velocity, if possible. Balance training should be incorporated prior to aerobic and muscle-strengthening training. For individuals with impaired ability, it is important to perform as much physical activity as possible.	Improvements in aerobic work capacity, muscle strength, and balance. Recommendations are universal, but for individuals with illness, there may be special recommendations. Medical advice may be required before exercise commences. Benefits of carrying out the activity are the same as for adults, and better functional health and independence.

2.1.4.1 Strategies

The newly introduced global action plan by WHO aims to provide updated guidance and an effective policy framework to promote physical activity at all levels. The plan addresses the need for global leadership and stronger coordination at regional and national levels, as well as the importance of a whole-of-society approach to achieve a paradigm shift towards valuing and supporting regular physical activity for all individuals across their lifespan, regardless of their ability.

The plan, along with the ACTIVE policy proposal, highlights a range of policy options that can be customized and adapted to local contexts to increase physical activity levels worldwide. These options include investing in new technologies, innovation, and research to develop cost-effective approaches for increasing physical activity, particularly in low-resource contexts. Additionally, the plan emphasizes the need for regular surveillance and monitoring of physical activity levels and policy implementation [19].

2.1.4.2 Digital Solutions for Promoting Physical Activity

Digital technologies are increasingly being used to promote physical activity and improve health outcomes. The use of mobile and wearable devices, such as smartphones and smartwatches, has enabled the monitoring and tracking of physical activity in real-time, providing individuals with feedback on their progress and encouraging them to maintain an active lifestyle (as depicted in Figure 4, Figure 5 and Figure 6) [29]. Moreover, several studies have demonstrated the effectiveness of wearable systems in increasing physical activity and improving health outcomes, both in healthy individuals [30][31] and those with chronic diseases [32][33]. Therefore, digital solutions have the potential to reach millions of people and assist health professionals in providing ongoing monitoring and support to patients.

In this context, this doctoral thesis aims to review existing technological solutions for physical activity monitoring and identify opportunities for improvement. The thesis will examine both optical and wearable motion capture systems and explore the potential of digital solutions to improve the accuracy and reliability of physical activity monitoring. Additionally, the thesis will consider the challenges and opportunities associated with the use of digital technologies in promoting physical activity and improving health outcomes.

Overall, the use of digital solutions for promoting physical activity has the potential to improve health outcomes and reduce the burden of non-communicable diseases. By leveraging the power of technology, individuals can monitor and track their physical activity, receive feedback and support, and maintain an active and healthy lifestyle. As digital technologies continue to evolve, there are significant opportunities to further improve the accuracy and effectiveness of physical activity monitoring and promote health and well-being for all.

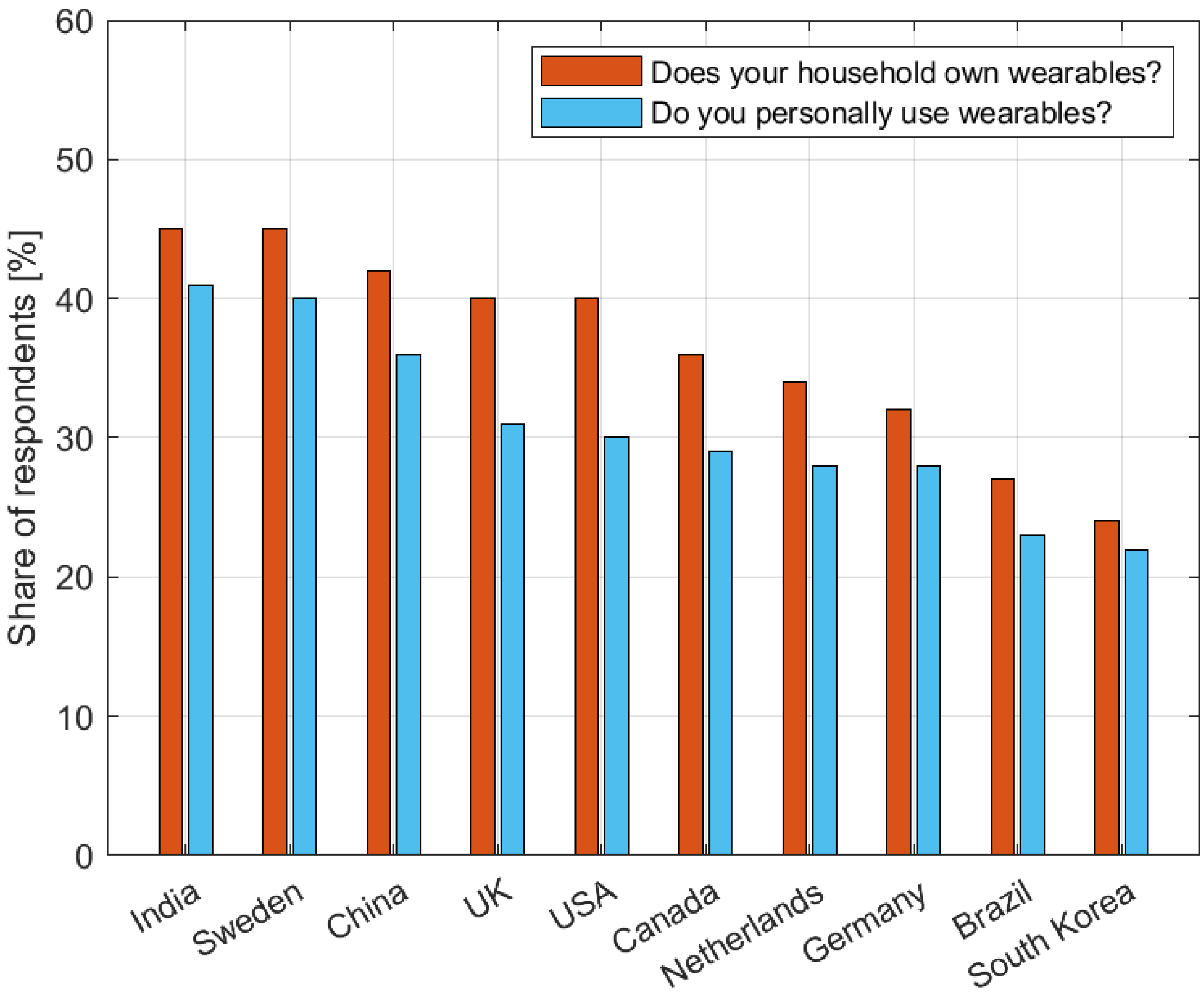


Figure 4 Wearables ownership and usage [34]

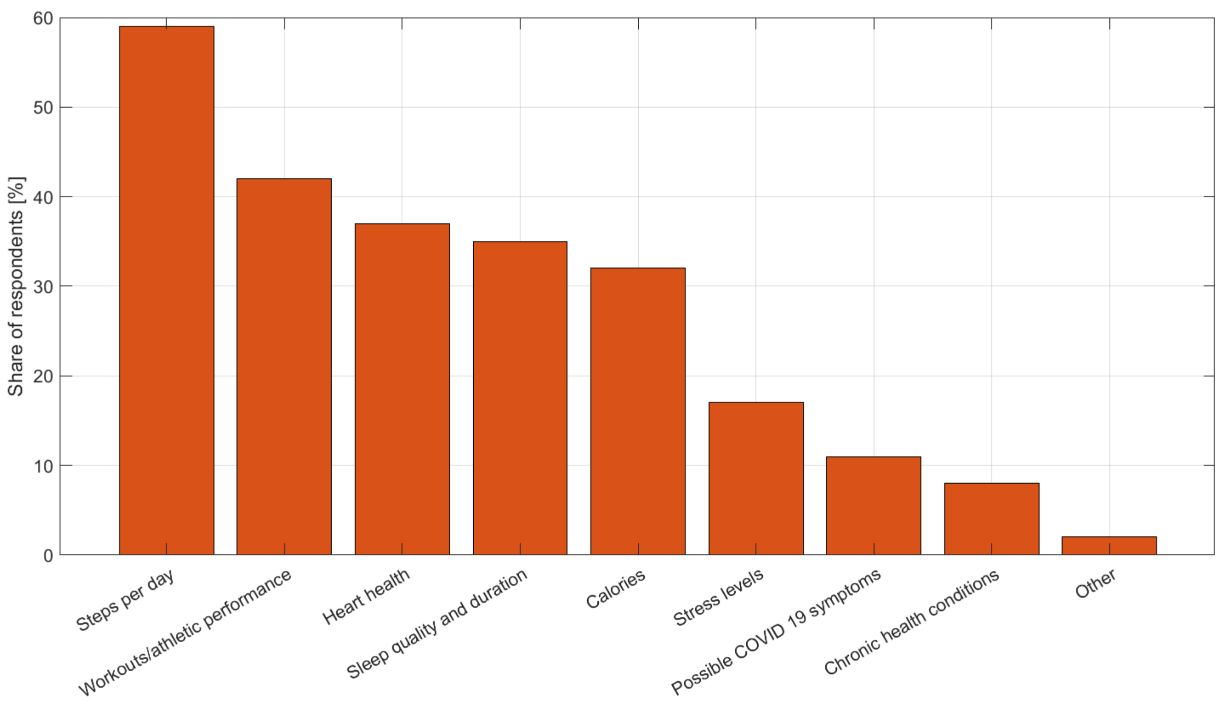


Figure 5 Reasons to use smartwatches in the United States [34]

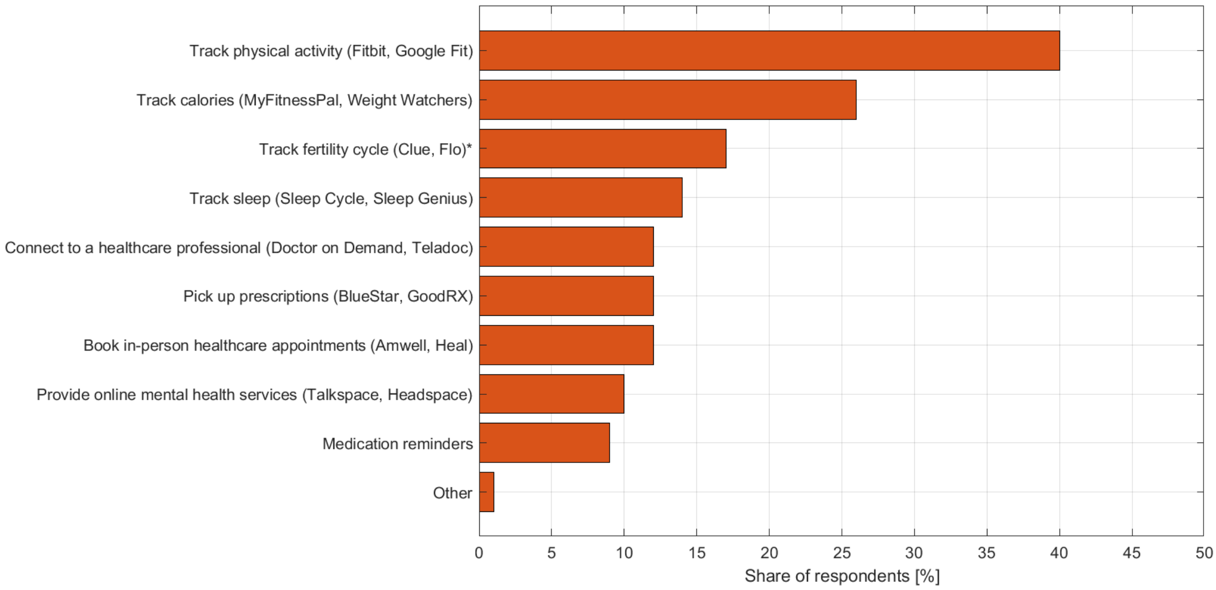


Figure 6 Usage of health and medical apps among mobile gamers in the United States [34]

2.2 Technological solutions for Physical Activity Monitoring

Motion capture is the process of digital recording of human movement. It is a multidisciplinary application field that features the interaction of recently developed technology for different areas, such as human ergonomics, entertainment, computer graphics, medical applications, sports, and other fields. Motion capture systems are mostly extended into two categories: a) optical systems and b) wearable systems [11][35]. In the following subchapter, both categories of motion capture systems are reviewed.

2.2.1 Optical Systems

Optical sensing encompasses a large and varying collection of technologies assembled into single or multiple cameras. By using various image processing techniques, the 3D position of the subject being recorded is determined. Data acquisition is traditionally implemented using special markers attached on anatomical landmarks in correspondence with the joints involved in the analysis, however, more recent systems can generate accurate data without additional makers [36][37].

2.2.1.1 Marker-based Optical Systems

Marker-based optical systems determine position by using multiple cameras to track predetermined points (markers) on the subject’s body segments, aligned with specific anatomical landmarks. The position is estimated using multiple 2D images of the working volume. Stereometric techniques correlate common tracking points on the tracked objects in each image and use this information along with knowledge concerning the relationship between each of the images and camera parameters to calculate position. The markers can either be passive (reflective) or active (light emitting). Reflective systems use infrared (IR) LEDs mounted around the camera lens, along with IR pass filters placed over the camera lens and measure the light reflected from the markers. Optical systems based on pulsed-LEDs measure the infrared light emitted by the LEDs placed on the body segments [11]. The benefit of active markers over passive ones is that the measurements are more robust. However, active markers do require additional cables and batteries, so the freedom of movement is more limited. In addition, the maximum sample frequency is lowered when multiple markers are used, as the signal of each individual marker needs to have a distinguishable frequency by which it can be identified.

Marker-based systems are more accurate than the other systems and in literature are often regarded as the gold standard, with Vicon system often chosen as a representative of the passive systems, and Optotrak as an active one [38][39]. However, marker-based systems have several limitations, including long preparation times, soft tissue artifacts, and the potential hindrance of specific movements due to marker placement. These systems can be costly and require a large space to accommodate all the necessary cameras for analysis. The accuracy and reliability of marker-based systems are highly dependent on the expertise and precision of the professional responsible for placing the markers on anatomical landmarks. However, there is often variability in marker positioning for transverse plane movements between different professionals or sessions, which can decrease the reliability of the measurements [37]. Additional limitations of the marker-based systems include the requirement for line-of-sight between cameras and markers, leading to data interruptions when markers are out of view, and high sensitivity to setup alterations, such as accidental camera shifting. Furthermore, marker-based systems are mostly used indoors in dark environments to avoid interference from bright sunlight, further limiting their practical use [39].

2.2.1.2 Marker-less Optical Systems

With the rapid advancement of computer vision research, marker-less capture of human movement data has become possible through the use of just optical cameras and computer vision algorithms. These methods utilize 2D video data combined with generative or discriminative algorithms to estimate human pose in 3D (Figure 7) [40]. Generative approaches involve fitting a pre-defined model of the subject to 2D visual cues or 3D cues with the help of silhouette matching algorithms. In contrast, discriminative algorithms, particularly deep neural networks, detect a sparse set of learned features such as joint key points that describe a subject's pose [41]. Discriminative algorithms are often called model-free algorithms because they avoid iteratively tuning the parameters of a body model to fit the image. Compared to generative approaches, discriminative algorithms have faster processing times, improved robustness, and reduced dependence on an initial guess. However, they may have reduced precision and require a large database of training data from which they can learn how to infer a result. Therefore, it is not uncommon to combine algorithms, with discriminative approaches used as initial guesses for generative approaches [40].

Marker-less optical systems based on computer vision algorithms also have some common drawbacks: real-time image recognition can be challenging, and it may require expensive high-quality and/or high-speed cameras to capture the necessary data. The accuracy of the system is also heavily influenced by the experimental setup, specifically the position of the camera in relation to the object's trajectory and the number of cameras used. Additionally, increasing the camera resolution can result in a decrease in feasible maximum sampling frequencies [39].

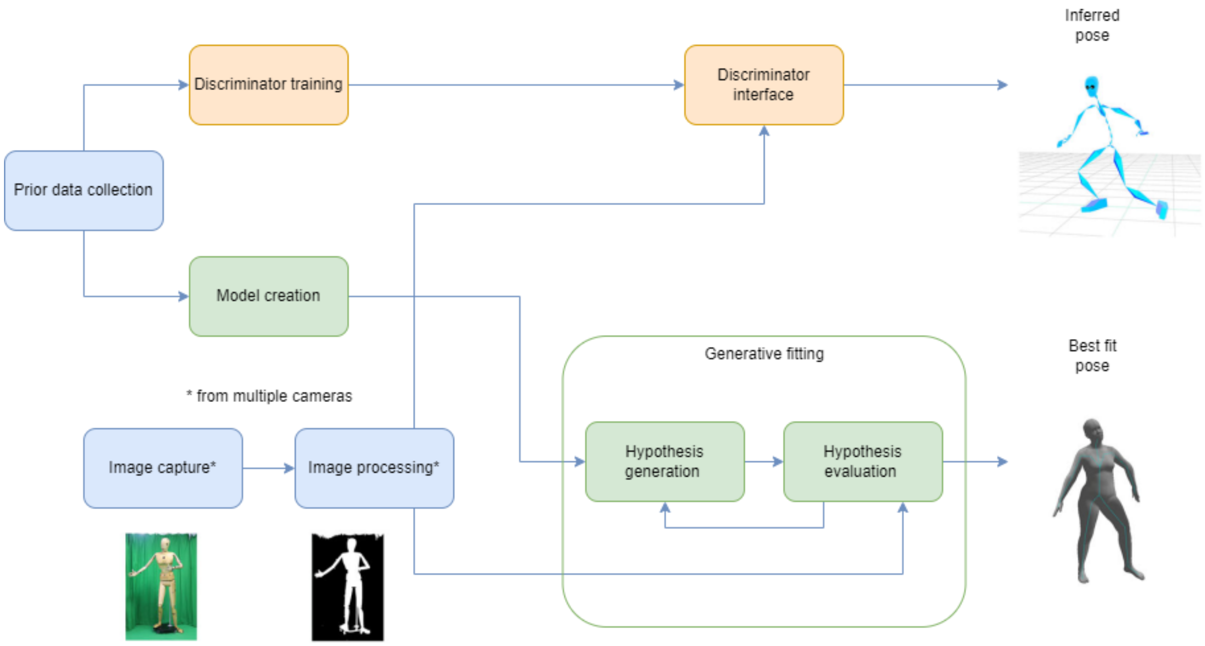


Figure 7 General structure of a marker-less motion capture. Adopted from [40]

There is another commonly used type of marker-less system that utilizes depth-sensing cameras instead of traditional cameras and complex computer vision algorithms. These systems create a depth map, where each pixel represents the distance of a point in space from the camera. Depth information helps mitigate issues that affect traditional camera systems, such as poor lighting, shadows, reflections, and cluttered backgrounds. Depth-sensing camera systems range from narrow-baseline binocular-stereo camera systems (e.g., the PointGrey Bumblebee or the Stereolabs Zed camera) to active cameras that project light into the scene to sense depth (e.g., Microsoft's Kinect). These active, depth-sensing camera systems, often referred to as RGB-D cameras due to their ability to capture both color and depth, have demonstrated effectiveness in real-time full-body pose estimation for interactive systems and games. While these systems are advantageous due to their simplicity and affordability, they are limited by reduced accuracy and reliability compared to marker-based systems, a small field of view, and difficulties in detecting dark surfaces that absorb light, shiny surfaces that result in specular reflection, and rough surfaces if the angle of incidence of incoming light is too large [39][40].

2.2.2 Wearable Systems

Unlike optical systems, wearable systems do not have cameras and, therefore, provide more flexibility without spatial constraints [12]. In this case, a system is compounded of different wearable devices attached to a subject's body. Wearable devices are designed using a wide range of technologies, the most significant ones are revied below.

2.2.2.1 Electromagnetic Systems

According to van der Kruk et al. [39], electromagnetic systems (EMSs) use the time-of-flight of electromagnetic waves to determine the unknown positions of measurement transponders. EMSs are capable of providing large capture volumes, but they are generally less accurate than marker-based optical systems. Unlike marker-based systems, EMSs do not require a line-of-sight to determine the positions of the transponders, and the human body is transparent to the field applied. However, EMSs are sensitive to ferromagnetic materials in the environment, which can decrease the accuracy of the data, and they also have lower sample frequencies, which can limit their use in fast-moving activities such as sports analysis.

There are several versions of EMS systems available, including the Global Navigation Satellite System (GNSS), Local Position Measurement system (LPM), Wireless Ad-hoc System for Positioning (WASP), Radio Frequency IDentification system (RFID), and Ultra-

Wide Band system (UWB). Among these systems, the GPS-GLONASS dual-frequency system of the GNSS shows promise in terms of range-accuracy combination. The GNSS system is a satellite navigation system that includes GPS, GLONASS, and GALILEO. The system relies on satellite data to determine the location of the receiver, and the accuracy of the system depends on its specifications.

EMS systems, other than GNSS, can be used indoors as they use local base stations instead of satellite signals. LPM is a system that consists of base stations positioned throughout the area and transponders worn by subjects. The system can determine the 3D position of the transponder via time-of-flight, but the accuracy of the system is limited by the number of base stations that receive the signal. WASP is a system that uses tags and anchor nodes placed at fixed positions to track participants in 2D. The accuracy of WASP is limited by the bandwidth of the transmitted radio signal.

RFID is a wireless non-contact system that uses electromagnetic waves and fields to transfer data from a tag attached to an object to an RFID reader. RFID tags can be active or passive, with passive tags having a limited range and lifetime due to their reliance on magnetic fields for power. The communication between RFID tags and readers can be affected by various factors such as attenuation, cross paths of signals, and interference from other RFID tags and readers, as well as other RF devices.

2.2.2.2 Ultrasonic Systems

Ultrasonic localization systems are commonly utilized in short-range measurements, especially in motion capture applications. By utilizing ultrasonic transmitters and receivers, these systems are capable of tracking the position of various body parts. The position of an object can be estimated using the time-of-flight of an ultrasound wave as it travels through the air. These systems are also referred to as acoustic measurement systems since they operate using sound waves. The difference between sound and ultrasound is that the latter is inaudible to the human ear, making it an advantageous tool for research purposes. One limitation of ultrasonic systems is their restricted range compared to sound. Additionally, the directionality of ultrasound can pose challenges in dynamic measurement scenarios [39].

2.2.2.3 Magnetic Systems

Magnetic motion capture systems generally consist of a transmitter and various receivers placed upon different parts of the body: the transmitter generates a magnetic field, which is subsequently intercepted by the receivers. Given that receivers are body-worn, movement of the human body in the presence of the external magnetic field (as generated by the transmitter) also changes the position of the receivers. Given the spatial variation of the receivers with respect to the transmitter, movement can be detected. More specifically, both the transmitter and the receiver(s) of magnetic motion capture systems contain three orthogonal coils. Movement leads to change in the relative flux linkage, which, in turn, can be captured and post-processed to monitor movement.

As any other system, magnetic motion capture systems are associated with their advantages and disadvantages. For instance, they are cheaper than optical systems and provide similar performance and with relatively less markers on the body, without suffering from line-of-sight issues (no occlusions). A disadvantage, however, is brought up in the case where receivers are tethered to a control unit. In doing so, subject mobility is restricted. Nevertheless, wireless versions of these systems are also available. Another main drawback is the sensitivity of magnetic motion capture to the presence of metals in the building or the surrounding environment. This is attributed to the generation of eddy currents (in the presence of external magnetic fields) and the fields produced by them. Tough algorithms exist to compensate for these effects, any related calibration would be only valid for a predefined scenario (for instance, a specific metal structure used in the building) [42].

2.2.2.4 Inertial Systems

Inertial systems, also commonly named Inertial Measurement Unit (IMU), are often composed of an accelerometer and a gyroscope. The former serves to measure the sum of gravitational and inertial linear acceleration, while the latter measures angular velocity. Sometimes, they are further combined with a magnetometer which provides information about the local magnetic field vector components.

To capture motion, IMUs are first calibrated and then placed on different parts of the human body. The goal is to detect the orientation of diverse body segments and, eventually, monitor motion. The process of deriving motion from IMUs is highly complex, and there are several methods of doing so. More specifically, IMUs rely strongly on the accelerometer data which can be integrated once and twice to obtain velocity and position, respectively. Similarly, the gyroscope provides angular velocity, which can be integrated and differentiated to obtain angular position and angular acceleration, respectively. Expectedly, the aim is to determine the orientation of the rigid body on which the sensor is placed. This can be achieved solely by the accelerometer itself; however, a combination of the information obtained by the accelerometer and gyroscope can help in determining the body's orientation more accurately and precisely. Nevertheless, the aforementioned process of integration introduces errors, which further cause the sensors to drift. This is one of the biggest disadvantages of IMUs, with drift issues increasing linearly (integrated once) or quadratically (integrated twice) with time. For mitigation, hardware and/or algorithmic solutions may be pursued. Notably, the magnetometer becomes handy here as a hardware solution that provides an additional reference (i.e. using the local earth's magnetic field). But unfortunately, magnetometers are susceptible to magnetic interference from the environment and the presence of ferromagnetic materials. As an alternative, algorithmic-based or combined hardware and algorithmic solutions may be used [42].

2.2.3 System Selection

Van der Kruk et al. [39] have proposed sport categories along with the most plausible measurement system categories, which are also generally applicable to the selection of systems for physical activity monitoring (Figure 8). The selection of a system depends on the field of application, the type of activity, and the space where the activity takes place. Two main categories are defined: team sports and individual sports. In team sports, systems are typically used for tracking the position, distance, velocity, and acceleration of players, where occlusions are common, and accuracy is not crucial as for technique analysis. Thus, EMSs are the most suitable. On the other hand, individual sports require higher accuracies, and they are further divided into larger and smaller volume sports. Smaller volumes can be covered by highly accurate marker-based optical systems, while individual sports in larger volumes present challenges in measuring kinematics. The most appropriate measurement options are marker-less optical systems based on computer vision algorithms and IMU systems, but their application often necessitates developing a suitable algorithm, either for tracking (in the case of marker-less optical systems) or for fusion filtering (in the case of IMU).

Although optical systems belong to the category characterized by high accuracy due to the need for highly controlled conditions, the limited volume covered by a large number of cameras, the problem of occlusion, expensive and fixed infrastructure where the positions and orientation of the cameras must remain unchanged during the measurement, the applicability of such systems is limited to specialized laboratories and experts for carrying out measurements. Therefore, the application of optical systems is reduced and oriented mostly towards specialized requirements for monitoring (e.g. clinical studies) or testing the accuracy of other systems. Due to the independent fixed infrastructure, the elimination of occlusion problems, usability and the price, the increasing application is directed specifically towards wearable systems [43][44][45].

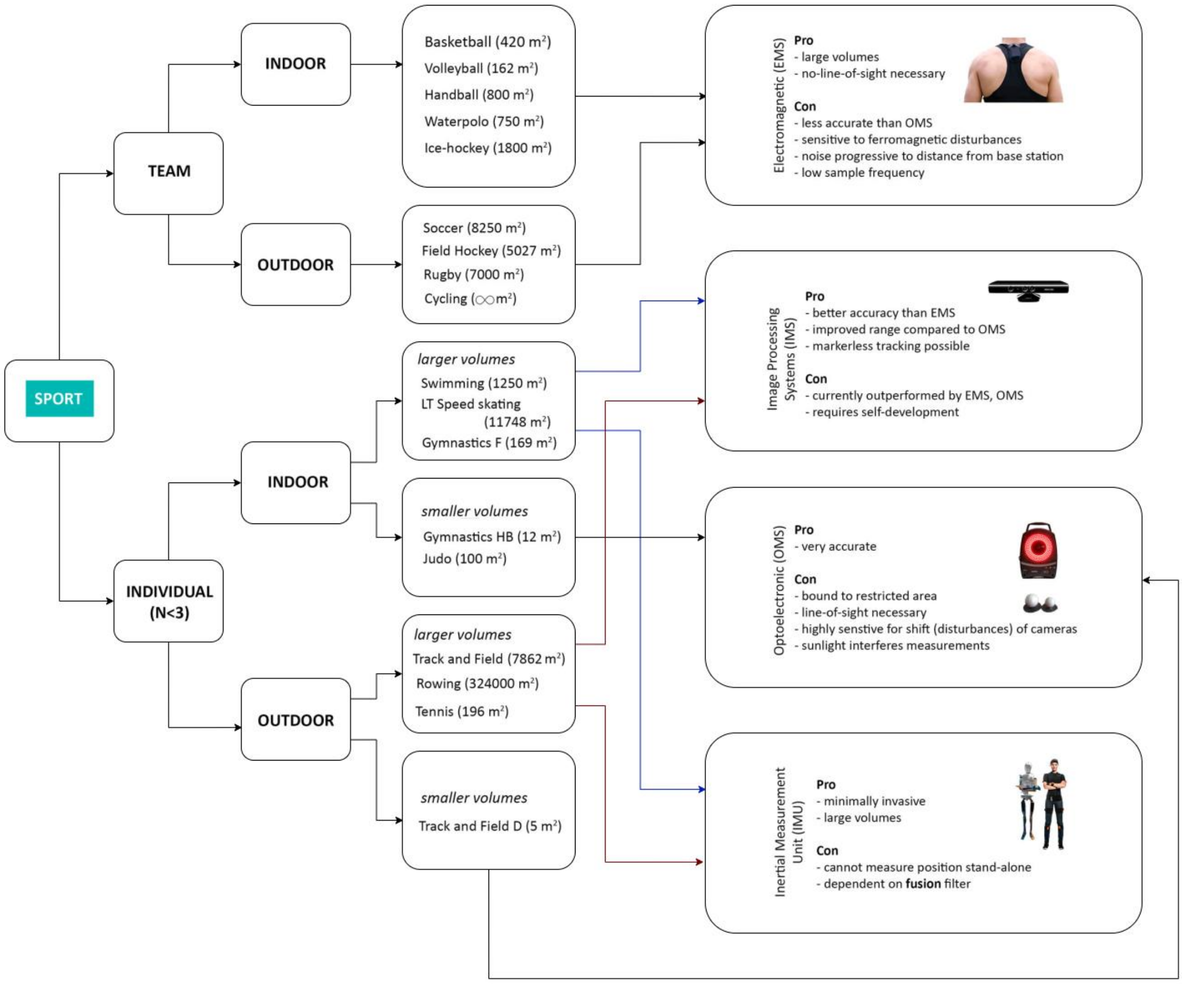


Figure 8 Sport categories with measurement system categories. In the figure, IMS is equivalent to a marker-less optical system and OMS is equivalent to a maker-based optical system. Adopted from [39]

2.3 Wearable Systems for Physical Activity Monitoring and Assessment

Wearable systems are composed of body-worn devices that can provide mobile and continuous monitoring of the human body. Each device, i.e. sensor unit is equipped with motion sensors, processing units, and wireless and memory components. The primary objective of the system is to acquire raw sensor data and perform signal processing techniques to extract meaningful insights. To achieve a high level of user acceptance and adherence, a wearable system must not impose any significant restrictions on user mobility and comfort.

The main deployment objective of any wearable system is to improve its wearability and the ease of use, which has significant implications. Firstly, it necessitates that sensor units are powered by a battery. Using a large energy source would hinder mobility and, therefore, is not acceptable. Secondly, wearability concerns preclude the use of wired communication schemes, which can interfere with natural human movements. Finally, reducing the form factor of sensor units is crucial for wearability. It can be done by reducing the size of the sensor unit's components such as the processor, memories, sensors, and the battery. While technological advancements have enabled substantial reductions in the size of microprocessors, sensors, and memories, battery size reduction has lagged behind, indicating that the size of the battery remains the limiting factor in the form factor of wearable sensor units. This observation implies that, at present, the form factor of wearable sensor units is primarily dictated by the size and weight of the battery. The requirement for extreme battery efficiency motivates the need for lightweight and highly efficient signal processing algorithms and optimization techniques. The signal processing, however, needs to exhibit sufficient reliability and sensitivity in extracting the relevant parameters [46].

The utilization of wearable systems is highly sought after due to their ability to provide objective and measurable data in non-laboratory settings. Furthermore, depending on the number and locations of the sensing units, wearable systems can vary greatly in the scope of possible tasks from general action recognition to extracting a very specific detail about a movement. This property makes wearable systems extremely useful in physical activity monitoring and assessment.

The use of wearable systems can be classified into two primary categories: medical and non-medical applications. Traditional healthcare practices rely on doctors to observe patients and use their personal experience to diagnose symptoms or require patients to undergo examinations in a laboratory environment. In contrast, wearable devices enable remote and continuous patient monitoring. Additionally, wearable systems are increasingly being used in sports training, where the ability to evaluate movement quality and provide feedback is crucial. Traditionally, these tasks were performed by human coaches who relied on their personal expertise and experience. However, coaching services can be expensive and often involve coaching multiple trainees simultaneously, limiting their ability to provide detailed feedback for each individual. An automated system that can assess the overall performance of an individual and pinpoint problem areas in the individual's movements facilitates performance assessment and increases the effectiveness of unsupervised practice. In addition to sports training, the application of such system is also applicable during additional recreation, which is recommended by WHO. Wearable systems can provide more effective and safer individual performance of physical activity, as well as additional motivation to continue engaging in physical activity [4][5][6][46].

Wearable systems have been used to monitor different types of physical activity, both aerobic and muscle-strengthening, but still primarily with an emphasis on aerobic (87%). The discrepancy may be attributed to the current limited ability of wearable systems to monitor functional parameters, such as the muscle strength in the upper and lower extremities or movement execution performance. Presently, exercise monitoring wearables primarily focus on physiological metrics, such as step count, distance traveled, and cardiometabolic parameters (including heart rate, energy expenditure, maximum oxygen consumption, oxygen saturation, and blood pressure) [47]. Therefore, the rest of the thesis will be directed towards a less researched area, the use of wearable systems through muscle-strengthening physical activity, i.e. using wearable devices (IMUs) during strength exercises.

System of this nature typically consists of two main parts: sensors for data acquisition and algorithm that will provide appropriate assessment and feedback (Figure 9).

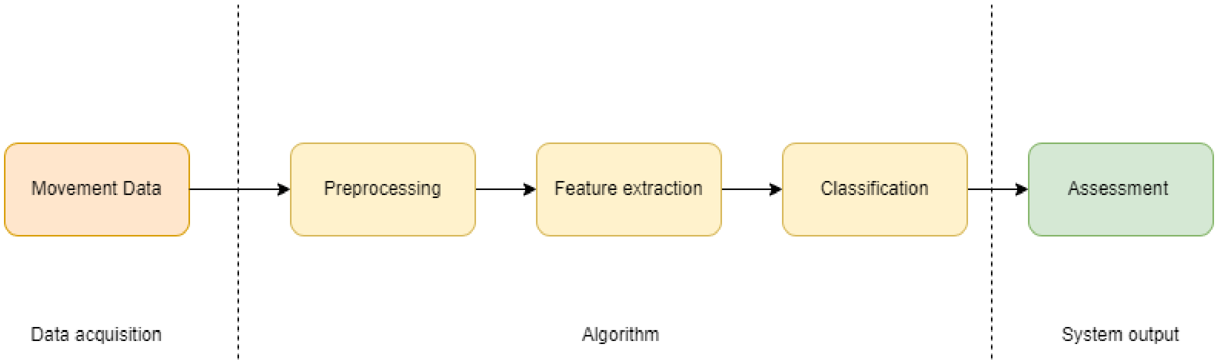


Figure 9 A flow diagram of the wearable system for physical activity monitoring and assessment

2.3.1 Data Acquisition

IMU is attached to different locations on the body and provides a continuous time-series of data. It is mostly based on multi-axis combination of accelerometers, gyroscopes and magnetometers but sometimes also with additional sensors such as GPS and/or Heart Rate (HR) monitor. Different sensors produce different types of raw data, which are sampled in a multivariate time series depending on sensors' frequencies.

2.3.1.1 Number and Placement of Sensors

The location and attachment of IMUs are crucial factors that influence the measurement of bodily movements. However, the ideal placement of sensors for specific applications remains a subject of considerable discussion and debate [48]. IMUs can be positioned on various parts of the human body [43][49][50][51]. Common locations for IMUs include wrist, upper arm, ankle, thigh, chest/trunk, lower back etc. Generally, it is customary to employ one or several IMUs, although the quantity seldom surpasses five units. Multiple IMUs aided in system output since conjunctions between feature values at different locations were useful for discriminating many activities. However, in some studies [50][52] it has also been shown that performance of system is not too compromised if the number of used IMUs is reduced to only two, on wrist and thigh.

2.3.1.2 Sensors Configuration

Digital accelerometers, gyroscope and magnetometers are configurable, allowing their users to tailor the raw data generation to the needs of their application. Different configuration options include the number of axes, the range of output data and the sampling frequency. Upon reviewing the existing literature [51][52], it seems apparent that there is a lack of agreement within the research community regarding the optimal selection of configuration parameters for specific types of activities. Range of acceleration is from ±2 g to ±16 g, angular velocity from ±500 to ±2000 °/s and magnetic field from ±1 to ±4 G, with sampling frequency range up to 100 Hz. Although energy consumption may not represent a significant obstacle in controlled environments during data collection, it poses a considerable challenge when data is gathered in natural settings, particularly when the duration of the experiment surpasses the battery life of the sensor. Consequently, for prolonged experiments where battery lifetime is a concern, or when the creation of autonomous systems is desired, it is advisable to restrict the sensors' resolution and sampling frequency to a level that is no higher than necessary, to conserve energy.

2.3.2 Algorithm

2.3.2.1 Data Preprocessing

Data preprocessing is an essential step in the data mining process, aimed at addressing various characteristics of the sensor data, such as sampling rate, units, random noise, or malfunctioning. To this end, diverse preprocessing approaches have been proposed in the literature [43]. For instance, Fallmann et al. [53] applied a median filter to smooth the signal, while in [54] a third-order average filter was utilized to reduce random noise. Other approaches, such as low- and high-pass filtering, have been used to extract the acceleration components due to body movements and gravity and eliminate noise. Notably, in [55] [56], the authors highlighted that the low-frequency component of the acceleration reflects gravity, while the high-frequency component represents the dynamic motion of a human body. Additionally, [57][58] employed a low-pass Butterworth filter to separate these components effectively. Nevertheless, it is worth noting that in some investigations (e.g., references [59][60]), no preprocessing steps were undertaken, and the raw data were fed directly into a convolutional neural network.

2.3.2.2 Feature Extraction

To extract features from sensor data, it has become customary to use windowing techniques, which involve dividing signals into short time intervals. Three primary windowing techniques are typically utilized: a) sliding window, which partitions data into fixed-length windows, b) event-defined windows, which entail additional processing to locate specific events that further define data partitioning, and c) activity-defined windows, which rely on detecting changes in activity levels to partition data (Figure 10).

The sliding window approach is commonly favored for real-time applications as it does not necessitate additional processing treatments [49][61]. However, the appropriate selection of window length is critical, and it is essential to consider the trade-off between computational complexity and information content [62].

To implement event-defined windows, it is necessary to perform additional processing (beside filtering 2.3.2.1) to identify particular events, such as beginning or end of human movement during exercise. These events are subsequently utilized to define consecutive windows, as depicted in Figure 10b. As the time intervals between these events may not be consistent, the window sizes cannot be standardized. Various techniques have been proposed to detect beginning and end of movement [63][64][65][66][67], and this process is referred to in literature by the term “movement (or repetition) segmentation” [68].

Activity-defined windows rely on identifying the moments when there are changes in activity. These points are then used to create windows of sensor data, each representing a different activity (as shown in Figure 10c).

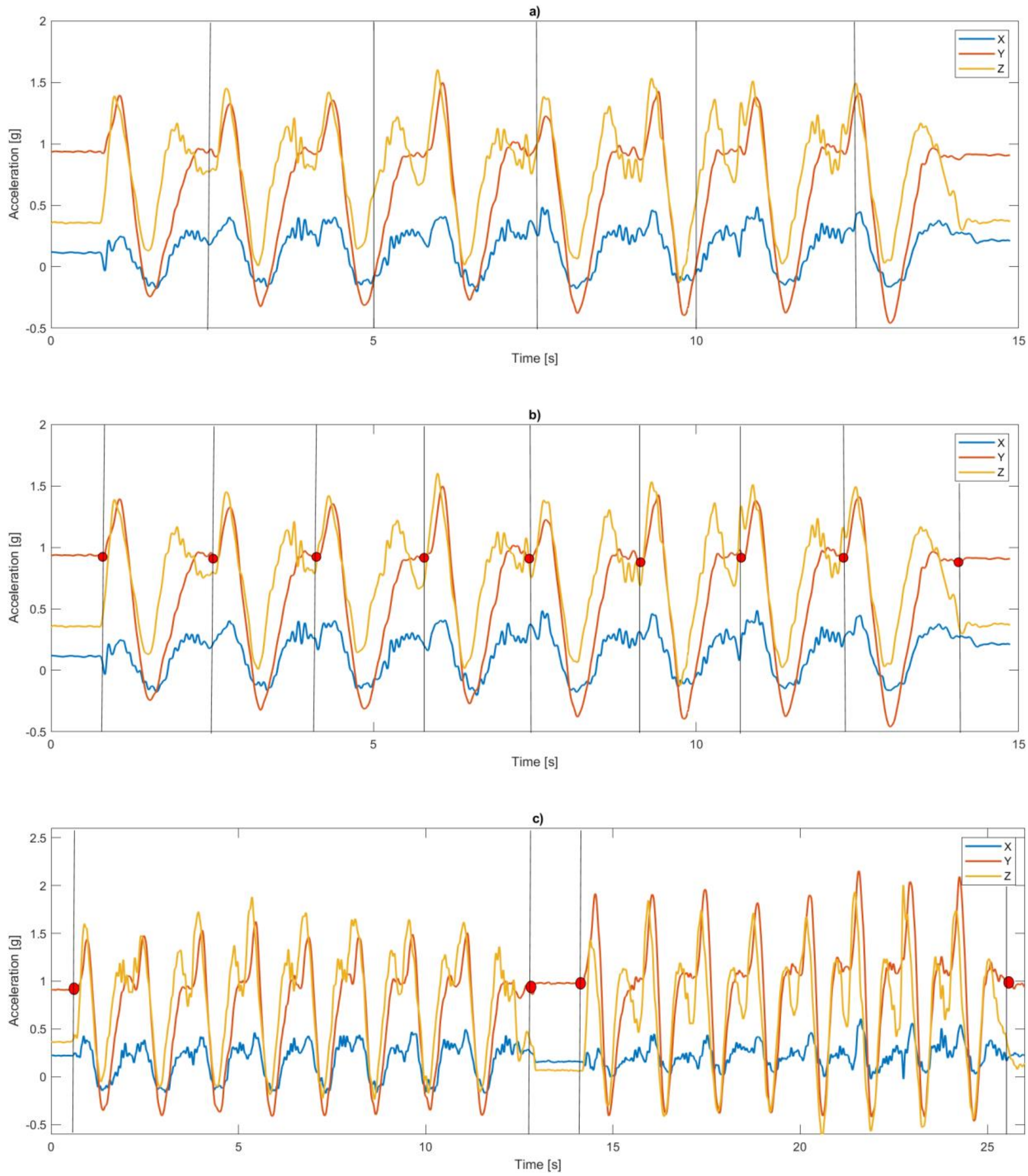


Figure 10 a) sliding windows, b) event-based windows and c) activity-defined windows

For each time window, feature extraction techniques are utilized to isolate relevant information and obtain quantitative measures that enable comparison of the signals. Moreover, these techniques serve to convert voluminous input data into a smaller set of features, typically referred to as a feature vector [69]. The extracted features can be broadly categorized into three groups: time-domain features, frequency-domain features and heuristic features [62]. The dimensionality of the feature set is a crucial factor in classification. It is advisable to use feature sets with a size equal to or smaller than the number of observations collected, as using larger feature sets can increase the risk of overfitting and result in poor classification performance on new data, which is known as the curse of dimensionality [70].

2.3.2.3 Classification

The process of classification in systems for monitoring and assessment can be divided in two parts, exercise recognition and exercise assessment.

2.3.2.3.1 Exercise Recognition

One commonly employed approach for the classification of exercise for the purpose of recognition involves the application of Machine Learning (ML) algorithms to analyze sensor data, with the aim of accurately identifying the exercise being performed. To achieve this, supervised learning techniques can be employed, whereby a model is trained on labeled sensor data and corresponding activities, allowing it to predict the activity being performed based on new sensor data. Alternatively, unsupervised learning techniques can be utilized to cluster sensor data into distinct activity patterns without prior knowledge of the activities being performed [71]. Popular ML algorithms for activity recognition include decision trees, Naïve Bayes classifiers, Hidden Markov Models (HMM), Support Vector Machines (SVM) [60], K-Nearest Neighbors (KNN) [72], and deep learning approaches, such as convolutional neural networks (CNNs) [73]. The process of selecting a ML algorithm that is appropriate for a specific dataset can be challenging. It is advisable to test multiple algorithms on a given dataset and choose the one that yields the most favorable results. In general, simpler ML algorithms may be more suitable due to their increased model transparency and computational efficiency. Consequently, if simpler algorithms (such as decision trees or logistic regression) exhibit similar performance as more complex algorithms (like random forests or neural networks), they may be more suitable for the intended application [50].

2.3.2.3.2 Exercise assessment

The methods for exercise assessment can be broadly classified into three categories: rule-based approaches, template-based approaches and discrete movement score approaches [68].

Rule-based approaches for exercises rely on a predetermined set of rules that are defined by human movement experts to assess the correctness of movements. The rules that define the executed movements generally consist of movement descriptors such as relative angles, velocities, or distances. For example, in the study by Bo et al. [74], the quality of squat exercises was assessed using knee and ankle angles.

Template-based approaches evaluate exercise performance by comparing training motion sequences with template motion sequences. The training sequences can be captured during a workout, while the template sequences are reference movements performed by either experienced subjects, coaches, clinicians, or subjects under the supervision of an expert. The metrics used to measure movement similarity in template-based approaches can be divided into two categories: distance functions - Euclidean distance, Mahalanobis distance or Dynamic Time Warping (DTW) [75] and probability density functions - Gaussian Mixture Model (GMM) [73] or HMM [76].

Discrete movement approaches involve classifying individual exercise repetitions into distinct categories, usually correct and incorrect movements, resulting in binary class values of 0 or 1. ML algorithms such as AdaBoost classifier [77], random forest [7][78], KNN [79], Naive Bayes [78], SVM [78], and CNN [80] have been utilized to distinguish between the two classes.

2.3.2.3.3 Performance Validation

According to research [50][70], ML models developed for classification should be validated by testing their performance on unseen data in real-world settings. It is important to avoid training and testing the ML model with repetitions from the same individual, as this can lead to classification performance inflation. Cross-validation (CV) methods, such as 10-fold CV or leave-one-subject-out CV, are recommended for assessing ML model prediction performance, particularly for small datasets. Personalized classifiers should follow a similar approach and use leave-one-observation-out CV. Model tuning is an important step in the ML model development process and should be governed by prediction performance on the training set, with hyperparameters and optimal feature subsets selected based on classification performance on the validation set. The final ML model should be assessed based on its performance on the testing set to provide an unbiased estimation of its classification performance.

2.3.3 Research Gaps

Movement segmentation involves extracting individual repetitions from a continuous motion sequence of an exercise. This is an important step for the monitoring and assessment of strength exercises, as most existing evaluation approaches rely on quantifying the quality of individual repetitions. Once a subject's movements are recorded using a wearable device, and multiple repetitions of the exercise are performed, the motion data must be segmented into instances of individual repetitions before evaluation techniques can be applied to produce quality scores. The overall quality of the exercise is typically calculated by averaging over the performance scores of individual repetitions [81].

Manual segmentation of motion sequences is commonly used in many studies [58][82][83], but it is not conducive to fully automated evaluation of strength exercises. There are two broad categories of approaches used for automated motion segmentation. The first type involves modeling the common characteristics that are shared by segment points, while the second type involves learning a segment pattern from a pre-existing library of templates [68].

Approaches in the first category often rely on domain-specific knowledge of the underlying data to select discriminative features for segmentation. For instance, kinematic zero-crossing methods are frequently used to perform exercise segmentation, determining segments based on zero crossings for the velocity or acceleration of joint trajectories [84][76]. Distance functions, such as Euclidean distance [85], Mahalanobis distance [86], and DTW distance [87], have also been employed. A deep learning-based approach has been introduced for segmentation of time-series data [88], in which an autoencoder network extracts representative features from input data, and the peaks in a distance function calculated from the features are selected as breakpoints for segmentation. Nonetheless, further post-processing is often necessary due to the high incidence of false positives.

The second category of approaches employs machine learning methodology to discover latent patterns from template libraries. Hidden Markov Models (HMM) are often used for segmentation of movement data, treating each segment as a hidden state, and utilizing the Viterbi algorithm to recover the state sequence [1]. Regression-based techniques are also employed, whereby a piecewise linear function is applied to fit the template data, and segmentation is performed when the difference between the data and the regression line is greater than a given threshold [89]. Traditional classifier methods such as Support Vector Machines (SVM) have also been utilized for movement segmentation, classifying all data points of motion sequences as either segment points or non-segment points [90]. In addition to traditional methods, approaches based on neural networks have also been explored and utilized [64].

Although there have been numerous studies on the segmentation of repetitive human movements, there are still gaps in the research that require attention. The current segmentation algorithms, such as those based on kinematic zero-crossing, HMM, and neural networks, have limitations with regards to their accuracy and reliability. Thus, there is a need for the development of more robust segmentation algorithms that can accurately and reliably segment repetitive human movements. As repetitive human movements often share similar characteristics across different exercises and tasks, exploring the potential of transfer learning for the segmentation of repetitive human movements is another research gap that could reduce the need for extensive training data and improve segmentation accuracy.

Once individual movements have been successfully segmented, evaluations can be performed. As mentioned previously (subchapter 2.3.2.3.2), movement assessment techniques fall under three categories: rule-based, template-based, and discrete movement score methods, each with their own advantages and disadvantages.

Rule-based methods are less computationally expensive and provide specific functional feedback, making them particularly useful in assessment. However, the lack of generalization and reusability for different exercises can lead to a large rule data set, difficult to synthesize within a workout framework. Additionally, when the complexity of the movement increases, it may be difficult to map the rule and obtain accurate movement assessment.

Template-based approaches have the main advantage of an automatic assessment process that can be easily generalized to different types of exercise. However, their main disadvantage is that they heavily rely on the availability and quality of the template motion sequences, making them less suitable for exercises with high variability in performance. Creating a template library can also be time-consuming and require significant expertise, making it difficult to apply the approach to new exercises or populations.

The main advantage of machine learning approaches in discrete movement score methods is their ability to learn from large amounts of data and adapt to different exercises, making them more flexible than rule-based or template-based approaches. Machine learning algorithms can also identify new patterns and relationships in the data that may not be apparent to human experts. However, a large amount of labeled data is required for training, which can be time-consuming and expensive to obtain. The performance of the machine learning algorithm also heavily depends on the quality and diversity of the training data, as well as the selection of appropriate features and algorithm parameters. Additionally, machine learning models are often considered "black boxes", which makes it difficult for human experts to understand and interpret the assessment results.

This doctoral thesis aims to address the existing research gaps by presenting a comprehensive procedure (chapter 5), method (chapter 3), and metrics (chapter 4) for the development of a closed-loop system for human movement monitoring and assessment using wearable devices during exercising. The proposed approach tackles several challenges, including the number and position of wearable devices, the selection of measurable quantities, the definition of the model, segmentation, classification, and assessment of the performance of individual movements and the entire exercise. By addressing these challenges, the proposed approach provides a robust framework for automatic and objective assessment of exercise performance.

To validate the effectiveness of the proposed procedure, the approach was tested on a group of 40 subjects during a workout session consisting of 9 strength exercises. The results demonstrated the feasibility and accuracy of the proposed approach for the assessment of exercise performance. The proposed approach provides a valuable tool for trainers and clinicians to monitor and evaluate exercise performance in real-time and to provide immediate feedback to the user. Additionally, it has the potential to improve the efficiency and effectiveness of rehabilitation programs by providing objective and quantitative measures of exercise performance. Overall, the proposed approach has the potential to enhance the quality of life and well-being of individuals by promoting physical activity and healthy habits.

3 MEASUREMENT METHOD OF HUMAN MOVEMENT VARIABILITY DURING EXERCISE USING SENSOR NODES WITH INERTIAL AND MAGNETIC SENSORS

A measure of human movement variability is a quantitative indicator that describes the degree of changes in the performance of movements during physical activity. It provides information about the consistency and stability of the movement pattern over time and can be used to assess the effectiveness of an exercise intervention or to identify potential risk of injury or dysfunction. Various methods and metrics have been proposed to measure human movement variability, including time-series analysis, fractal dimension, sample entropy, and coefficient of variation. These measures can be applied to different types of movements, such as gait, balance, or strength exercises, and can be obtained using different sensor modalities, such as inertial and magnetic sensors (IMUs), force plates, or optical motion capture systems.

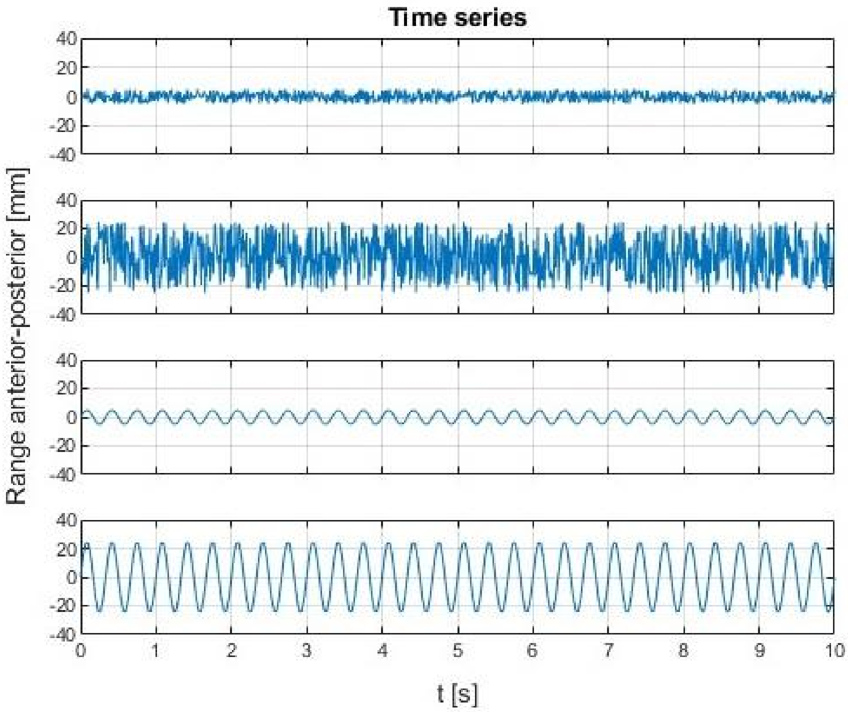
This chapter aims to provide an overview of the available tools and methods that can be utilized for measuring the variability of human movement during strength exercise by employing IMUs. In order to establish a reference for the number and placement of IMUs, defining the model, and selecting the relevant data to be monitored during exercise performance, controlled measurements were conducted using a limited number of subjects. The objective is to identify the most appropriate approach to analyze and quantify the variability of human movement during exercise, which is a crucial factor in ensuring optimal performance and reducing the risk of injury.

3.1 Movement Variability

The concept of human movement variability has been extensively studied in the literature and has given rise to various definitions [91]. These definitions can be broadly classified into two approaches. The first approach defines variability as the degree of variance or deviation from the mean and employs standard statistical methods, such as standard deviation and coefficient of variation, to quantify the extent of variability. These techniques are commonly referred to as linear measures. The second approach regards the fluctuations present throughout the movement as having meaning and structure. In this approach, the complexity, predictability, divergence, and self-similarity of these fluctuations are measured using various methods, collectively known as nonlinear measures. Examples of these measures include Lyapunov exponent, detrended fluctuation analysis, and entropy. It is crucial to note that the two approaches to variability are conceptually distinct and complementary. Therefore, when discussing variability, it is important to make a clear distinction between these two approaches.

According to a research [92], nonlinear analytical tools are useful in characterizing variability in terms of its structure, rather than just its magnitude. This concept is demonstrated in Figure 11, which features four time series signals with linear measures of range and nonlinear measures of Approximate Entropy (ApEn) for each signal. The first and second rows of signals appear random and disordered, with the range values reflecting differences in amplitude between the two signals. However, despite the differences in amplitude, the ApEn values for both signals are equivalent, indicating that the structure of the time series is consistent. On the other hand, the third and fourth rows depict sine wave time series that exhibit high levels of regularity, with the range values indicating differences in amplitude and the ApEn values being similar. Comparing the first signal with the third signal (and the second signal with the fourth signal) reveals that the amplitude, quantified by the range, is the same, while the structure of the series, described by the nonlinear ApEn value, is different. Therefore, the concepts of variability measured by the standard deviation (linear) and the structure of variability measured by ApEn (nonlinear) are fundamentally different, and they can exhibit an inverse relationship.

The use of nonlinear analytical tools, such as ApEn, is valuable in assessing the structure of variability, which can provide unique insights into complex systems. Higher ApEn values indicate a greater level of irregularity, while lower values indicate more regular or periodic behavior. Values close to zero represent the highest degree of regularity, while values close to two indicate the utmost level of irregularity. It is important to note that the different facets of variability presented through linear and nonlinear measures can provide complementary insights, contributing to a more comprehensive understanding of complex systems.



Range	ApEn
10.0	2.02
50.0	2.02
10.0	0.18
50.0	0.18

Figure 11 Comparison of linear and nonlinear measures. Adopted from [92]

3.1.1 Limitations

Linear measures, such as mean and standard deviation, are commonly used to quantify movement variability. However, they have some limitations when it comes to capturing the full extent of variability in movement. One limitation is that linear measures assume that variability is normally distributed. In reality, movement variability is often non-normal and may exhibit skewed or multi-modal distributions. This means that linear measures may not accurately capture the full extent of variability, especially if there are outliers or extreme values. Another limitation is that linear measures do not capture the structure or organization of variability in movement. Thus, two movements with the same mean and standard deviation may have different patterns of variability. Finally, linear measures do not capture the temporal dynamics of movement variability. Movement variability can change over time, and certain phases or directions of movement can become more or less variable, which linear measures may not capture [93][94].

Nonlinear measures present a clear advantage over linear measures for providing a comprehensive overview of movement variability. Nonetheless, nonlinear measures have their limitations that must be taken into account when examining movement variability. A major limitation is that the computation of nonlinear measures often requires lengthy time series, which may not be feasible for movements that are extremely limited. Additionally, the interpretation of nonlinear measures can be challenging as they require concurrent use of linear tools to establish associations and determine meaning. Furthermore, the validity of nonlinear measures for studying variability depends on the assumption that the differences between repetitions of a task are unpredictable, which is often not the case in practice. Finally, the complexity of nonlinear measures can make it challenging to determine which measures are most appropriate for a given application, and the outcomes can be sensitive to the choice of parameters and the quality of the data [92][95].

3.2 Materials and Methods

Segmenting repetitive human movements can be a useful approach for measuring variability in movement patterns. By dividing a repetitive movement into smaller segments, it is possible to assess the consistency and variability of each segment across multiple repetitions. This can provide valuable insights into how an individual is performing the movement and whether there are any areas where improvement is needed. Once the movement has been segmented, variability can be measured using various metrics, such as range of motion, joint angles, or velocity. These metrics can provide insight into how consistent an individual's movement is across different repetitions, as well as identify areas where there may be increased variability. Measuring variability in repetitive movements can be valuable for a variety of applications, such as assessing movement quality, monitoring rehabilitation progress, or identifying potential injury risk factors. By segmenting repetitive movements and measuring variability, it is possible to gain a deeper understanding of how individuals perform movements and identify areas where further improvement is needed.

The present study introduces two distinct techniques for counting and segmenting repetitions, one of which utilizes prior and domain knowledge [96] while the other does not. Moreover, this study also assesses the efficacy of various classifiers for accurately recognizing the type of exercise being performed, as well as the extent to which individual sensor features and the position of the IMU affect classification accuracy.

Considering the acknowledged limitations of currently available tools for measuring variability, Chapter 4 introduces a novel metric for evaluating the quality of movement. This metric is based on variability and is applied to movements that have been previously segmented.

3.2.1 Experimental Protocol

3.2.1.1 Participants

Six young healthy subjects aged 27 – 32 (4 males and 2 females, age: 29.7 ± 2.1 years, height: 178.3 ± 8.02 cm and weight: 75.9 ± 16.1 kg) were recruited for this research. Subjects did not have a current or recent musculoskeletal injury that would impair their exercise performance. Three subjects have no experience with gym or performing strength exercises, but the remaining three are regular gym participants and have extensive experience. Participation was completely voluntary, and all subjects gave their informed consent for inclusion before they participated in the study. The Human Research Ethics Committee at University of Zagreb, Faculty of Electrical Engineering and Computing approved the study protocol and informed consent. Verbal explanations were also provided to each subject at the start of the experiment session in order to ensure that participants understood what was required of them.

3.2.1.2 Performed Exercises

Each subject performed a cycle of exercises (workout) according to a pre-agreed protocol (number of repetitions and sets) in the presence of an expert. A complete movement of a strength exercise is commonly referred to as a repetition, and several such repetitions performed without any rest between them constitute a set. The task of the expert was to explain to the subjects how to perform a particular exercise and to keep records of performed movements, i.e. repetitions. The workout consisted of 9 strength exercises that focused on activating the whole body, not just individual extremities. The workout included: 1) Standing Front Dumbbell Raise, 2) Standing Dumbbell Lateral Raise with Arms Straight, 3) Standing Side Dumbbell Shrug, 4) Standing Dumbbell Curl with Rotation, 5) Bent-over Dumbbell Row, 6) Push-up, 7) Dumbbell Step-up, 8) Box Squat and 9) Heel Touch (Figure 12). The pace of exercise execution and breaks between sets and between individual exercises were adjusted by the subject in agreement with the expert, and the order of performing the exercises was the same for all subjects. Each subject performed the given workout once, leading to a total of 6 different sets of data from the measurements. The duration of workout of each subject was approximately 30 minutes.

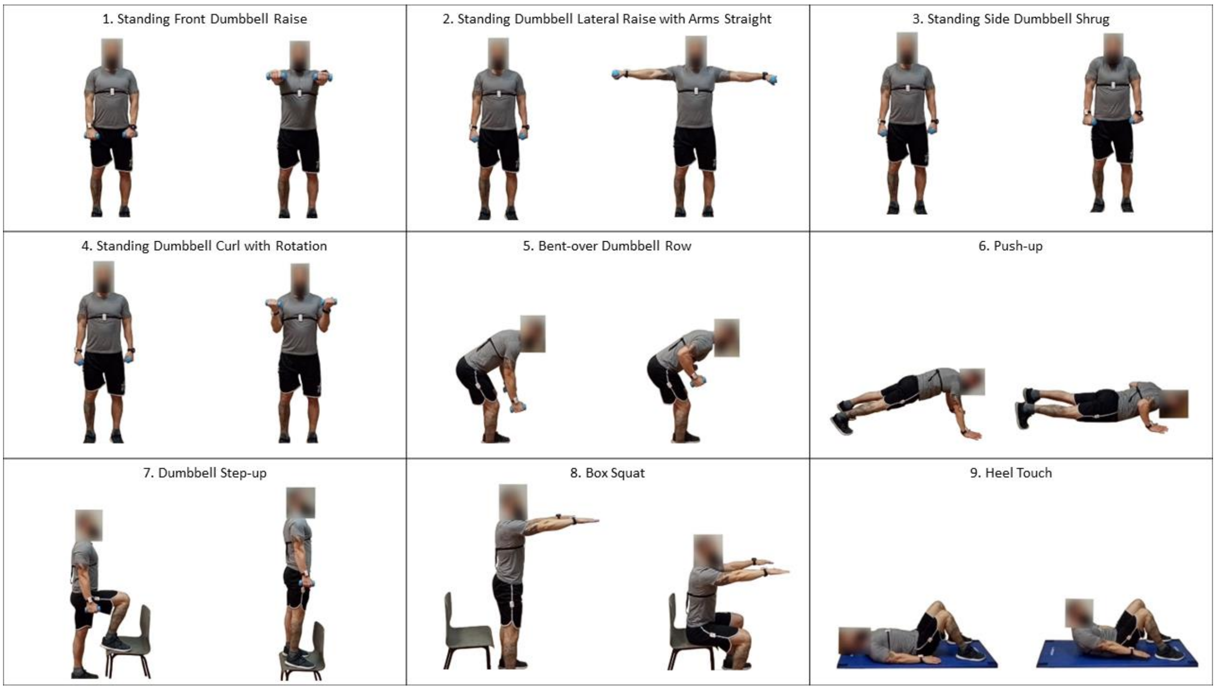


Figure 12 Nine strength exercises performed as part of the workout

3.2.1.3 Data Acquisition

The Shimmer3 IMU was utilized for data acquisition in order to monitor the performance of selected exercises. To achieve this, the optimal position for the IMUs was determined. The chosen position should enable monitoring of all performed exercises using as few IMUs as possible and a single algorithm. Based on previous experience with tracking physical activities [97][98][99], it was determined that at least one IMU per body segment primarily involved in the performance of the selected exercises should be placed. This resulted in a minimum of 3 IMUs, positioned on the wrist of the right hand, right thigh (mid-point, lateral surface), and frontally in the middle of the chest above the navel (Figure 13). The accelerometer range was set to ± 8 g, gyroscope to ± 500 °/s, and magnetometer to ± 1.3 G. The sampling frequency was set to 201.03 Hz. To ensure the highest level of sensor accuracy, calibration was carried out using the Shimmer 9DoF Calibration application. To eliminate unwanted high-frequency noise during each repetition, the nine signals were low pass filtered at f_c = 10 Hz using a Butterworth filter of order n = 2.

3.2.1.4 Data Labeling

During the workout, an expert was present with the subjects and used the Shimmer application ConsensysPro to label the beginning and end of each exercise, as well as the associated sets (activity-defined windows 2.3.2.2). Individual repetitions within sets were subsequently separated (annotated) manually.

Figure 13 The 3 IMUs positions: 1) right wrist, 2) chest (in middle above the navel)) and 3) right thigh (mid-point, lateral surface)

3.2.2 Signal Preparation and Processing

The data from the sensors was collected and saved using the software tool ConsensysPro, while Matlab was utilized for processing and analysis. The expert marked the beginning and end of each set in real-time using an event marker tool (ConsensysPro) during the measurement. By way of illustration, Figure 14 displays the raw acceleration signals and event markers obtained from the IMU located on the right wrist during the performance of three sets of Standing Front Dumbbell Raise exercise.

The sets were separated using event markers, and the acceleration components were subsequently processed. This involved scaling with a factor of g = 9.81 $\frac{m}{s^2}$ and calculating the *Acceleration Vector Magnitude* (*AVM*) according to expression:

$$AVM[i] = \sqrt{(a_x[i])^2 + \left(a_y[i]\right)^2 + (a_z[i])^2} - 1 \tag{1}$$

where i is the current data sample a_x, a_y and a_z represent respectively the acceleration signals in the x, y and z axes of the sensor. Acceleration and AVM are expressed in g units,

$1\ g = 9.81\ \frac{m}{s^2}$. In addition to the AVM calculated from the raw acceleration components, the *Vector Magnitude* (VM) was also calculated from the linear acceleration (AVM_{Linear}) and the angular velocity (referred to as the *Angular Velocity Vector Magnitude, AVVM*). The value of AVM_{Linear} is also expressed in g units, while $AVVM$ is expressed in °/s. The expression AVM_{Linear} and $AVVM$ were employed only in the repetition segmentation method described in the subchapter 3.2.4.2. However, in the other proposed methods, only AVM was utilized.

$$AVM_{Linear}[i] = \sqrt{(a_{xLinear}[i])^2 + (a_{yLinear}[i])^2 + (a_{zLinear}[i])^2} \tag{2}$$

$$AVVM[i] = \sqrt{(\omega_x[i])^2 + (\omega_y[i])^2 + (\omega_z[i])^2} \tag{3}$$

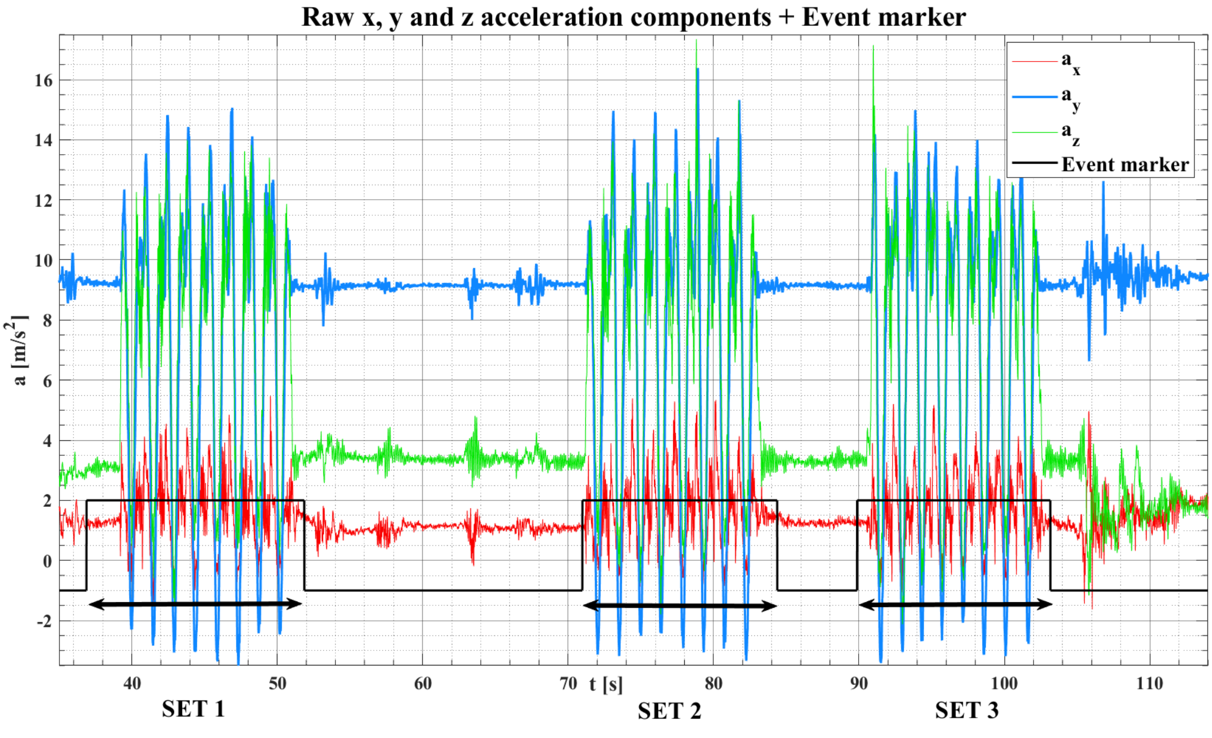


Figure 14 Three raw acceleration components and event marker signal during the performance of 3 sets of Standing Front Dumbbell Raise exercises. IMU position – wrist

3.2.3 Method with Domain Knowledge

It should be emphasized that this approach may not be universally applicable to all types of exercises, and prior knowledge of the exercise being performed (subchapter 3.2.5) is necessary to ensure the success of the algorithm. Furthermore, it is crucial to possess domain knowledge concerning the exercise, such as the selection of the relevant IMU position for subsequent signal processing (Table 3), as well as identifying whether the maximum or minimum of signal denote the beginning and end of the movement, among other pertinent considerations.

Table 3 The exercise and the IMU utilized to obtain the accelerometer readings

Exercise	IMU placement
1. Standing Front Dumbbell Raise	wrist
2. Standing Dumbbell Lateral Raise with Arms Straight	wrist
3. Standing Side Dumbbell Shrug	wrist
4. Standing Dumbbell Curl with Rotation	wrist
5. Bent-over Dumbbell Row	wrist
6. Push-up	chest
7. Dumbbell Step-up	thigh
8. Box Squat	thigh
9. Heel Touch	chest

3.2.3.1 Repetition Segmentation using Frequency Spectrum

After extracting the individual set and calculating the *AVM*, the subsequent step involves the segmentation of the repetitions within each set. In order for the algorithm to be efficient in terms of energy and applicable to embedded devices, the waveform of the *AVM* signal should be such that it can be segmented easily using simple and quick functions, like those used to identify local minima and maxima (Figure 18).

The first step in the segmentation process is to determine the frequency spectrum of the signal and the dominant frequency in the spectrum. Figure 15 shows the flow diagram of the algorithm by which individual repetitions are obtained from the set. The dominant frequency in the first step of the algorithm is assumed as the frequency of the peak amplitude in the spectrum. Figure 16 shows the spectrum of the signal from the 2nd set for the Heel Touch exercise. In the spectrum, the peak amplitude is marked with a red circle, and the corresponding frequency is 0.4 Hz.

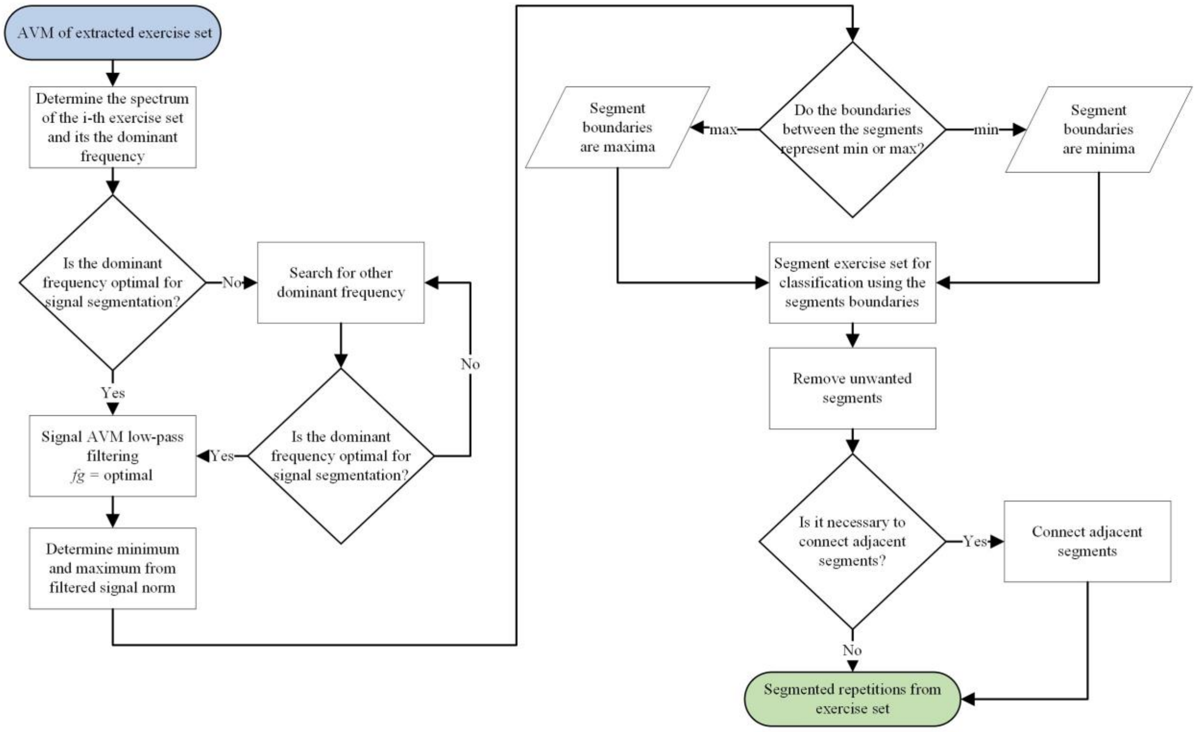


Figure 15 The process of repetition segmentation from one set

After calculating the dominant frequency in the spectrum, it is necessary to determine whether this frequency is optimal for repetition segmentation. In the case of Figure 16, the dominant frequency is also optimal for segmentation. However, if in the frequency spectrum of the signal, in addition to the dominant frequency, there is a lower frequency at which the signal has a pronounced amplitude (Figure 17), empirically it has been shown that for segmentation it is necessary to choose a lower frequency. In Figure 17, this amplitude in the spectrum is indicated by a red circle.

When the optimal frequency is determined, the *AVM* is filtered. A low-pass Chebyshev filter type 2 is used for filtering. The order of the filter depends on the passband and stopband frequency at which the signal is filtered. The optimal frequency is taken as the passband frequency, and the stopband frequency is twice as high as the passband frequency.

Minima or maxima of the *AVM* are used to define boundaries between segments, depending on the individual exercise. In exercise 9 (Heel Touch) and exercise 3 (Standing Side Dumbbell Shrug), maxima are taken, while in the others, minima are taken as the boundaries between the segments.

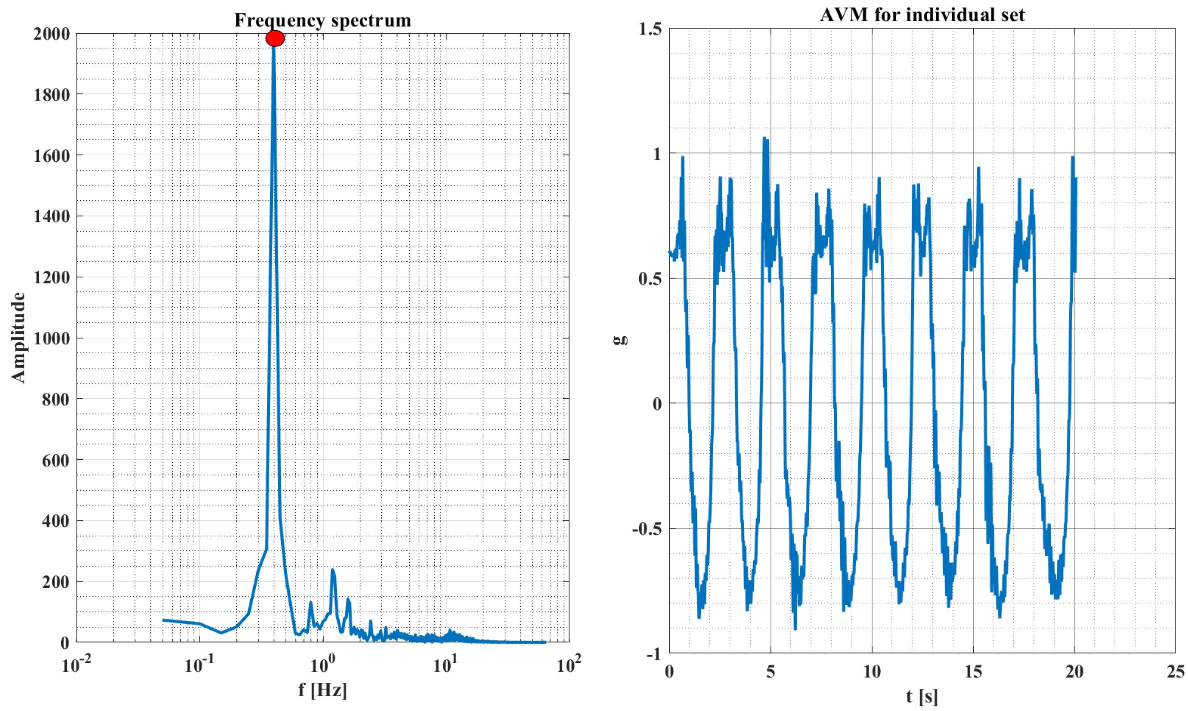


Figure 16 ***AVM*** **and its spectrum for Heel Touch exercise. In this case, the dominant frequency (red circle) is also optimal for segmentation. IMU position - chest**

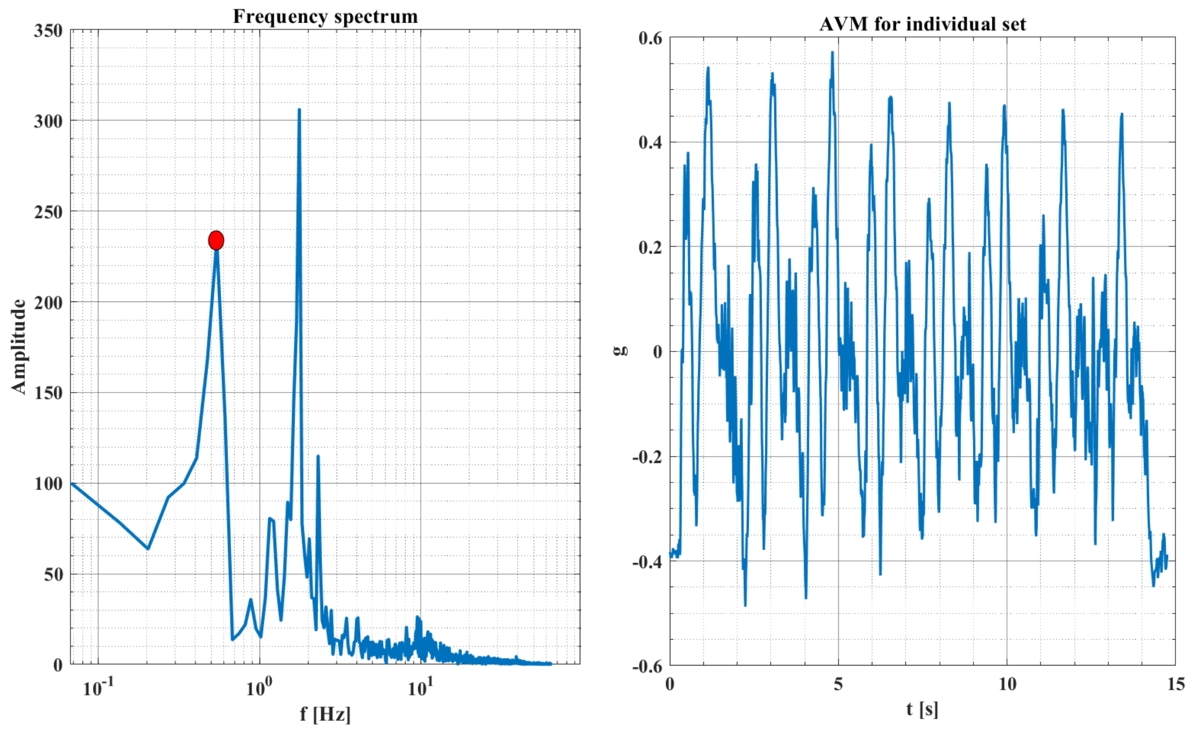
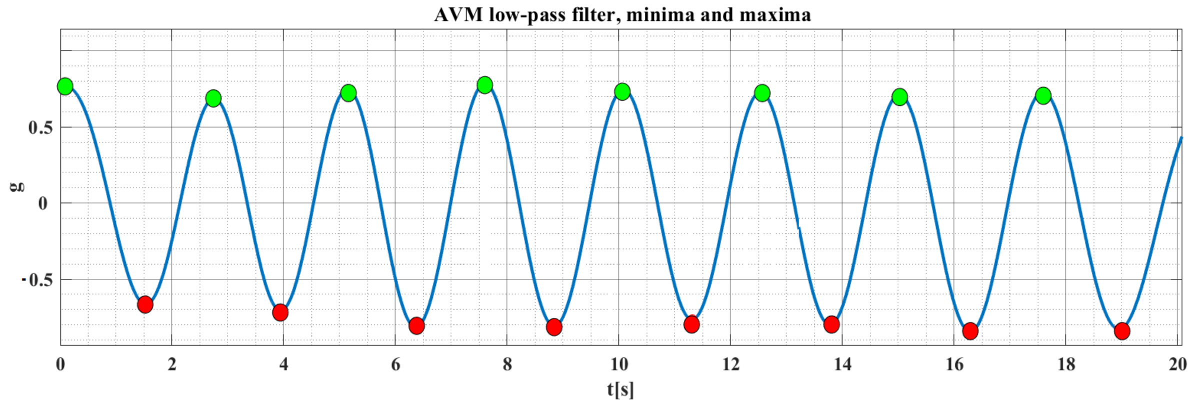


Figure 17 ***AVM*** **and its spectrum for Standing Dumbbell Lateral Raise with Arms Straight exercise. In this case, in addition to the dominant frequency there is a lower frequency (red circle) at which the signal has a pronounced amplitude; therefore, the dominant frequency is not optimal for segmentation. IMU position - wrist**

After repetition segmentation, it is necessary to remove the artifacts that most often appear before the first and after the last repetition. They are easy to eliminate by considering two criteria - the reciprocal value of the segmentation frequency (which roughly represents the average repetition time) and the maximum value per amplitude in the set. If any of the segments lasts less than half the average repetition time in that set and the maximum amplitude of that segment is not in the range determined by 50% of the maximum value in the whole set, that segment is discarded.



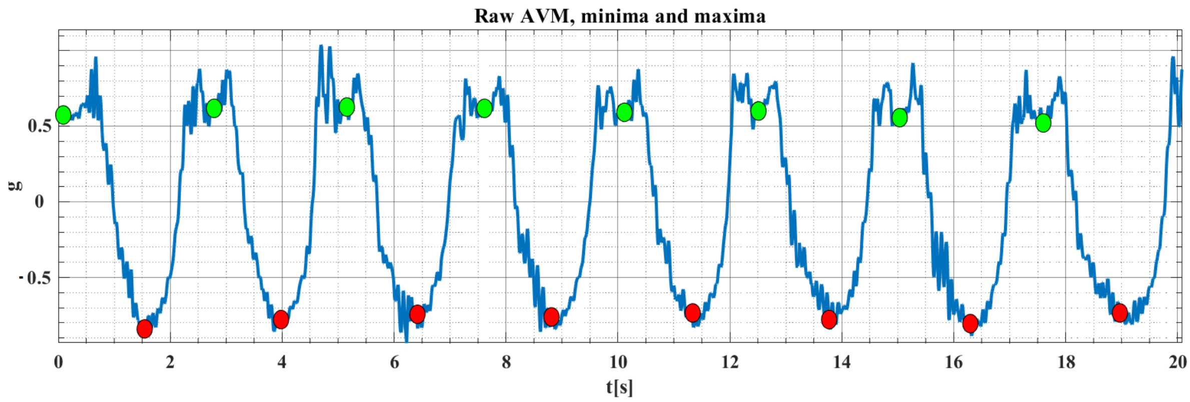


Figure 18 The upper part of the figure shows a low-pass filtered *AVM* signal for the Heel Touch exercise with the optimal frequency. The maxima are used to determine the boundaries between the segments, i.e. repetitions (green circle), and the minima (red circle) represent the middle of the performed movement within one repetition. At the bottom of the figure, there is an unfiltered *AVM* signal with crossed-out predetermined minima and maxima

The last step in the segmentation process is used only for certain exercises where it is necessary to connect adjacent segments. This is because two adjacent segments together actually form one repetition. This most commonly occurs with Dumbbell Step-up because of the pronounced pause that occurs when a person stands on a bench and pauses before returning to the starting position.

The current segmentation method, as previously explained, may result in the dominant frequency not aligning with the optimal frequency required for filtering, which prolongs the performance of the algorithm and also has an impact on the segmentation accuracy. In approximately 78.8% of the sets, the dominant frequency is optimal for signal segmentation, whereas in the remaining 21.2%, another frequency must be selected as optimal. Figure 19 shows the frequency ranges by exercises. The figure highlights that the majority of exercises have a frequency within the range of 0.3 to 0.9 Hz. This frequency range information can be used to expedite the process of determining the optimal frequency, and therefore a novel segmentation approach is proposed below.

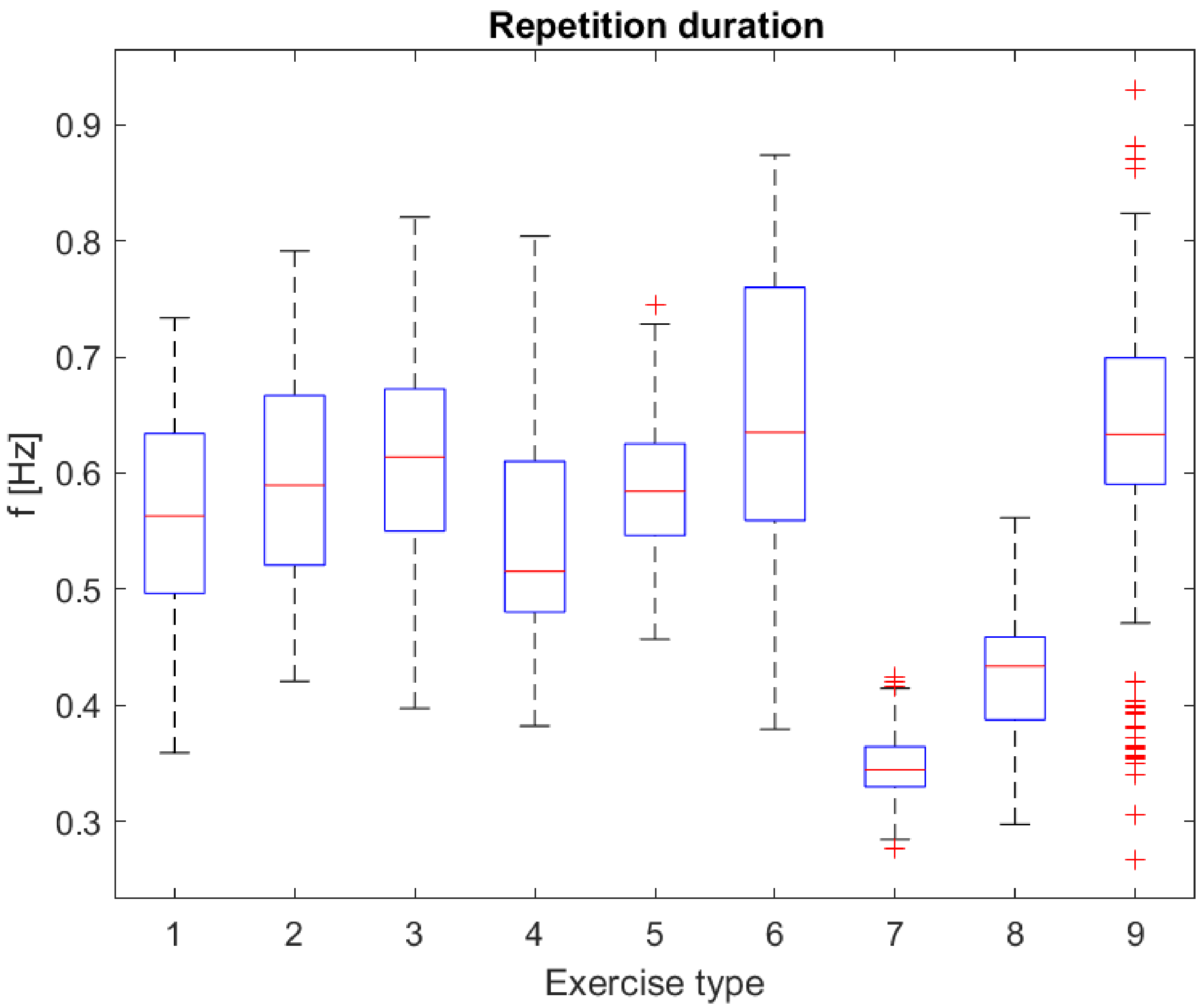


Figure 19 Range of frequencies for a particular exercise

3.2.3.2 Improved Repetition Segmentation with Band-pass Filtering

To further automate the segmentation presented in the previous subsection in terms of selecting the optimal frequency, an improved repetition segmentation method has been proposed, which includes an additional preprocessing of *AVM*. Preprocessing *AVM* consists of filtering by a band-pass filter whose cutoff frequencies are 0.25 Hz and 1.2 Hz, determined using the knowledge obtained from the previous segmentation method. Figure 20 shows the modified flow diagram.

Filtering with a band-pass filter removes most frequency components that are not relevant for repetition segmentation in which it is important to obtain prominent minima or maxima that mark the boundaries between repetitions in the sets.

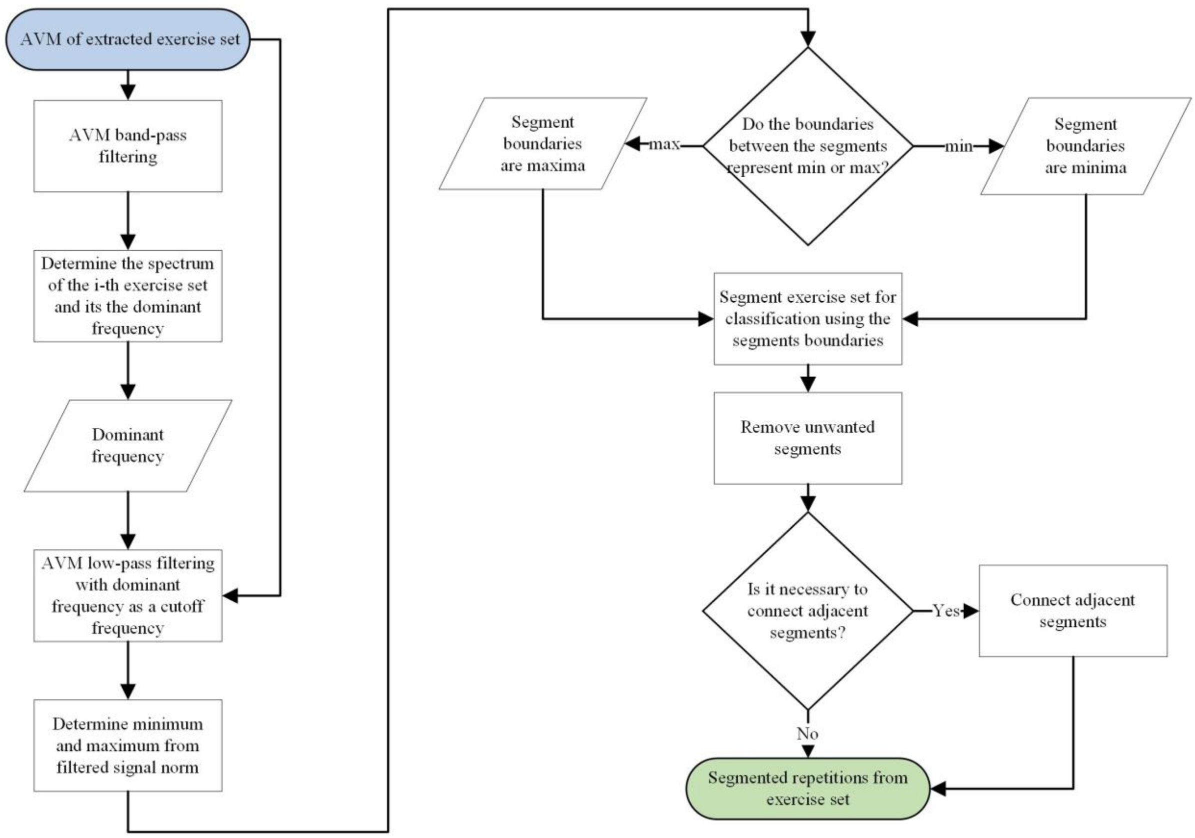


Figure 20 The process of improved repetition segmentation with band-pass filtering from one set

3.2.4 Method without Domain Knowledge

Aside from the methodology that leverages frequency spectrum and domain knowledge, alternative and more universal approaches have also been suggested, which rely on autocorrelation or energy as their foundational principles.

3.2.4.1 Repetition Segmentation using Autocorrelation

The proposed approach utilizes the autocorrelation of AVM signal which consists of repetitive human movements within the set. According to Box et al. [100], the autocorrelation function evaluates the correlation between successive values of a univariate time series y_t, specifically the correlation between y_t and y_{t+k}, where k = 0,...,K, and y_t denotes a stochastic process. The autocorrelation for lag k is:

$$r_k = \frac{c_k}{c_0} \tag{4}$$

$$c_k = \frac{1}{T}\sum_{t=1}^{T-k}(y_t - \bar{y})(y_{t+k} - \bar{y}) \tag{5}$$

where c_0 is the sample variance of the time series. Autocorrelation assumes values ranging between -1 and 1. A value of 1 signifies perfect positive autocorrelation, indicating a strong linear relationship between data points. Conversely, a value of -1 denotes perfect negative autocorrelation, signifying a strong inverse relationship. A value close to 0 implies no significant autocorrelation, suggesting that the data points are independent of each other. To ensure the algorithm's effectiveness, it is crucial to determine the minimum distance between peaks, which can be achieved either by empirical methods or by utilizing the optimal frequency property discussed in the previous subchapter 3.2.3.2. The total number of performed repetitions is calculated by dividing by two the number of detected peaks increased by one, $(N_p + 1)/2$. Additionally, the duration of each individual repetition can be inferred from the intervals between these peaks and may be utilized to facilitate the segmentation of each repetition. The inadequate detection of repetitions can be observed in Figure 21c, where the minimum distance between peaks was not considered, resulting in poor detection.

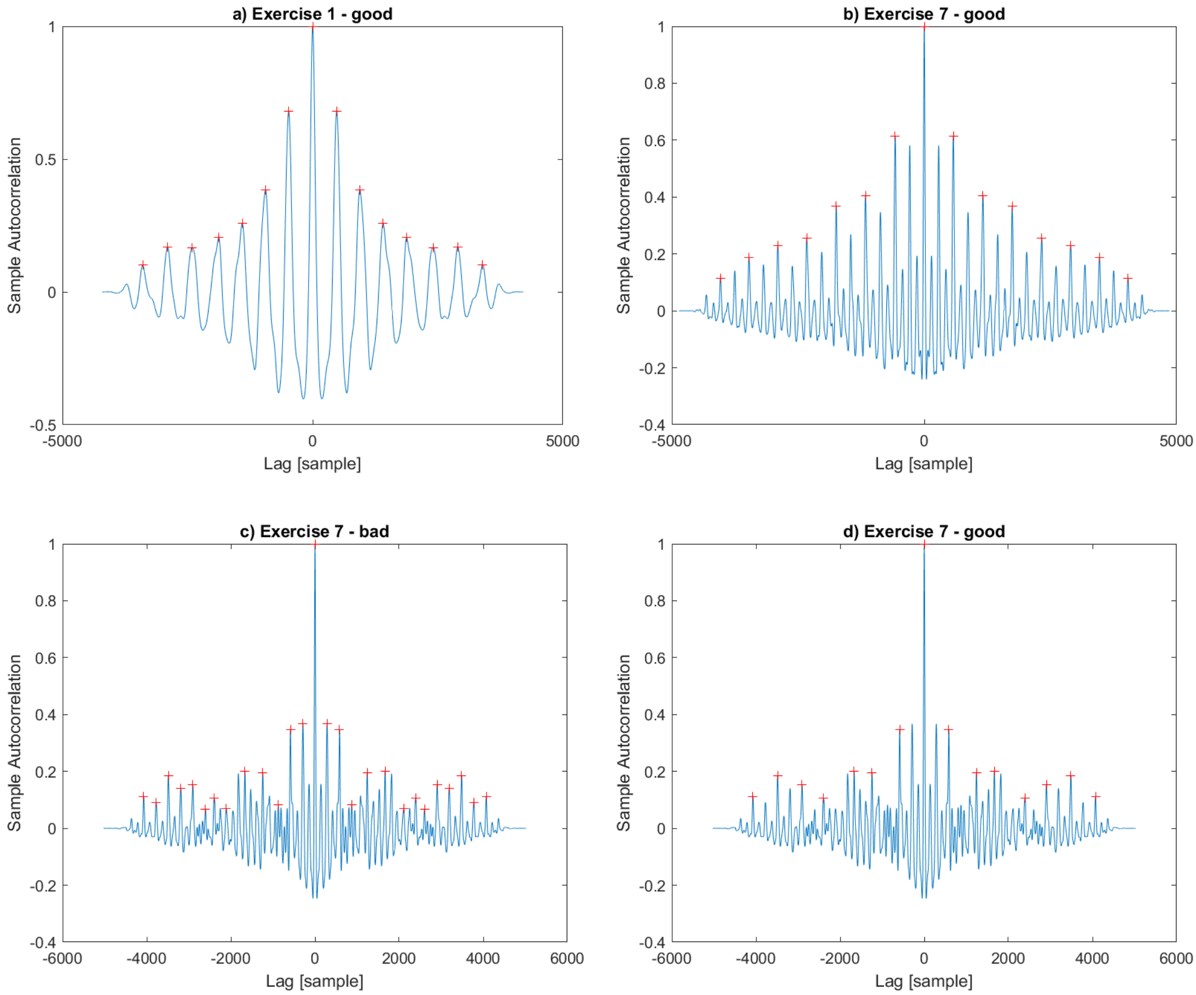


Figure 21 Autocorrelation method for good and bad example. Figure c) and d) shows a difference when using distance threshold. Executed 8 repetitions, IMU position – wrist

3.2.4.2 Repetition Segmentation using Energy

The proposed approach involved testing alternative sources of input data, including those from linear acceleration or angular velocity, in addition to the use of raw acceleration data. After extracting the individual set and calculating the AVM, AVM_{Linear} and $AVVM$ the subsequent step involves the segmentation of the repetitions within each set. Energy pattern in time series was calculated using method proposed in [101]. The rationale for this method is based on the observation that each repetition of an exercise generally comprises a sequence of arm movements resulting in a distinctive pattern of accumulated motion energy (Figure 22). Specifically, there are four key stages: 1) a rapid increase in accumulated energy from zero as the arm moves from an initial position to an ending position; 2) a decrease in accumulated energy as the arm briefly pauses at the ending position; 3) a second increase in accumulated energy as the arm moves back from the ending position to the initial position; and 4) a sudden drop in accumulated energy as the hand comes to rest at the initial position for a brief period of rest.

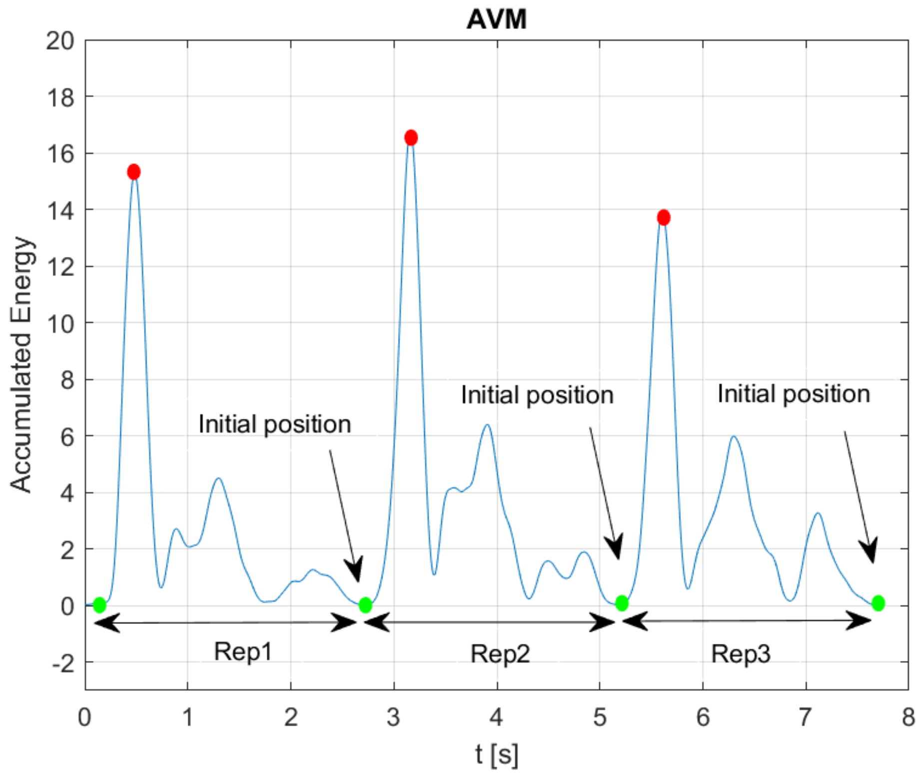


Figure 22 Accumulated energy pattern for *AVM*. IMU position – wrist

3.2.5 Classification – Exercise Recognition

A vector of nine features (standard deviation, variance, mode, median, range, trimmean, mean, skewness and kurtosis) was determined for 3-axis acceleration, angular velocity, and Euler angles from IMU on wrist, chest and thigh making the overall vector of 243 features. Combinations of this features with different locations was tested using SVM classifier on whole set (based on event marker, which corresponds to the activity-defined windows in subchapter 2.3.2.2) compared with sliding windows with 50% overlapping. For technique with sliding windows, three different window lengths were tested: 1, 2 and 4s. To evaluate the performance of a models on an independent dataset, 5-fold CV was done. In addition to the commonly used SVM algorithm, other machine learning algorithms, including KNN, Ensemble, and Naïve Bayes, were employed.

3.3 Results

This chapter outlines the results obtained from the method without domain knowledge. Detail results from the method with domain knowledge are documented in our prior publication [96].

3.3.1 Counting, Segmentation and Variability

Utilizing methods based on autocorrelation or energy to extract and count (segment) movements, the study initially focused on the IMU on the wrist, with multiple settings tested to identify the optimal combination. The autocorrelation method was evaluated on AVM signals, in two modes of operation: one that disregards the minimum distance between consecutive repetitions and a modified version that considers it. The energy method was assessed with three modes of operation, including different signal inputs: AVM, AVM_{Linear}, and $AVVM$, but with the same algorithm. The F-scores for repetition detection are presented in Figure 23, and the difference between the actual number of repetition counts and the number of detected counts is expressed through an error count within one set (Figure 24 and Figure 25). The results indicate that the autocorrelation methods yielded better outcomes for eight out of nine exercises, with an advantage observed for the modified version. Further detailed results are provided in the Appendix section (Table A 1 - Table A 16).

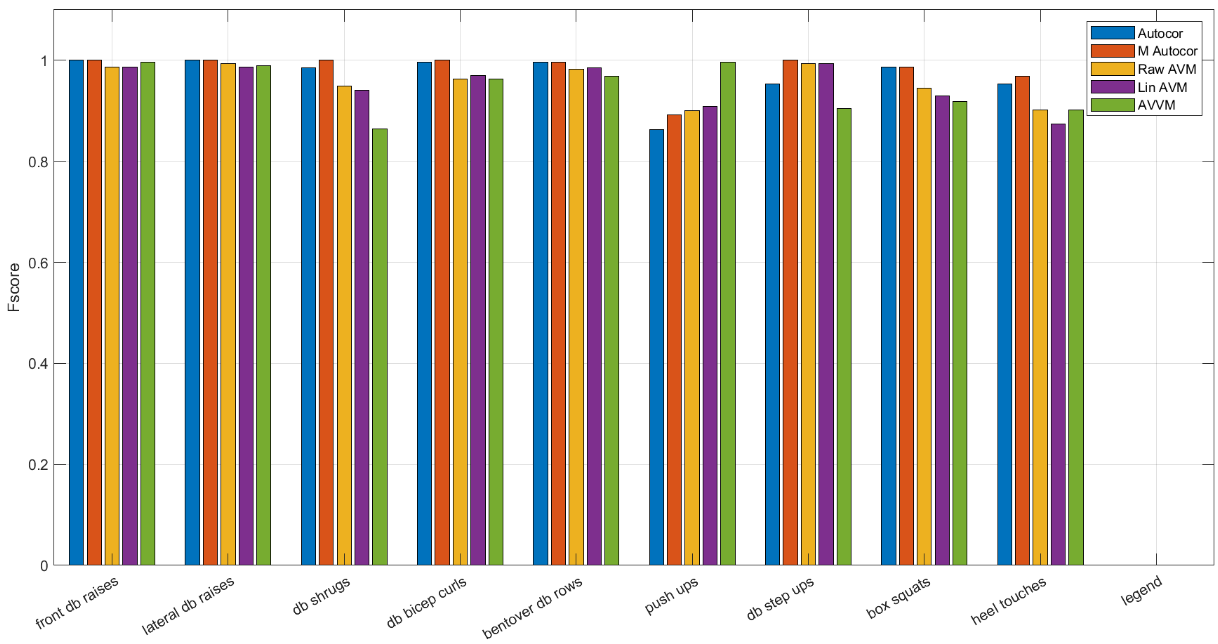


Figure 23 Repetition detection F-scores for all subjects using 5 different modes of operation: autocorrelation (Autocor), modified autocorrelation (M Autocor), energy with raw AVM (Raw AVM), energy with linear AVM (Lin AVM) and energy with $AVVM$ (AVVM). IMU position – wrist

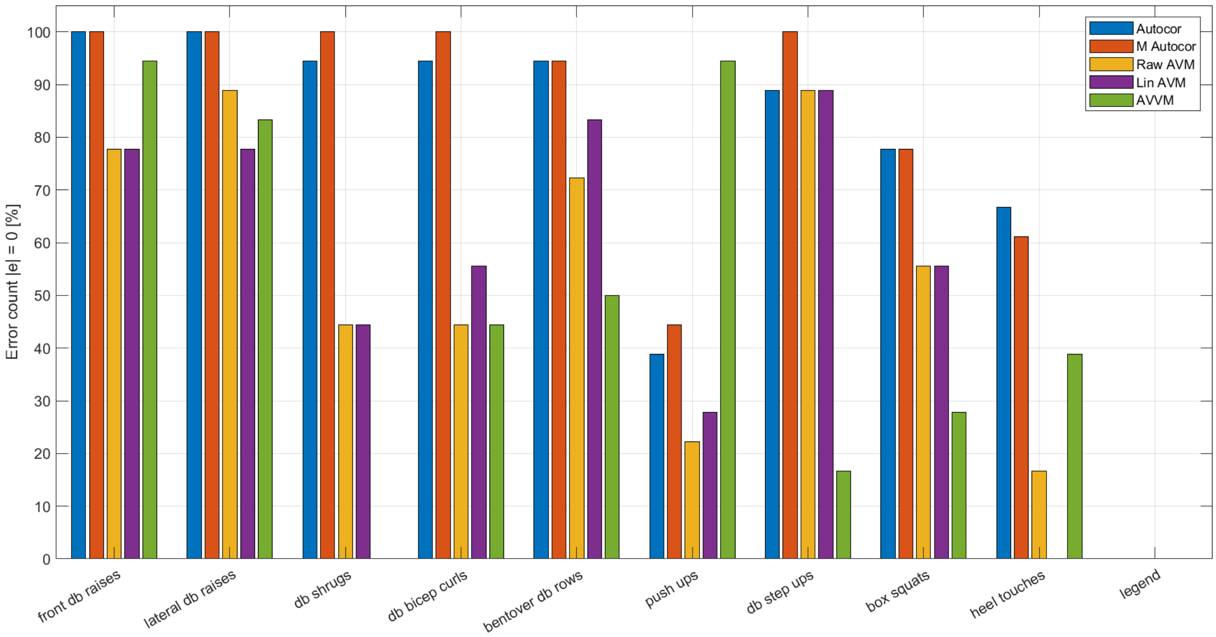


Figure 24 Repetition counting performance when error count is 0 using 5 different modes of operation: autocorrelation (Autocor), modified autocorrelation (M Autocor), energy with raw *AVM* (Raw AVM), energy with linear *AVM* (Lin AVM) and energy with *AVVM* (AVVM). IMU position – wrist

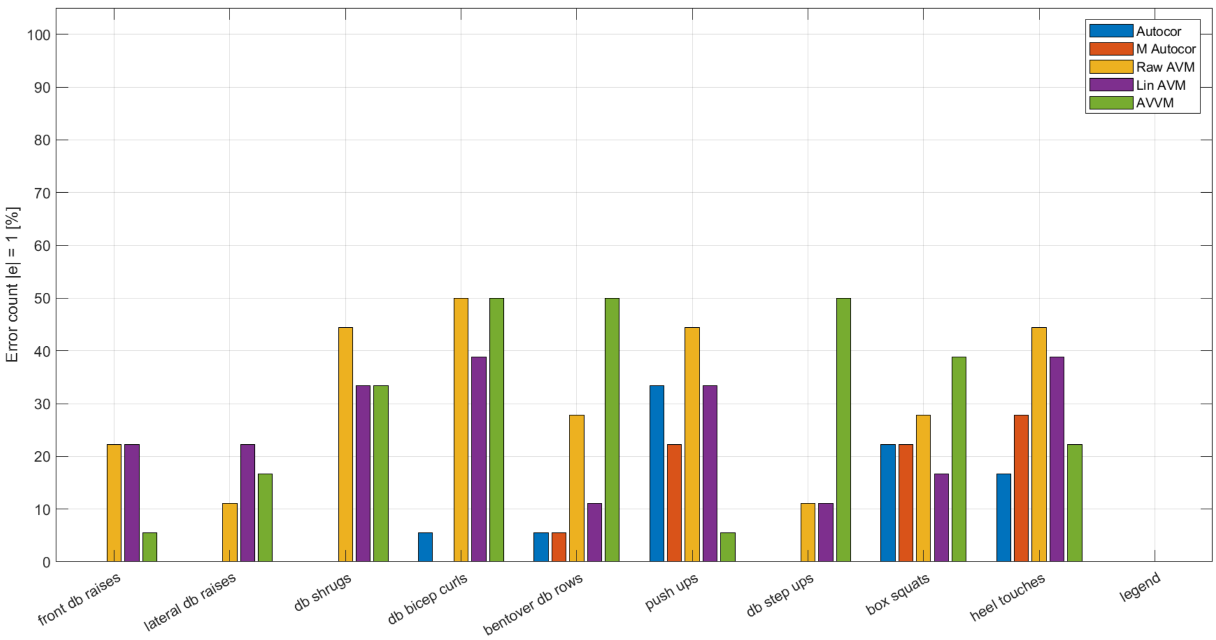


Figure 25 Repetition counting performance when error count is 1 using 5 different modes of operation: autocorrelation (Autocor), modified autocorrelation (M Autocor), energy with raw *AVM* (Raw AVM), energy with linear *AVM* (Lin AVM) and energy with *AVVM* (AVVM). IMU position – wrist

In addition to the F-scores for repetition detection and error count for each exercise, the segmented repetition durations for the modified autocorrelation method, energy method with raw AVM, and the actual repetition duration are presented in the Figure 26.

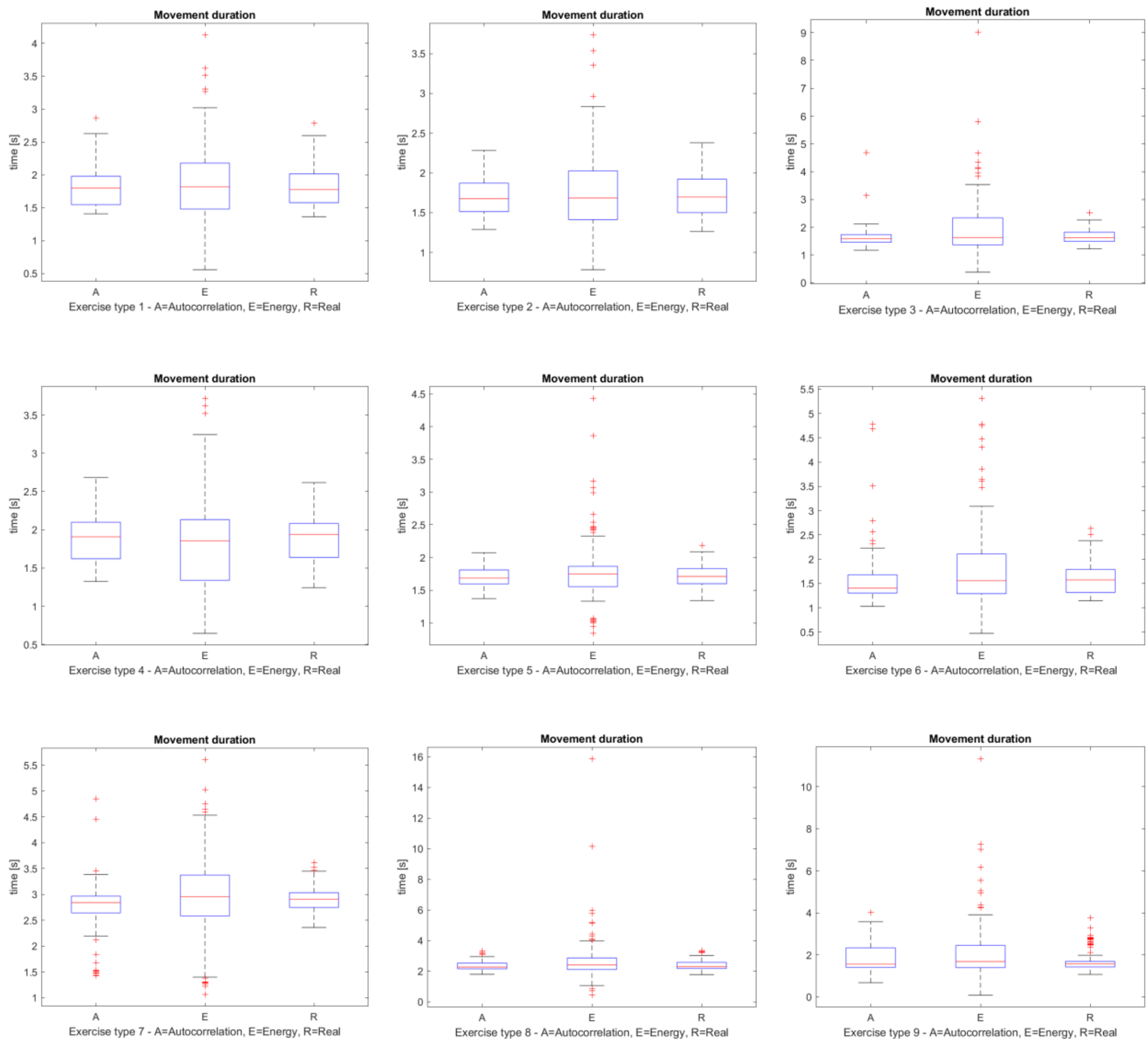


Figure 26 Movement duration for 9 exercises using 2 different methods, modified autocorrelation or energy, compared with real time duration

Given the comparatively poorer results observed for push-ups, box squats, and heel touches, the study also evaluated the modified autocorrelation method on the remaining two IMUs (Figure 27, Figure 28 and Figure 29). Regarding push-ups and box squats, both IMU locations exhibit better levels of accuracy. In contrast, for heel touches, the chest IMU appears to yield marginally superior results.

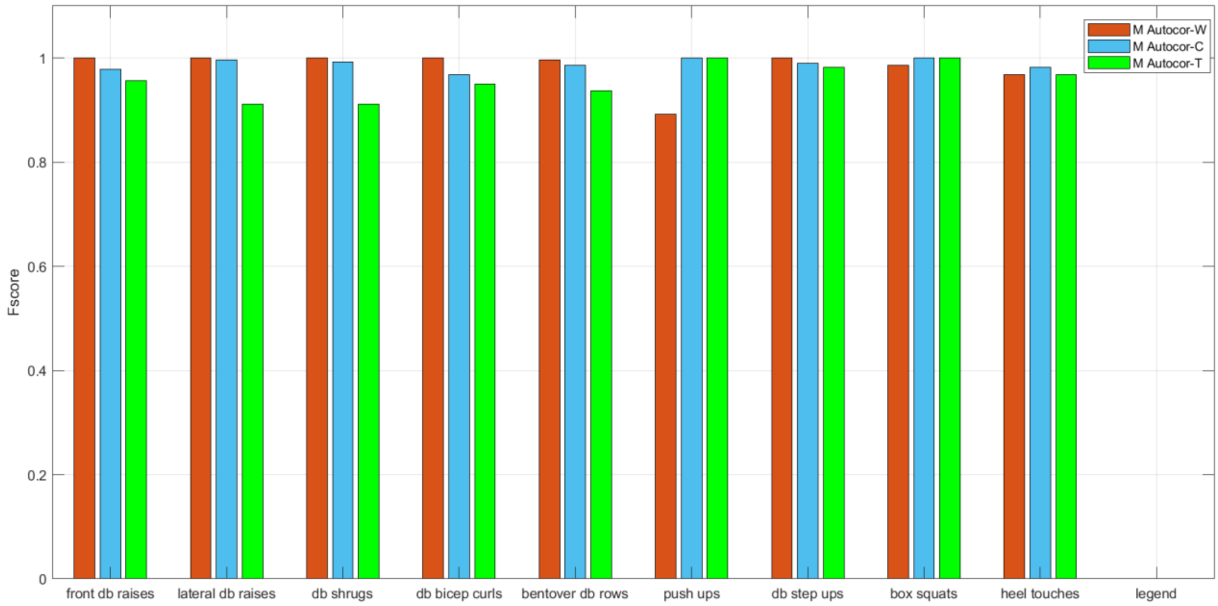


Figure 27 Repetition detection F-scores for all subjects using modified autocorrelation method on 3 different IMU positions: IMU position - wrist (M Autocor-W), IMU position - chest (M Autocor-C), IMU position - thigh (M Autocor-T)

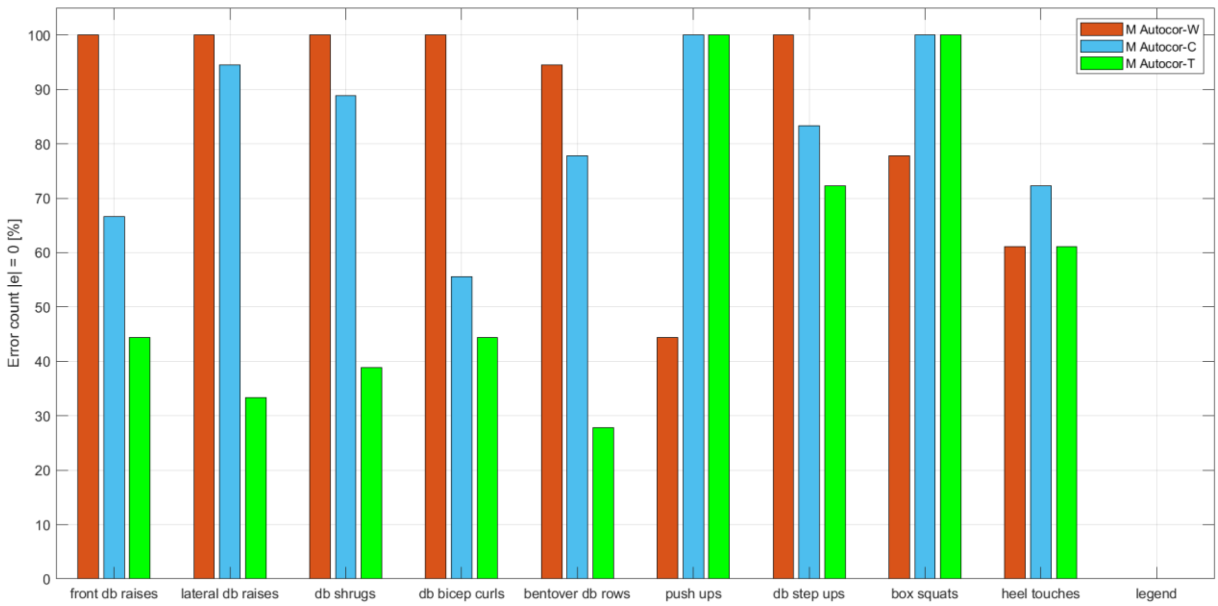


Figure 28 Repetition counting performance when error count is 0 using modified autocorrelation method on 3 different IMU positions: IMU position - wrist (M Autocor-W), IMU position - chest (M Autocor-C), IMU position - thigh (M Autocor-T)

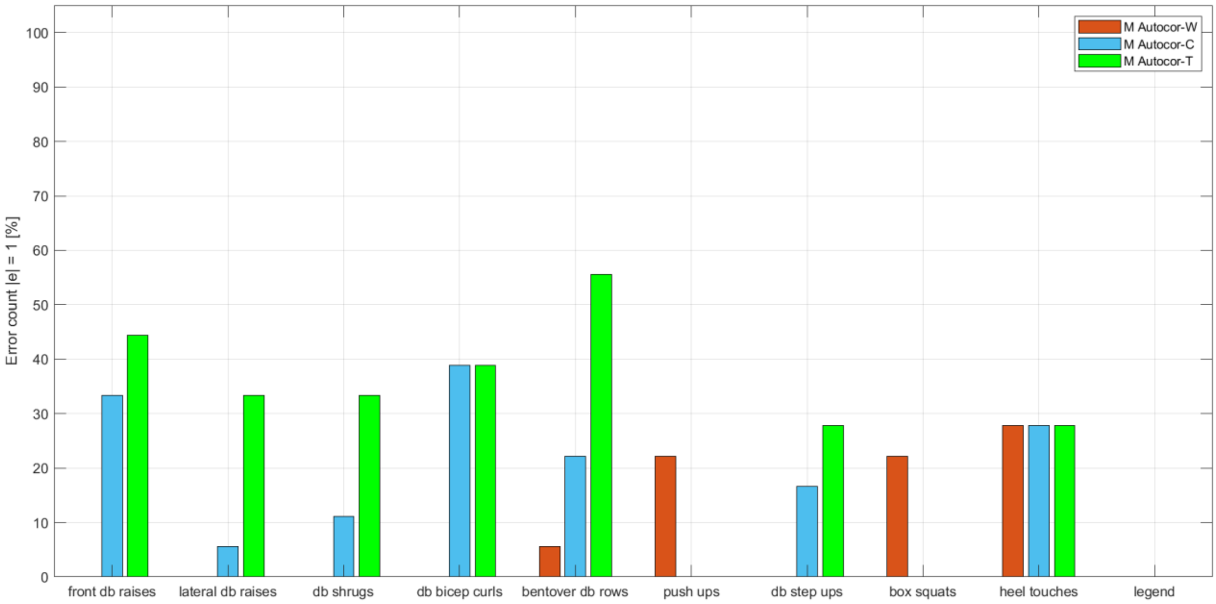


Figure 29 Repetition counting performance when error count is 1 using modified autocorrelation method on 3 different IMU positions: IMU position - wrist (M Autocor-W), IMU position - chest (M Autocor-C), IMU position - thigh (M Autocor-T)

The peak values of the attained accelerations and angular velocities were calculated on the segmented repetitions and are presented in the Figure 30 - Figure 38. Subjects 1, 2, and 3 possess extensive experience in performing strength exercises, whereas subjects 4, 5, and 6 have no prior experience. The obtained values and their variability are subject to variations based on the specific exercise performed and the individual characteristics of each subject. Overall, individuals with prior experience in strength exercises exhibit slightly lower variability in their maximum acceleration values.

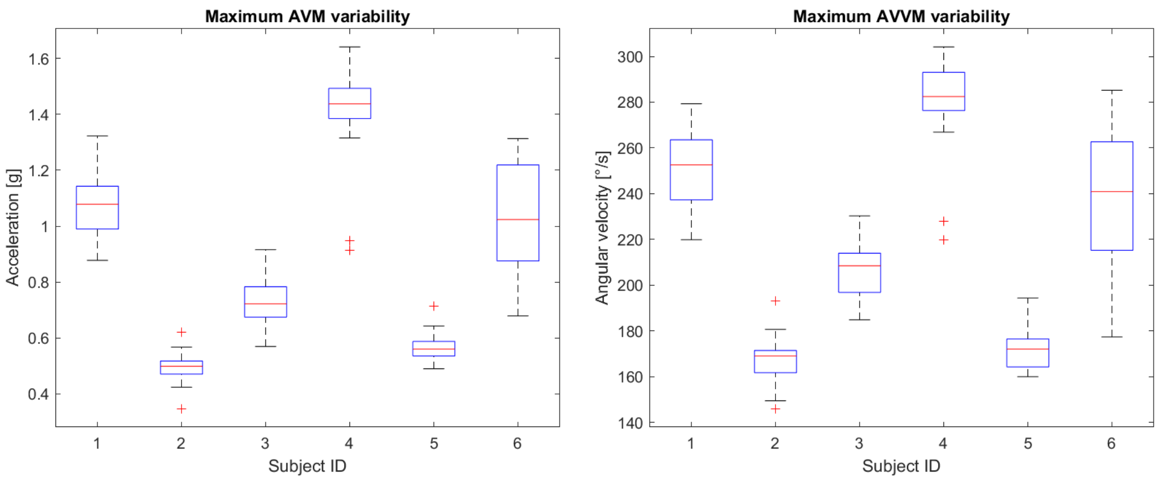


Figure 30 Maximum AVM and AVVM variability for exercise no. 1

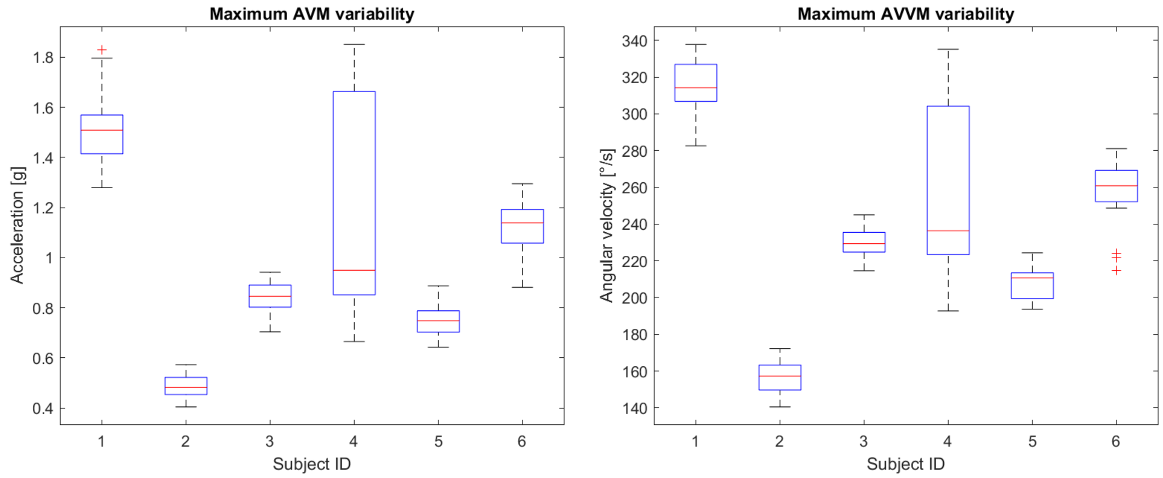


Figure 31 Maximum AVM and AVVM variability for exercise no. 2

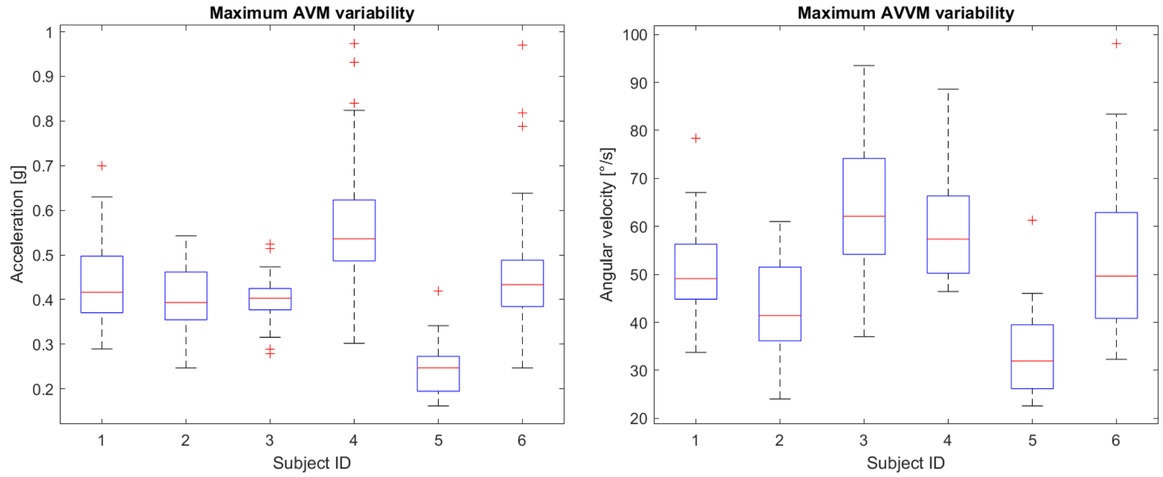


Figure 32 Maximum AVM and AVVM variability for exercise no. 3

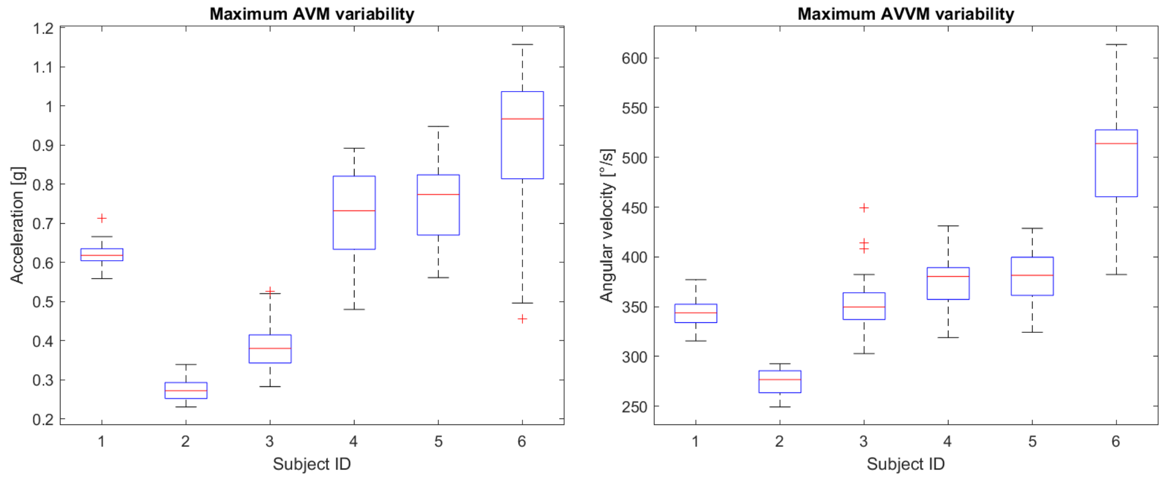


Figure 33 Maximum AVM and AVVM variability for exercise no. 4

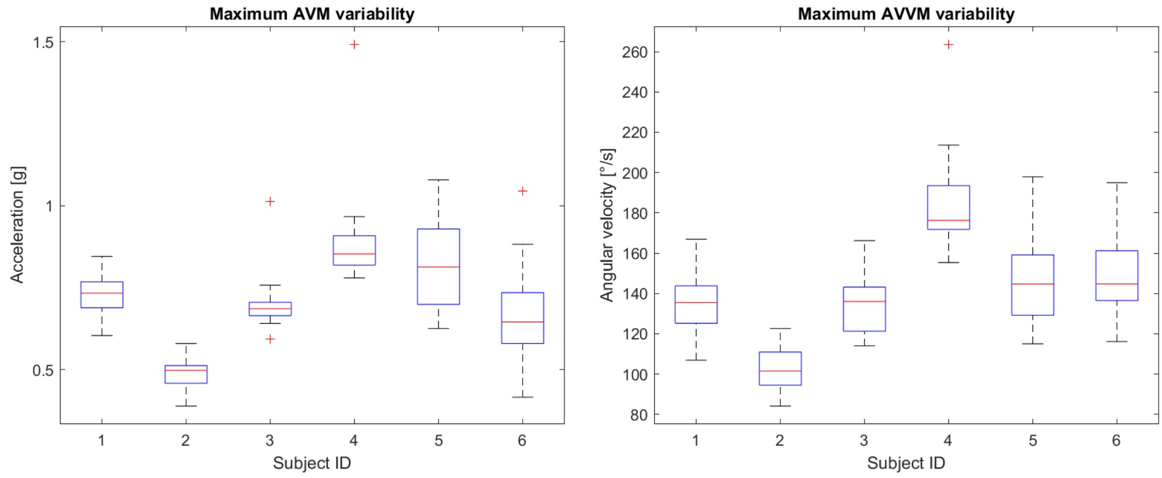


Figure 34 Maximum AVM and AVVM variability for exercise no. 5

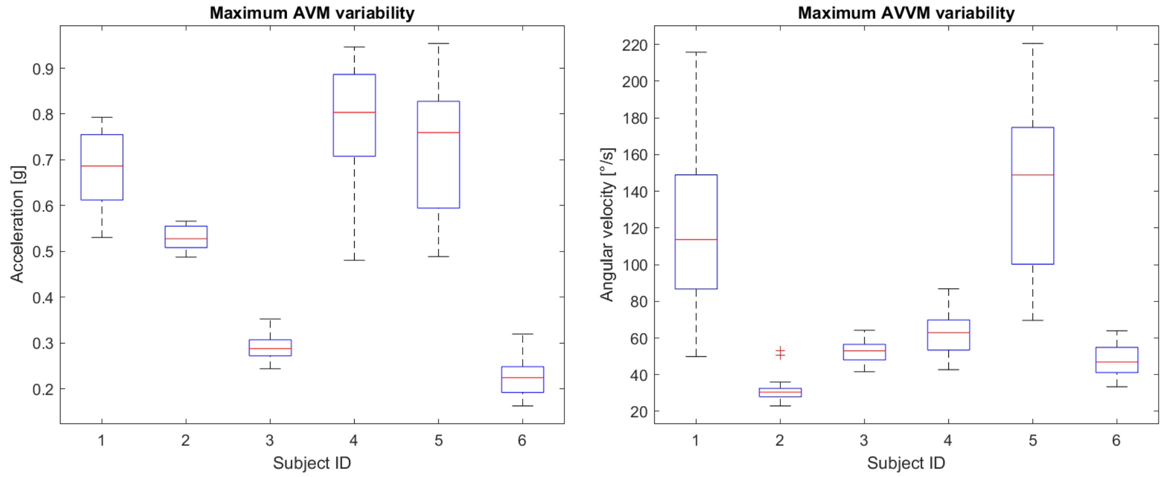


Figure 35 Maximum AVM and AVVM variability for exercise no. 6

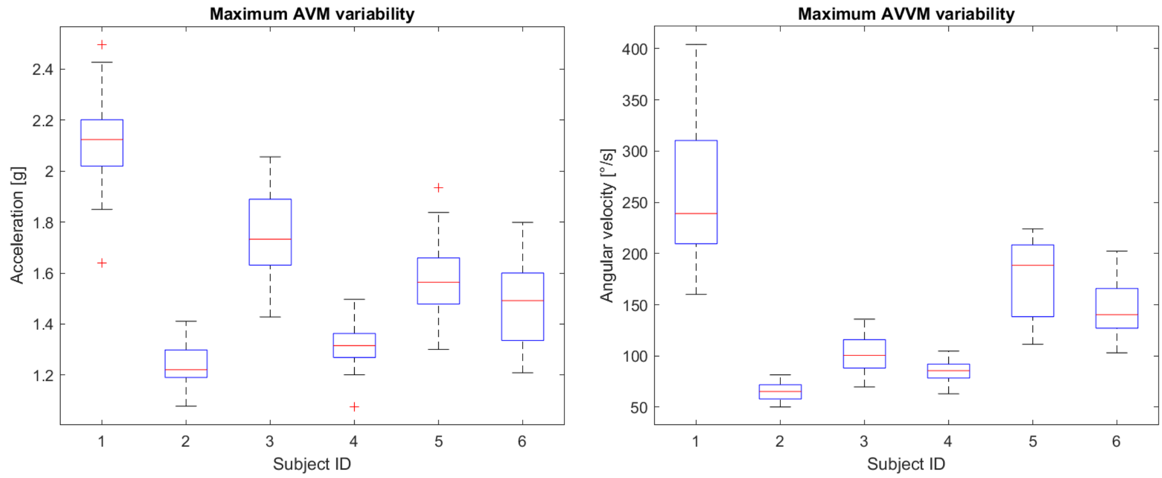


Figure 36 Maximum AVM and AVVM variability for exercise no. 7

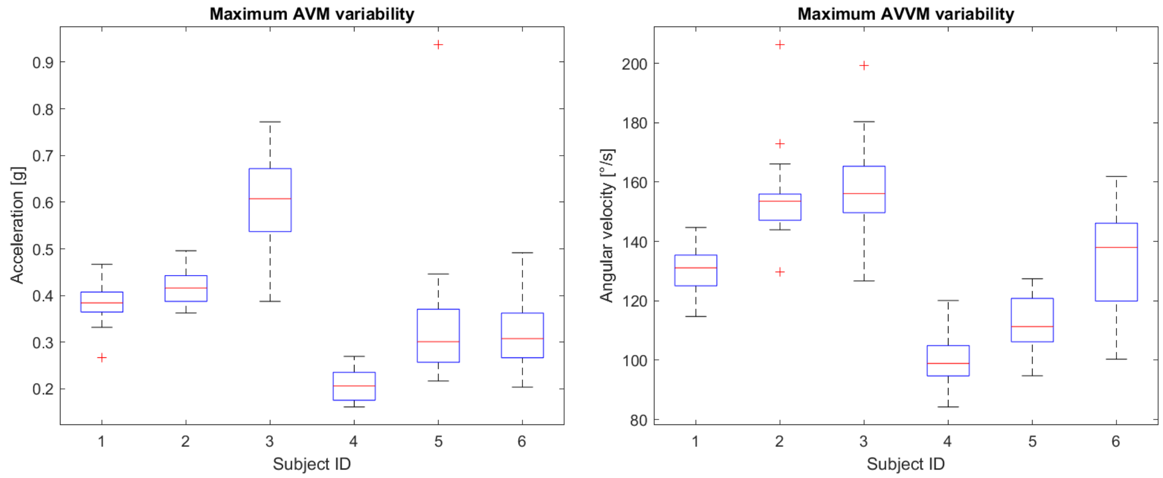


Figure 37 Maximum AVM and AVVM variability for exercise no. 8

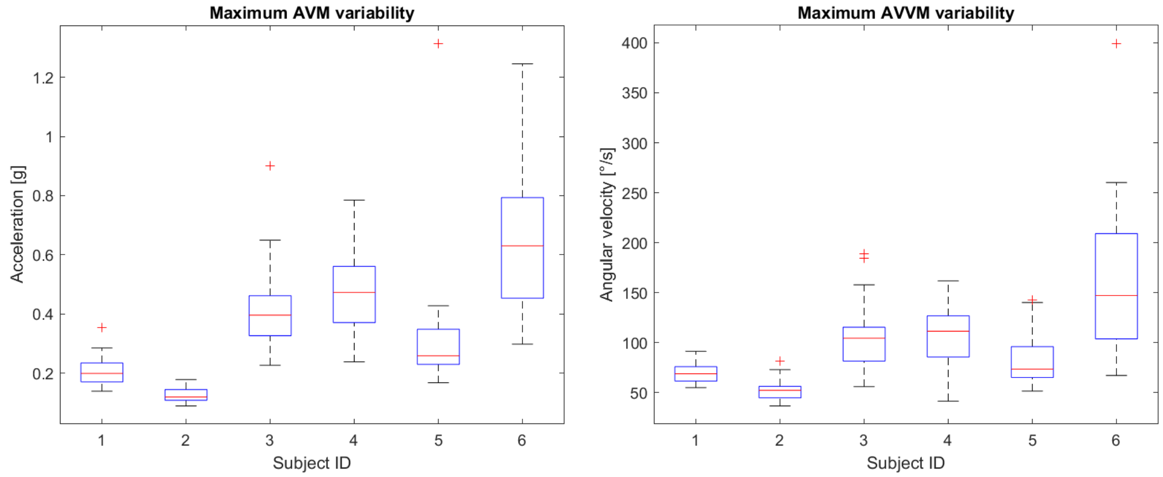


Figure 38 Maximum AVM and AVVM variability for exercise no. 9

3.3.2 Classification – Exercise Recognition

The present study reports the results obtained with respect to the location of the IMU and the sliding window technique, as detailed in Table 4, with additional findings related to the activity-defined technique presented in Table 5. Notably, the highest level of accuracy is achieved when utilizing a combination of all three IMUs. When utilizing a single IMU, the highest accuracy is observed with placement located at the wrist. The sliding window technique produces slightly better results, around 99%.

Table 4 Comparison of overall 5-fold cross validation test accuracy for different combination of IMUs based on different sliding window lengths with 50% overlapping. Input data from 3 axis acceleration, angular velocity, and Euler angles during workout

	Wrist	Chest	Thigh	W+C	W+T	W+C+T
w = 1s	Acc = 95.9%	Acc = 94.3%	Acc = 93.8%	X	X	X
w = 2s	Acc = 97.9%	Acc = 97.1%	Acc = 95.8%	Acc = 98.6%	Acc = 99.0%	Acc = 99.2%
w = 4s	Acc = 99.1%	Acc = 98.1%	Acc = 96.2%	Acc = 99.2%	Acc = 99.4%	**Acc = 99.4%**

Table 5 Comparison of overall 5-fold cross validation test accuracy for different combination of IMUs based on Activity Defined Window (ADW). Input data from 3 axis acceleration, angular velocity, and Euler angles during workout

	Wrist	Chest	Thigh	W+C	W+T	W+C+T
Event	Acc = 96.3%	Acc = 88.3%	Acc = 84.0%	Acc = 98.1%	Acc = 98.8%	**Acc = 98.8%**

Furthermore, the study investigated the impact of various input parameters on the classifier's performance, in addition to exploring the influence of location. The findings indicate that there is no substantial discrepancy in performance (< 1%) when utilizing acceleration, angular velocity, and Euler angles as input data, as opposed to solely utilizing acceleration. The overall results are presented in Table 6, with further detailed outcomes exhibited in Figure 39 and Figure 40. Nine classes include: 1 - Standing Front Dumbbell Raise, 2 - Standing Dumbbell Lateral Raise with Arms Straight, 3 - Standing Side Dumbbell Shrug, 4 - Standing Dumbbell Curl with Rotation, 5 - Bent-over Dumbbell Row, 6 - Push-up, 7 - Dumbbell Step-up, 8 - Box Squat, and 9 - Heel Touch.

Table 6 Comparison of overall 5-fold cross validation test accuracy for different combination of input data and IMUs.

Input Data	Wrist, w=4s	W+C+T, w=4s	Wrist, ADW	W+C+T, ADW
Acceleration Angular velocity Euler angles	**Acc = 99.1%**	Acc = 99.4%	**Acc = 96.3%**	**Acc = 98.8%**
Acceleration Angular velocity	Acc = 98.1%	**Acc = 99.5%**	Acc = 92.6%	Acc = 96.3%
Acceleration	**Acc = 98.8%**	**Acc = 99.3%**	**Acc = 95.7%**	**Acc = 98.1%**
Angular velocity	Acc = 91.6%	Acc = 97.2%	Acc = 88.9%	Acc = 95.1%
Euler angles	Acc = 96.4%	Acc = 99.2%	Acc = 95.1%	Acc = 93.2%
AVM	Acc = 82.4%	Acc = 96.0%	Acc = 82.1%	Acc = 94.4%

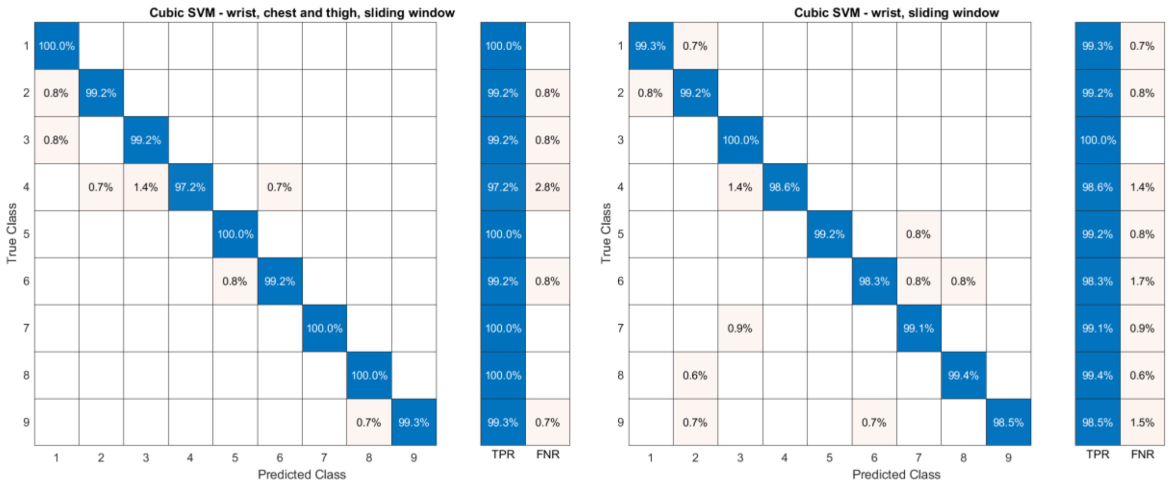


Figure 39 Exercise classification with SVM, sliding window 4s with 50% overlapping. IMU position – wrist, chest and thigh (left); wrist (right). Input data – acceleration, angular velocity, Euler angles

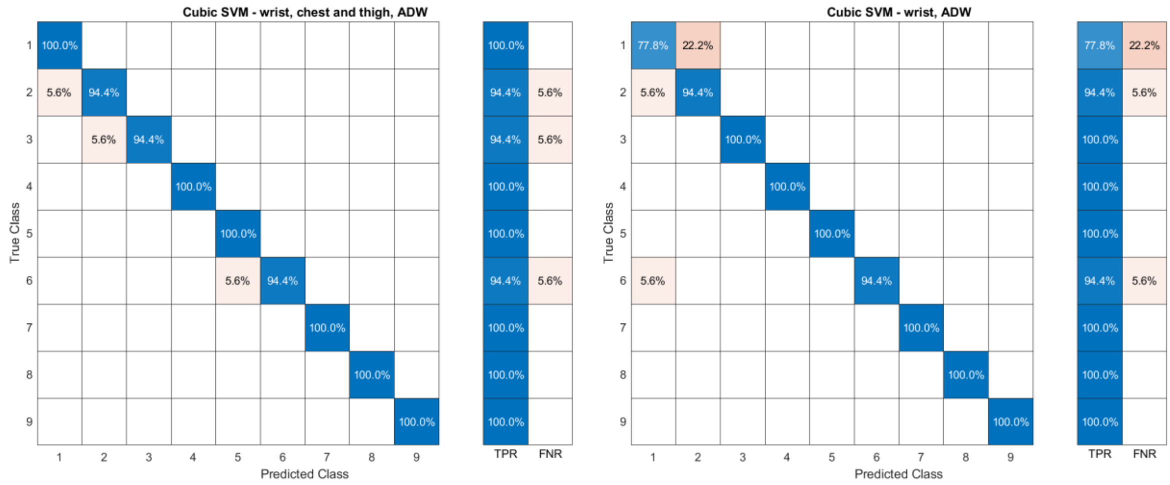


Figure 40 Exercise classification with SVM, ADW. IMU position – wrist, chest and thigh (left); wrist (right). Input data – acceleration, angular velocity, Euler angles

In addition to the commonly used SVM algorithm, other machine learning algorithms, including KNN, Ensemble, and Naïve Bayes, were employed. Figure 41 shows that the SVM algorithm consistently produces the highest level of accuracy, irrespective of the windowing technique or the placement of the IMU.

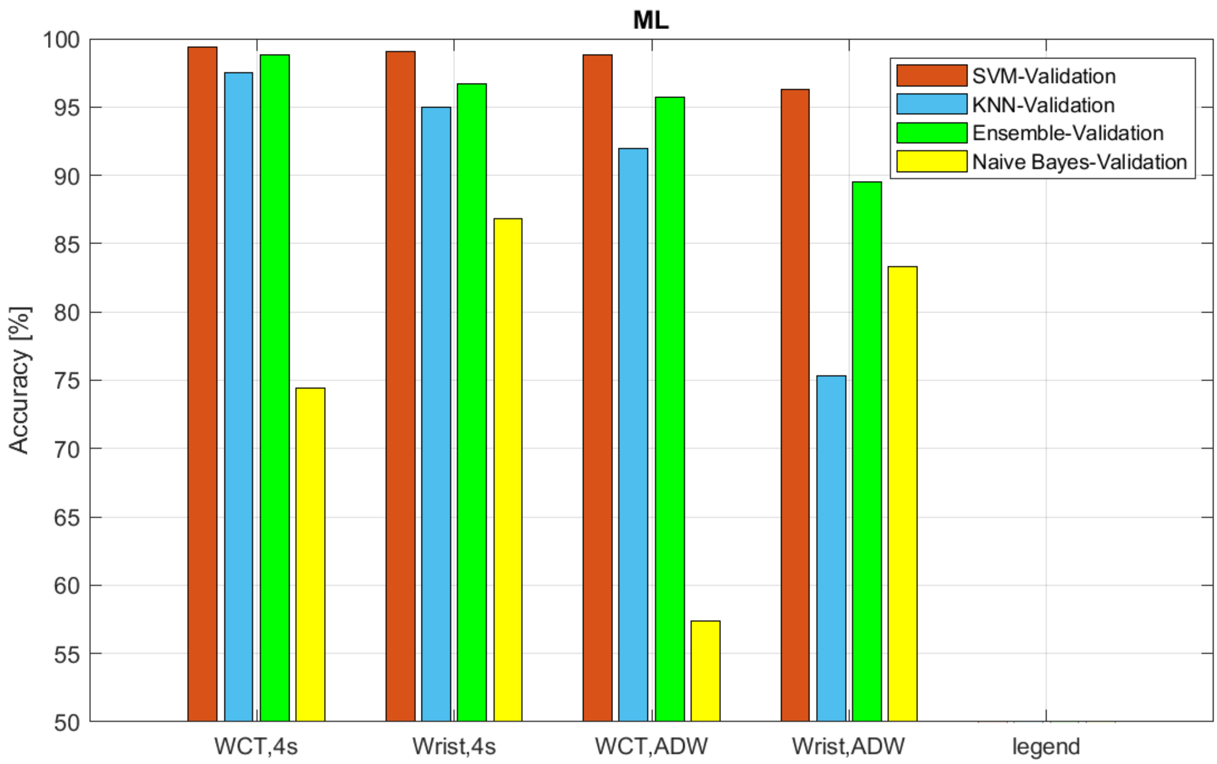


Figure 41 Score comparison for different ML model types

3.4 Discussion

Through a controlled experimental setup and a limited number of subjects, measurements were conducted to establish a reference point for sensor selection, positioning, model definition, and data monitoring during exercise performance.

The defining characteristic of strength exercises is the repetition of specific movements within a certain time interval. Two methods without domain knowledge have been proposed for extracting and counting or segmenting individual movements using only accelerometer signals. In order to simplify signal processing and eliminate the influence of IMU orientation, only one parameter, *Acceleration Vector Magnitude (AVM)*, was observed. The first method is based on autocorrelation, while the second is based on energy. The autocorrelation-based method achieved an F-score > 98% when data was acquired from the wrist IMU only, while a result of > 99% was achieved with data from two IMUs, one on the wrist and one on the chest. The energy-based method achieved a slightly lower result with an F-score > 95%. An advantage of both methods is that they can be used on a wider range of exercises intended for the whole body and do not require previous and domain knowledge of the exercise being performed.

The difference between the actual number of repetition counts and the number of detected counts was presented through error count. During the counting of repetitions of an individual exercise using only the IMU on the wrist, a repetition performance without a single error is 86.4%, or 95.1% if the possibility of one error within the set is included. Smaller accuracy occurs with push-ups, squats and heel touches exercises, but by adding the IMU sensor on the chest, the accuracy increases to 96.3% without a single error, or to 100% if the possibility of one error within the set is included. After successful segmentation, it is easy to determine the parameters that are important for measuring movement variability, such as movement execution time, maximum acceleration amplitude, angular velocity, and the like. In order to further expand the proposed method, a classifier based on machine learning was added to recognize the movement or the exercise being performed. A window length of 4 sec with an overlap of 50% proved to be the best choice (accuracy > 99%), using the input data from the accelerometer and gyroscope from the IMU located on the wrist, chest, and thigh. Using the input data only from the accelerometer and the IMU on the wrist, an accuracy of 98.8% was achieved.

With domain knowledge method [96], out of a total of 1656 movements, i.e. repetitions, 1652 were successfully segmented, segmentation of 4 repetitions was not successful, and 6 signal segments were incorrectly classified as repetitions. An accuracy of 99.4%, recall 99.7%, precision 99.6% and F-score 99.7% is achieved, which we find comparable and better then reported in literature. To the author's knowledge, no research has been done so far with the same selection of exercises and position of IMUs, so it cannot be directly compared with the existing literature, but we have listed the most relevant ones. In their study, Guo et al. [101] compared the repetition segmentation accuracy of two different IMUs in two different positions, a smartwatch on the wrist and a smartphone on the upper arm. They achieved an average accuracy of 99%. It is necessary to mention that their choice of exercises primarily referred to exercises in which the arm represented the dominant body segment and they used the data obtained from all three sensors, accelerometer, gyroscope and magnetometer. In [4], the authors achieved segmentation recalls a minimum of 84.1% for IMU located in the ear to a maximum of 91.6% on the wrist. A wider range of body activation was present during workout and only accelerometer signals were used. Pernek et al. [87] in their research detected and separated repetitions using a method based on the DTW algorithm. They chose a very wide range of exercises with which they managed to activate the whole body. The data were obtained from an accelerometer inside a smartphone that was located at 3 different locations, wrist, ankle, or on the top of the weights, depending on the exercise. The average F-score, precision and recall for all exercises and environments was 99.3%, 100% and 98.8%.

When it comes to recognizing segmented repetitions, in [101] was achieved with an average accuracy of 95% for a smartwatch on the wrist and 91% for a smartphone on the upper arm. A light-weight classifier (Support Vector Machine) was used on 27 features extracted from the acceleration in the world coordinate system. In [4] classification mean accuracy achieved a minimum of 78.4% for IMU located in the ear to a maximum of 97.2% on the chest. The template for the DTW algorithm in the process of classification was chosen randomly 50 times to avoid redundancy. O'Reilly et al. [7] implemented a method for tracking and recognizing lower-limb exercises with wearable sensors. They placed 5 IMUs on subjects (on the thighs, shanks, and lumbar) and achieved 99% accuracy. Furthermore, for a single IMU placed on the shank, they obtained 98% accuracy.

Regardless of the small number of subjects in the proposed research, overall accuracy is comparable with the abovementioned studies. Detailed classification results can be analyzed using Figure 39 and Figure 40, and the author's observations can be found in the previous subchapter.

As indicated before, a main disadvantage of the research is a small number of subjects, and therefore through future work (Chapter 5), the plan is to implement the proposed algorithm on a more natural environment; and to compare the accuracy of our algorithm with other common classification methods implemented on larger groups.

4 MOVEMENT EXECUTION METRICS DURING EXERCISE BASED ON MEASUREMENTS USING SENSOR NODES WITH INERTIAL AND MAGNETIC SENSORS

Movement execution metrics during physical exercise are a set of measurements and quantifications that are used to assess and analyze movement patterns and characteristics. These metrics comprise various aspects of movement, including velocity, acceleration, joint angles, and range of motion, among others. They are employed to evaluate the quality of movement execution, identify potential areas for improvement, and track progress over time [68][73][78][102][103][104].

The current chapter introduces a novel metric that allows for the numerical description of individual movements using data gathered from IMUs.

4.1 Metrics

During qualitative analysis, the exercise parameters that are monitored include linear acceleration, angle achieved from beginning to the end of the movement, and movement duration. These three parameters enable a universal description of every movement in terms of time, space, and change of velocity. In a template-based approach, the similarity between trajectories for chosen parameters would be measured through model-less or model-based metrics, which can lead to the complex calculation or the need to provide a certain size of memory to store templates. On the other hand, in a rule-based approach, a small set of rules is often determined that is related to a particular exercise, leading to a lack of generalizability. Therefore, the proposed metric (Figure 42) combines the good sides of both approaches, with low computational complexity from the rule-based approach and a short time of defining new references for comparison using the template-based approach.

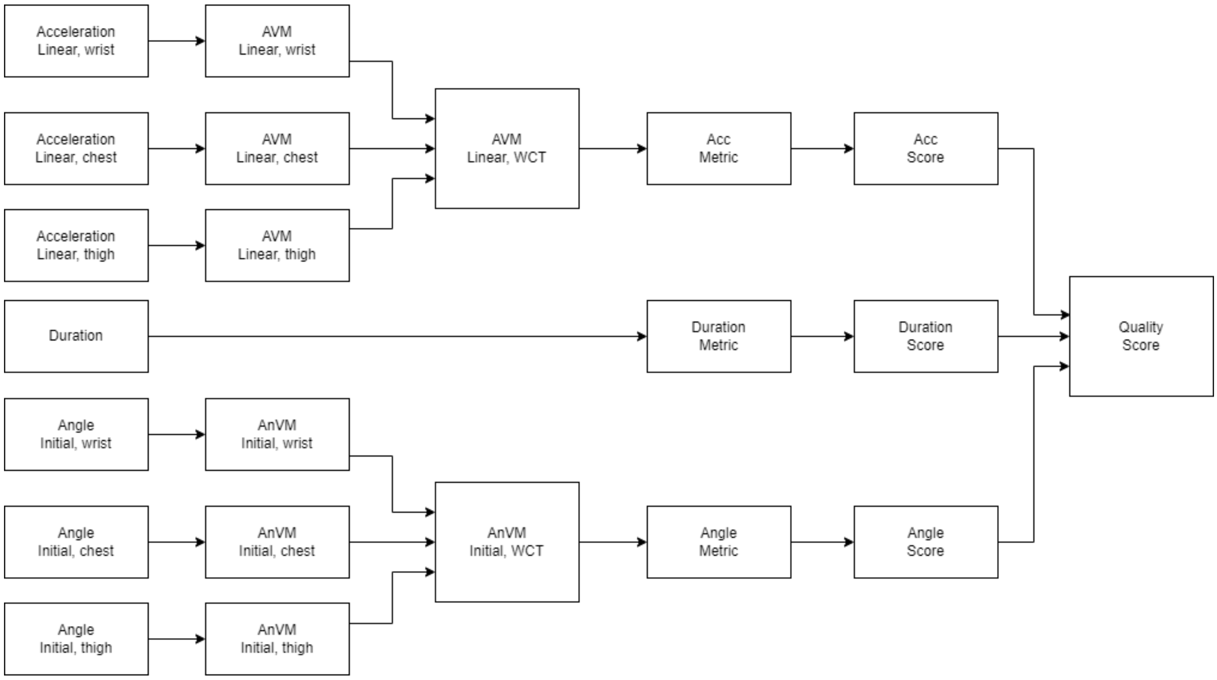


Figure 42 Flow diagram for movement execution metric

To establish the metric, linear acceleration, angular velocity, orientation, and duration from individual movement are required as input data. From most available off-shelf IMU, the output includes: sensor acceleration $\boldsymbol{a}_{sensor}$, angular velocity $\boldsymbol{\omega}_{Sensor}$ and strength of magnetic field $\boldsymbol{m}_{Sensor}$ as three-dimensional vectors, as well as orientation expressed as a four-dimensional vector in quaternions ${}_{E}^{S}\boldsymbol{q}$. ${}_{E}^{S}\boldsymbol{q}$ describes the orientation of frame Earth (E) relative to frame Sensor (S). $\boldsymbol{a}_{sensor}$ is the sum of two components, linear acceleration $\boldsymbol{a}_{Linear}$ and gravitational acceleration $\boldsymbol{g}_{Sensor}$. Thus, $\boldsymbol{a}_{Linear}$ can be expressed as [55]:

$$\boldsymbol{a}_{Linear} = \boldsymbol{a}_{Sensor} - \boldsymbol{g}_{Sensor} \tag{6}$$

The gravity vector in sensor frame $\boldsymbol{g}_{Sensor}$ is an unknown parameter, but the gravity vector in earth frame is known and expressed as:

$$\boldsymbol{g}_{Earth} = [0 \quad 0 \quad 1] \tag{7}$$

Using the orientation vector ${}_{E}^{S}\boldsymbol{q}$, or rotation matrix ${}_{E}^{S}\boldsymbol{R}$, it is possible to convert $\boldsymbol{g}_{Earth}$ in $\boldsymbol{g}_{Sensor}$ [105]:

$$\boldsymbol{g}_{Sensor} = {}^{S}_{E}\boldsymbol{R}\, \boldsymbol{g}_{Earth}$$

(8)

where rotation matrix can be represented using orientation in quaternions:

$$ {}^{S}_{E}\boldsymbol{R} = \begin{bmatrix} 2q_0^2 - 1 + 2q_1^2 & 2(q_1q_2 + q_0q_3) & 2(q_1q_3 - q_0q_2) \\ 2(q_1q_2 - q_0q_3) & 2q_0^2 - 1 + 2q_2^2 & 2(q_2q_3 + q_0q_1) \\ 2(q_1q_3 + q_0q_2) & 2(q_2q_3 - q_0q_1) & 2q_0^2 - 1 + 2q_3^2 \end{bmatrix}$$

(9)

$${}^{S}_{E}\boldsymbol{q} = [q_0 \quad q_1 \quad q_2 \quad q_3]$$

(10)

In addition to linear acceleration, an important parameter for the proposed metric is the angle ($\boldsymbol{\theta}_{Initial}$) in 3D that the IMU attached on particular body segment makes in relation to the start position, i.e. initial position. $\boldsymbol{\theta}_{Initial}$ can be obtained by integrating the angular velocity expressed in initial position frame $\boldsymbol{\omega}_{Inital}$, from the beginning ($t_{beg}$) to the end time ($t_{end}$) of movement execution:

$$\boldsymbol{\theta}_{Initial}(t) = \int_{t_{beg}}^{t_{end}} \boldsymbol{\omega}_{Initial}(t)\, dt$$

(11)

$\boldsymbol{\omega}_{Inital}$ can be obtained using the orientation vector ${}^{I}_{S}\boldsymbol{q}$ or rotation matrix ${}^{I}_{S}\boldsymbol{R}$:

$$\boldsymbol{\omega}_{Initial} = {}^{I}_{S}\boldsymbol{R}\, \boldsymbol{\omega}_{Sensor}$$

(12)

$${}^{S}_{I}\boldsymbol{q}^{*} = {}^{I}_{S}\boldsymbol{q} = [q_0 \quad -q_1 \quad -q_2 \quad -q_3]$$

(13)

$${}^{S}_{I}\boldsymbol{q} = {}^{S}_{E}\boldsymbol{q} \otimes {}^{S}_{E}\boldsymbol{q}^{*}_{Initial}$$

(14)

where ${}^{S}_{E}\boldsymbol{q}^{*}_{Initial}$ represents the conjugate of the initial orientation and indicates the moment at which the IMU is before the start of the execution of the movement of the exercise, i.e. initial position. The result of quaternion multiplication ($\otimes$) is a quaternion ${}^{S}_{I}\boldsymbol{q}$ that describes the rotation from initial orientation to the current orientation.

To obtain a one-dimensional vector and a parameter that does not depend on the orientation of the IMU placement, vector magnitude was calculated for linear acceleration (AVM_{Linear}) and angle ($AnVM_{Initial}$):

$$AVM_{Linear}[i] = \sqrt{(a_{xLinear}[i])^2 + (a_{yLinear}[i])^2 + (a_{zLinear}[i])^2} \tag{15}$$

$$AnVM_{Initial}[i] = \sqrt{(\theta_{xInitial}[i])^2 + (\theta_{yInitial}[i])^2 + (\theta_{zInitial}[i])^2} \tag{16}$$

In cases where the workout routine consists of complex exercises such as squats or push-ups, or when the whole body is activated during the workout and not just individual muscle groups or body segments, it is recommended that all three wearable devices are used for quality measurement, namely the IMU on the wrist, thigh, and chest. To ensure that the most important body segment contributes the most to the qualitative assessment, i.e. the segment that achieves the highest amplitudes, and to avoid the use of additional algorithms for measuring dominant signals, the sum of squares is calculated, and the square root of that sum is taken:

$$AVM_{LinearWCT}[i] = \sqrt{(AVM_{LinearW}[i])^2 + (AVM_{LinearC}[i])^2 + (AVM_{LinearT}[i])^2} \tag{17}$$

$$AnVM_{InitialWCT}[i] = \sqrt{(AnVM_{InitialW}[i])^2 + (AnVM_{InitialC}[i])^2 + (AnVM_{InitialT}[i])^2} \tag{18}$$

where $AVM_{LinearW}$, $AVM_{LinearC}$ and $AVM_{LinearT}$ is AVM_{Linear} from wrist, chest and thigh, respectively.

As mentioned earlier, to avoid saving the entire movement trajectory, every exercise is described by only three parameters, movement duration ($Duration_{Metric}$), and the maximum magnitude values determined by the linear acceleration (ACC_{Metric}) and angle ($Angle_{Metric}$):

$$Acc_{Metric} = \max\left(AVM_{LinearWCT}\right)$$

(19)

$$Angle_{Metric} = \max\left(AnVM_{InitialWCT}\right)$$

(20)

To put the extracted parameters into some context, i.e. to provide a score, it is necessary to compare them with some reference value. This comparison can be made with either personal or generally defined metrics:

$$Acc_{Score} = \frac{Acc_{Metric} - Acc_{MetricPersonal}}{Acc_{MetricPersonal}}$$

(21)

$$Angle_{Score} = \frac{Angle_{Metric} - Angle_{MetricPersonal}}{Angle_{MetricPersonal}}$$

(22)

$$Duration_{Score} = \frac{Duration_{Metric} - Duration_{MetricPersonal}}{Duration_{MetricPersonal}}$$

(23)

In an optimal scenario, the deviations in acceleration, angle, and time should be minimized, ideally as close to zero as possible. If we assume that the proposed three parameters represent the three dimensions of the new coordinate system, then the distance from the center of this coordinate system can be regarded as a measure of the $Quality_{Score}$:

$$Quality_{Score} = \sqrt{(Acc_{Score})^2 + (Angle_{Score})^2 + (Duration_{Score})^2}$$

(24)

In addition to qualitative analysis of human movement during strength training exercises, it is customary to provide information regarding the number of repetitions performed. To that end, a quantitative metric, i.e. $Quantity_{Score}$ is also proposed:

$$Quantity_{Score} = \frac{Rep_{Completed}}{Rep_{Assign}} * 100\%$$

(25)

where $Rep_{Completed}$ is the number of performed repetitions and Rep_{Assign} is the number of assigned repetitions by system, expert or user.

In Figure 43, an example of the application of the quality score to real data is illustrated. During the push-up exercise, it is apparent that three repetitions deviate from the others, as observed with both the newly proposed metric and the frequently utilized method of comparing trajectories using Dynamic Time Warping (DTW). Therefore, it may not be necessary to employ a computationally intensive method that compares the entire trajectory to achieve the desired outcome. Rather, the proposed metric alone may be adequate. It has also been empirically determined that the proposed metric can be used universally for all exercises (Figure 44 - Figure 51). Figure 51 also demonstrates how the proposed metric combines both quantities, $AVM_{LinearWCT}$ and $AnVM_{InitialWCT}$ in one score.

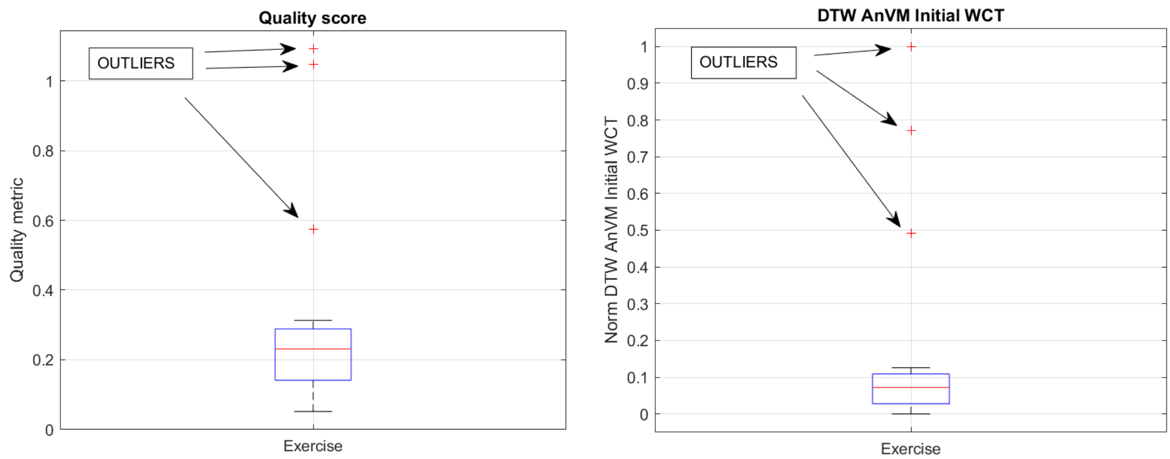


Figure 43 Metrics and repetition outliers for exercise no. 6

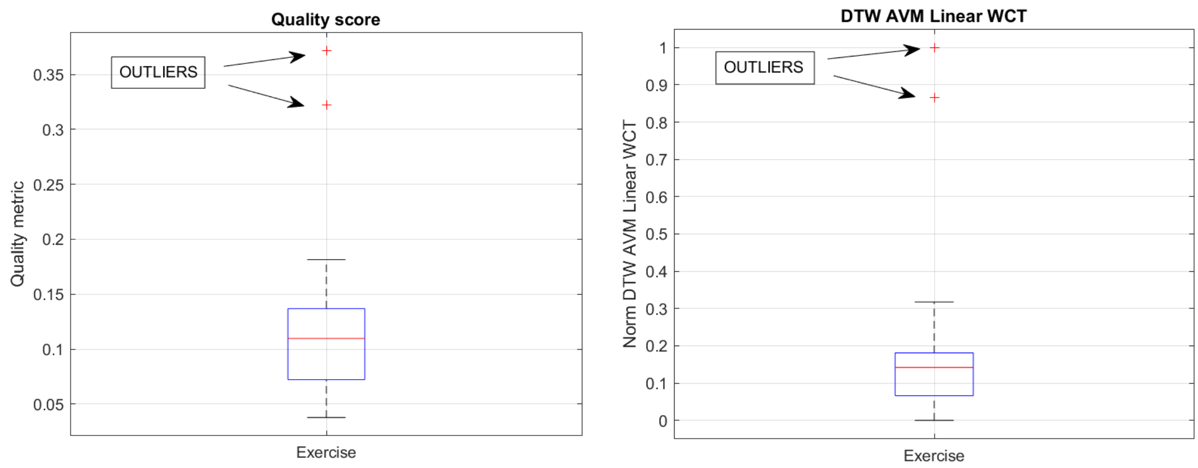


Figure 44 Metrics and repetition outliers for exercise no. 1

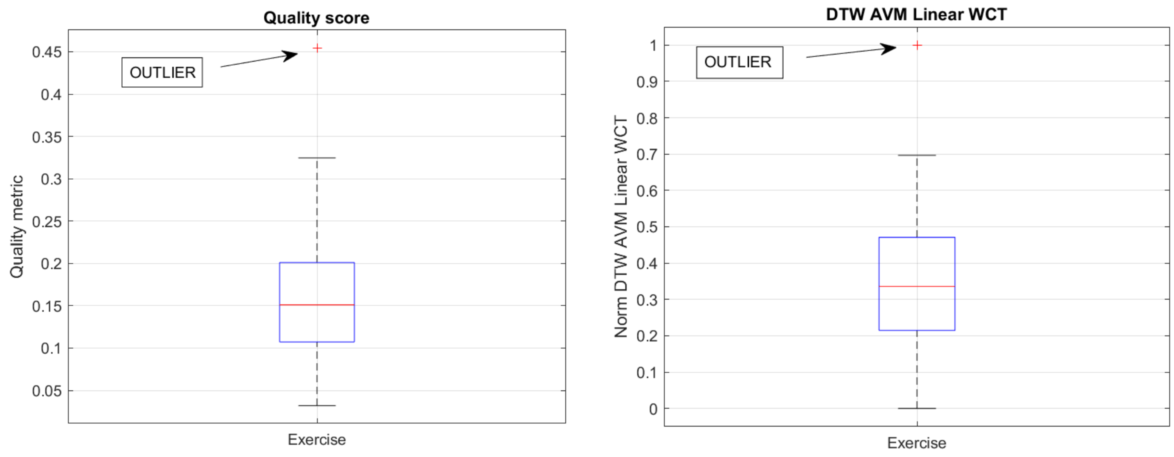


Figure 45 Metrics and repetition outliers for exercise no. 2

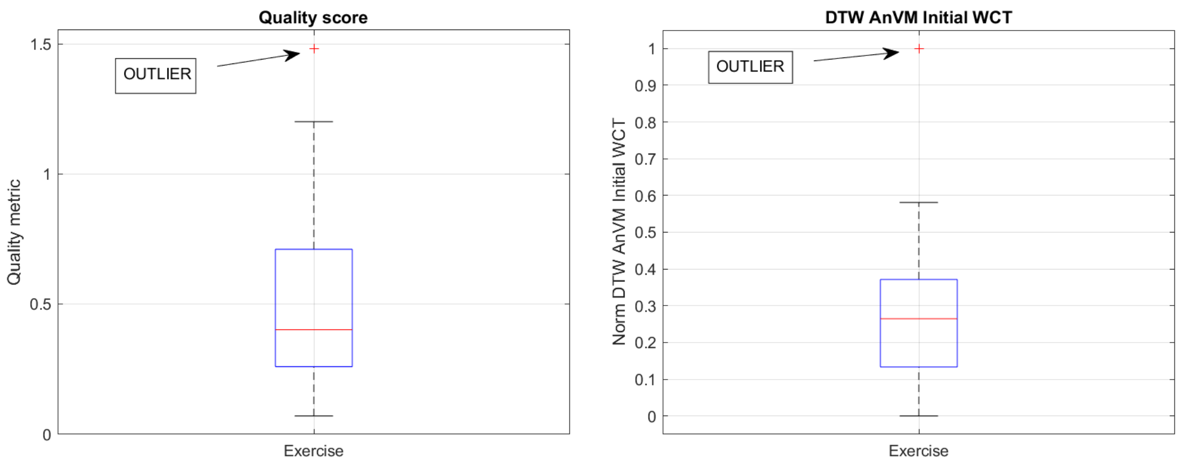


Figure 46 Metrics and repetition outliers for exercise no. 3

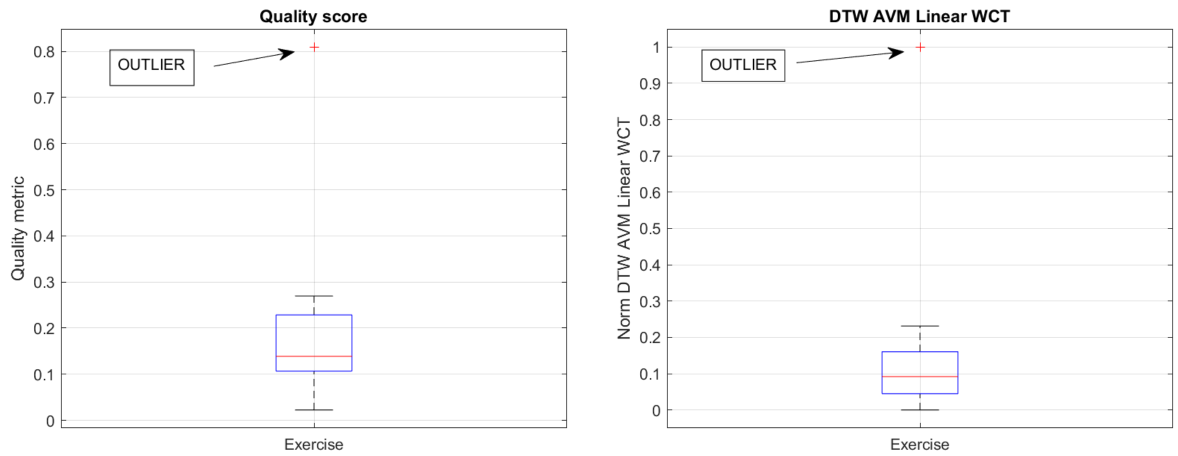


Figure 47 Metrics and repetition outliers for exercise no. 4

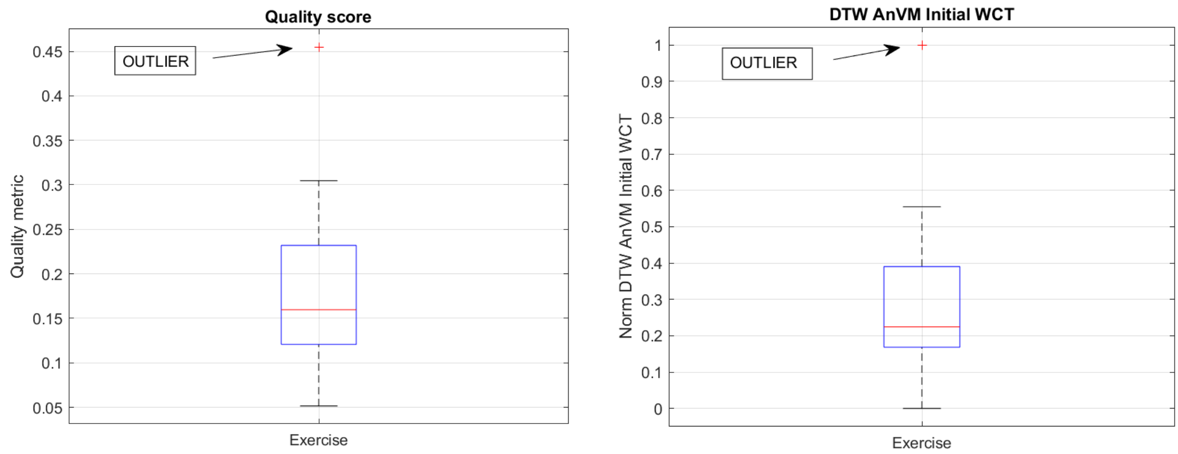


Figure 48 Metrics and repetition outliers for exercise no. 5

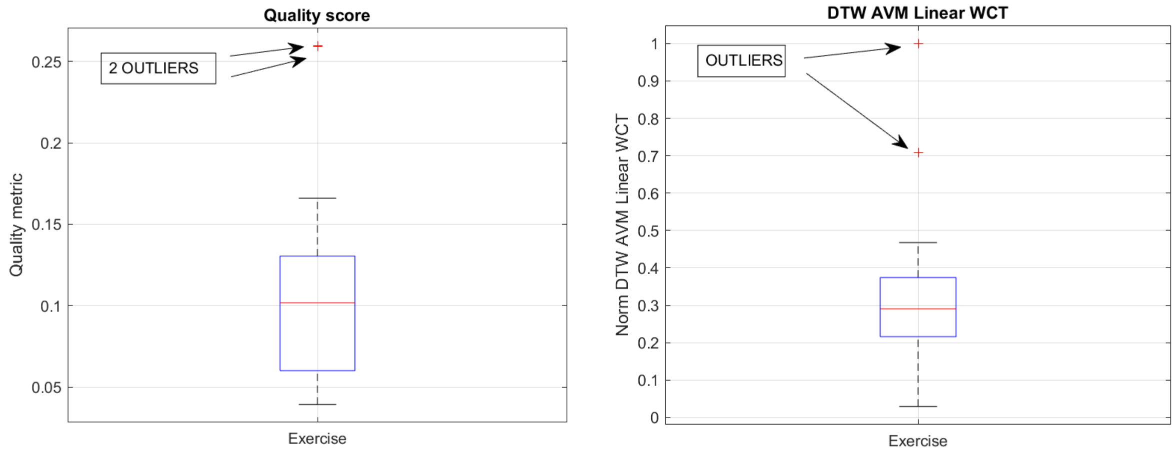


Figure 49 Metrics and repetition outliers for exercise no. 7

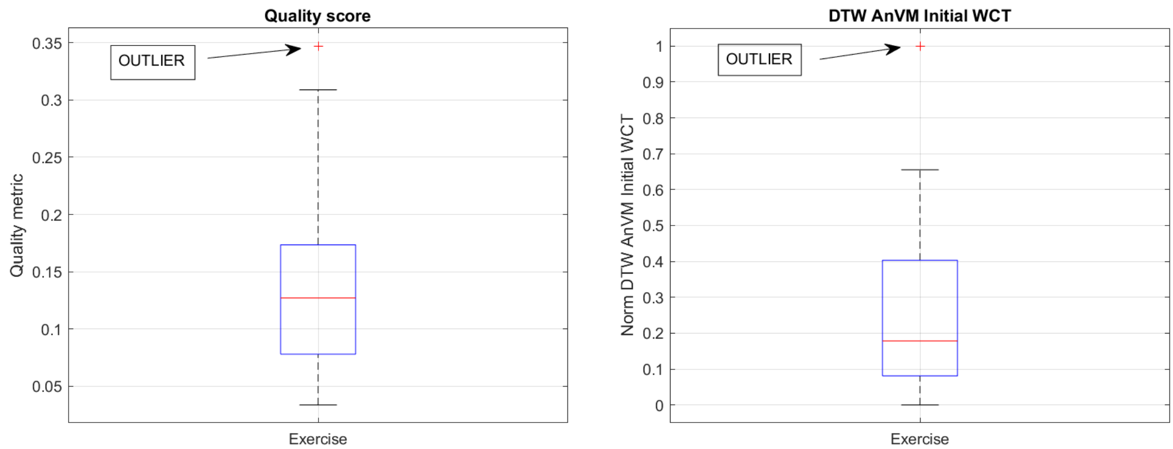


Figure 50 Metrics and repetition outliers for exercise no. 8

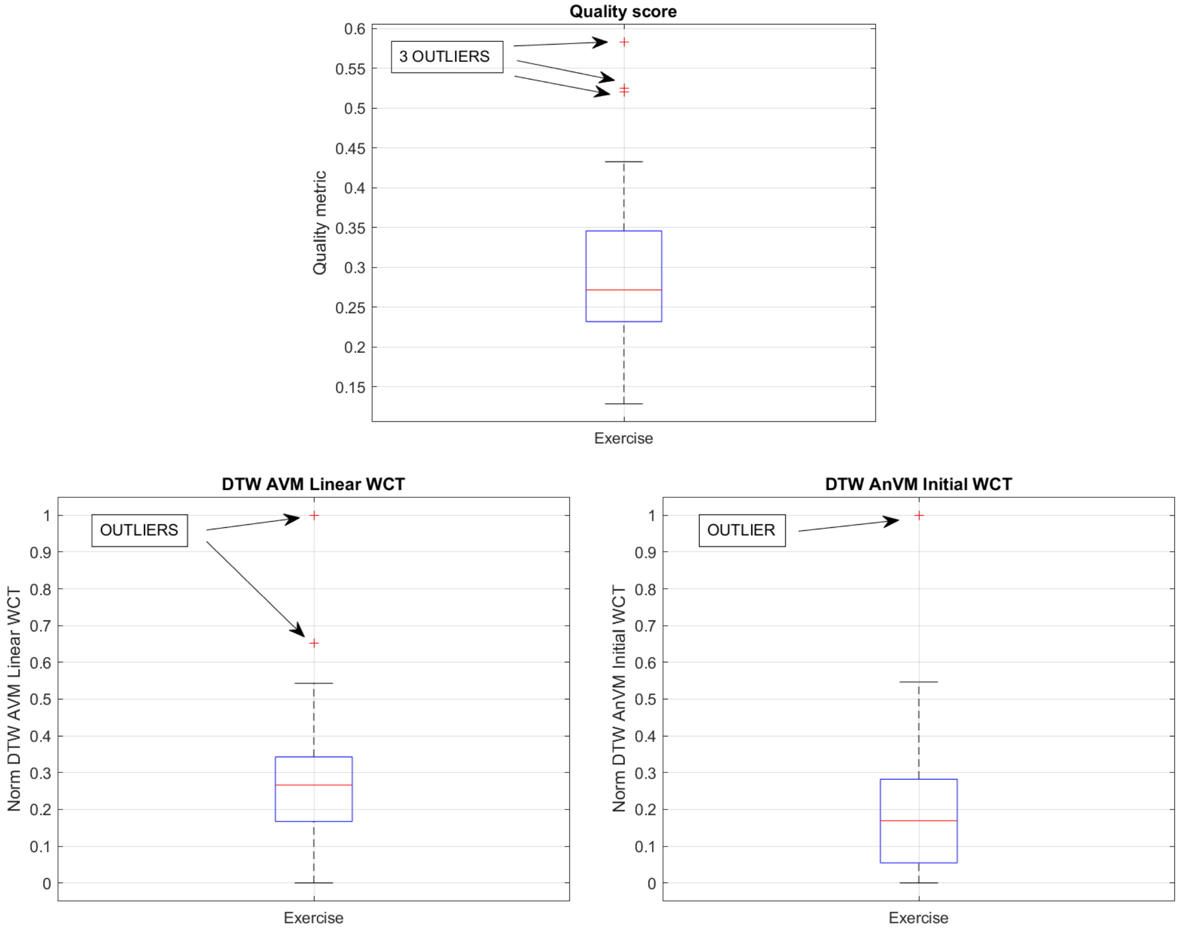


Figure 51 Metrics and repetition outliers for exercise no. 9

4.2 Discussion

Movement execution metrics during exercise can be divided into two categories, rule-based or template-based. The rule-based approach requires the identification of specific parameters, such as joint positions, angles, and speed, to define a particular movement pattern. This method is advantageous in terms of low computational complexity, but it involves a time-consuming process of determining the parameters for each movement. In contrast, the template-based approach involves recording a single movement as a reference for comparison with subsequent repetitions. While this approach offers the advantage of quicker definition times, it is limited by the need for a pre-recorded movement template and may not account for individual differences in movement patterns. To address the limitations of these approaches and achieve greater generalization, a novel approach is proposed. This method involves generating newly created quantities based on the initial orientation of the individual being assessed, which can then be compared using a new score function. This approach allows for the assessment of individual repetitions using a universal metric, independent of orientation of the IMU placement or the position of the individual.

Furthermore, the proposed metric can be applied to a larger group of individuals (Chapter 5), including those with different characteristics, and can be used with either a personal mode or a general mode template for comparison.

5 PROCEDURE FOR QUANTITATIVE AND QUALITATIVE MONITORING OF EXERCISE PERFORMANCE USING SENSOR NODES WITH INERTIAL AND MAGNETIC SENSORS AND MEASUREMENT OF HEART RATE

This chapter introduces the concept of movement quality, which refers to an individual's ability to execute fundamental movement patterns during exercise, in a controlled, efficient, and safe manner. Movement quality is determined by various factors such as muscular coordination, joint alignment, and cognitive ability to understand movement demands. It is widely acknowledged that limitations in movement quality can stem from decreased joint range of motion (ROM), muscle strength and joint stability, and neuromuscular control. It is important to note that movement quality may vary depending on an individual's age and developmental status and can also be influenced by suboptimal muscle activation sequencing and postural muscle activation [106].

The performance of strength exercise with poor technique is widely accepted to result in the development of muscular imbalances and postural deviations [107], which may lead to reduced movement quality. As poor movement quality has been demonstrated to affect joint loading, strength and power expression, and the ability to complete movement tasks effectively, it is not a desirable training outcome [108]. Conversely, performing strength exercise with optimal technique ensures maximal benefits are obtained by loading the joints of the body safely and efficiently during exercise, thus enhancing safety and limiting the likelihood of imbalances. Furthermore, individuals with higher levels of movement quality tend to benefit more from traditional training modalities than those with lower levels [109], indicating that movement quality is crucial not only for optimizing training safety but also for maximizing performance-related outcomes.

Movement quality assessment is commonly performed through visual appraisal of movement by experts in occupational, sporting, and clinical settings [110]. Although visual appraisal is useful in coaching, data-driven quantitative methods can enhance movement assessment by increasing objectivity and reducing errors associated with visual-based appraisal. Furthermore, data-driven methods can detect new and important movement features that may not be easily visible to the human eye. Movement assessment currently involves a subjective, quantitative measure where movements receive a numerical score based on visual observations by a rater. In literature, overall scores show strong intra-rater reliability for both novice and experienced raters. However, inter-rater reliability for some movements may be poor due to the dynamic nature of the movement and the rater's perspective. The rater may only see the performance from one vantage point, making it difficult to observe scoring criteria that are out of view or occluded by the athlete's body. Furthermore, the literature supports the agreement that inter-session (participants tested during two separate sessions) reliability of subjective movement assessment is inadequate. To address these limitations, the development and implementation of a framework as a data-driven substitute to objectively categorize movement quality during exercise is a potential solution [9][111][112].

5.1 Materials and Methods

The present study introduces the procedure for quantitative and qualitative monitoring of exercise performance using IMU. The procedure can be divided into three distinct modes of operation, and the selection of the mode depends on the intended application and desired feedback from the user. The first mode is the most fundamental, providing feedback to the user solely on the quantity of movement performed, specifically the number of repetitions completed (Figure 52 1). This mode is well-suited for experienced individuals engaging in independent training, where it is important to track the number of repetitions executed, regardless of the type of exercise. In contrast, another mode of operation not only provides information on the quantity of repetitions but also evaluates the quality of the movements (Figure 52 2). This mode is intended as a virtual trainer for individuals who seek additional information on their performance of a particular exercise. In the final mode of the operation, it is assumed that prior and domain knowledge of the exercise sequence is available, such as during rehabilitation. The mode can provide real-time feedback on the performance of each movement as soon as it is completed, enabling the user to make immediate adjustments to their exercise technique (Figure 52 3).

In the remaining part of the chapter, the first two modes of operation are explained in detail through experimental research, while detail information for the third can be found in one of our previous works [98]. In the remaining part of the text, we will refer to the first operating mode as the basic assessment mode, and the second as the advanced assessment mode.

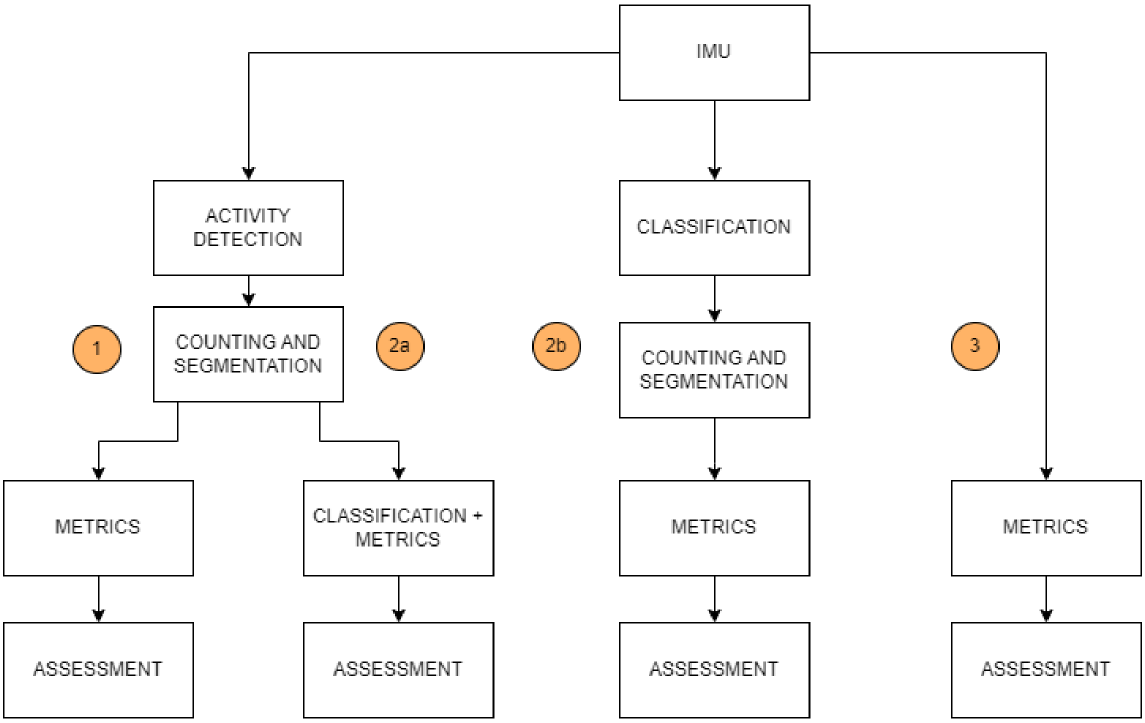


Figure 52 Proposed procedure for quantitative and qualitative monitoring of exercise performance

Furthermore, alongside the evaluation of quality and quantity utilizing IMUs, the monitoring of heart rate (HR) was conducted during exercise sessions.

5.1.1 Experimental Protocol

5.1.1.1 Participants

Forty healthy subjects aged 19 – 62 (28 males and 12 females, age: 28.7 ± 6.0 years, height: 178.7 ± 9.1 cm and weight: 82.7 ± 20.5 kg) were recruited for this research. Subjects did not have a current or recent musculoskeletal injury that would impair their exercise performance. From 40 subjects, eleven of them do not currently engage any physical activity during the week, while three of them engage in it once, six twice, eight three times, seven four times, two five times, one six times and two seven times per week. 17 subjects have no experience with gym or performing strength exercises, but the remaining 23 subjects were familiar with such a form of activity at some point in their lives. Participation was completely voluntary, and all subjects gave their informed consent for inclusion before they participated in the study. The Human Research Ethics Committee at University of Zagreb, Faculty of Electrical Engineering and Computing approved the study protocol and informed consent. Verbal explanations were also provided to each subject at the start of the experiment session in order to ensure that participants understood what was required of them.

5.1.1.2 Performed Exercises

Each subject performed a workout consisted of 9 strength exercises: 1) Standing Front Dumbbell Raise, 2) Standing Dumbbell Lateral Raise with Arms Straight, 3) Standing Side Dumbbell Shrug, 4) Standing Dumbbell Curl with Rotation, 5) Bent-over Dumbbell Row, 6) Push-up, 7) Dumbbell Step-up, 8) Box Squat and 9) Heel Touch. The exercises performed were carried out following the same procedure outlined in the subchapter 3.2.1.2.

5.1.1.3 Data Acquisition

Data acquisition was carried out following the same procedure outlined in the subchapter 3.2.1.3. Furthermore, alongside the accelerometer, gyroscope, and magnetometer sensors, HR was also measured using ECG Unit, which is available as an additional sensor on the IMU (Shimmer3 ECG) located on the chest. The recommended configuration with four electrodes positioned on the right arm (RA), left arm (LA), left leg (LL), and right leg (RL), as stated by reference [113], was employed (Figure 53). This electrode arrangement facilitates the measurement of three bipolar leads, specifically Lead I (LA-RA) as the ECG vector signal from the RA position to the LA position, Lead II (LL-RA) as the ECG vector signal from the RA position to the LL position, and Lead III (LL-LA) as the ECG vector signal from the LA position to the LL position, with RL serving as the reference electrode. The HR measurement was obtained from the most commonly used lead, Lead II, utilizing the Shimmer application ConsensysPro.

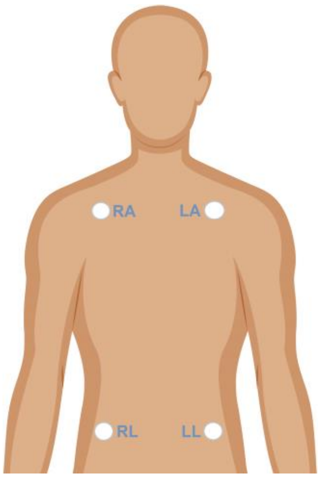


Figure 53 Positioning of the electrodes for ECG measurement

5.1.1.4 Data Labeling

Throughout the workout sessions, an expert was physically present with the subjects and utilized the Shimmer application ConsensysPro to label the beginning and end of each exercise, along with the associated sets (activity-defined windows 2.3.2.2). Individual repetitions within sets were subsequently separated and annotated manually. Moreover, the exercise expert assigned an overall assessment to the workout performance by ranking them based on a three-tiered scale, with a score of 3 representing the highest rating, 2 for middle rating, and 1 for the lowest rating.

5.1.2 Signal Preparation and Processing

The preparation and processing of signals for the accelerometer, gyroscope, and magnetometer were executed in accordance with the procedures delineated in subchapter 3.2.2. Additionally, a moving average filter was implemented to enhance the HR signal by reducing high-frequency noise and fluctuations. Furthermore, the total energy expended during movement was calculated using accelerometers placed on the wrist, chest, and thigh, representing the overall intensity of a specific physical activity. The area under the curve of the squared linear acceleration was employed to calculate accelerometer intensity.

5.1.3 Basic Assessment Mode – 1)

Figure 54 displays the flow diagram for basic assessment mode. The input of time-series IMU sensor readings passes though the activity detection section, where non-workout activities are filtered out. The subsequent stage involves the repetition counting and segmentation component, which processes the IMU sensor readings identified to contain workout activities. The metrics section then conducts a quantitative analysis of the sensor readings and generates an output assessment.

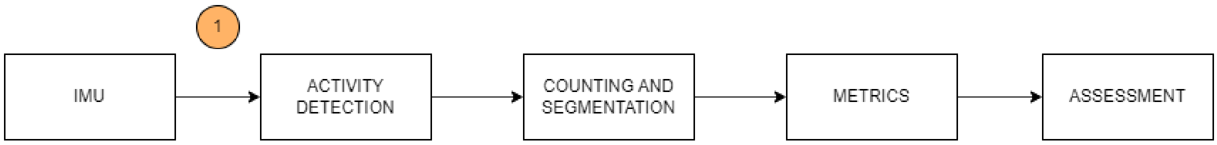


Figure 54 Flow diagram for basic assessment mode

The available data label from the event marker tool, which was utilized by the expert to mark the beginning and end of each set, was employed for activity detection. In the absence of additional marked data for activity detection, simpler algorithms well-established in the literature can be utilized [101].

The counting and segmentation process utilized a method without domain knowledge (autocorrelation based) presented in subchapter 3.2.4.1.

The output assessment is presented as a quantitative score, which is expressed using the equation (25) elucidated in subchapter 4.1.

5.1.4 Advanced Assessment Mode – 2)

Figure 55 displays the flow diagram for advanced assessment mode, which can yield the same output assessment via two distinct signal processing flows.

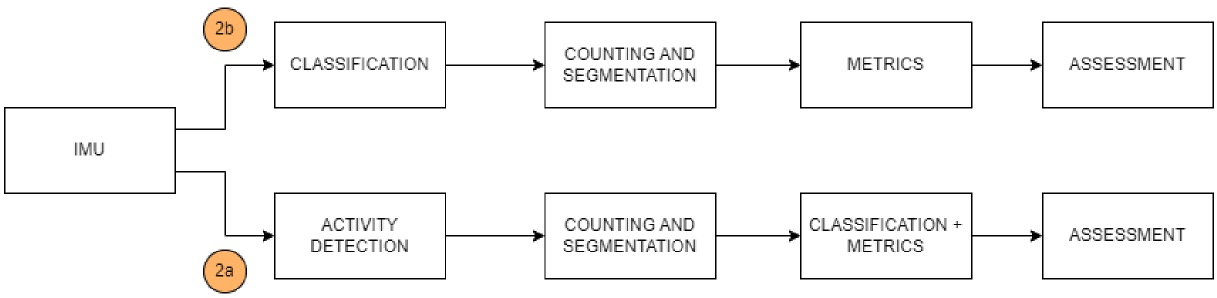


Figure 55 Flow diagram for advanced assessment mode

5.1.4.1 Advanced Assessment Mode – 2a)

The first signal processing flow shares a structure similar to that presented for the basic assessment mode 5.1.3. The primary differentiation lies in the final step, where in addition to quantitative metrics, the qualitative metrics for individual repetition need to be calculated. As the algorithm lacks prior knowledge of the particular exercise being performed, it is necessary to recognize it. The classification can be done at either a “high level”, by recognizing the entire activity window, or at a “low level”, by recognizing segmented individual movements.

For high level classification, exercise recognition is performed using two different windows technique (sliding windows and activity-defined windows), SVM algorithm, and a vector of 243 features, already detail explained in subchapter 3.2.5.

For low level classification, i.e. recognition of individual repetition, a vector of nine features, including standard deviation, variance, mode, median, range, trimmean, mean, skewness, and kurtosis, was computed for 3-axis acceleration, angular velocity, and Euler angles from IMU placed on the wrist, chest, and thigh. In addition to the 3-axis acceleration, angular velocity, and Euler angles obtained directly from the IMU output, these quantities were also computed with respect to the initial position, as explained in subchapter 4.1, and as such are independent of the orientation of the individual IMU placement. This approach ensured the overall vector of 567 features. The combinations of these features with different IMU locations were tested using various machine learning algorithms. To reduce the number of features entering the machine learning algorithm without compromising the accuracy, Maximum Relevance Minimum Redundancy (MRMR) characteristic features were selected and tested. Validation was performed using 5-fold cross-validation, and the test was conducted at a ratio of 70/30.

Following the repetition classification stage, the output assessment is presented as a qualitative and quantitative score. This score is calculated using the equation (24) and (25) described in subchapter 4.1.

5.1.4.2 Advanced Assessment Mode – 2b)

In the second signal processing flow, the input of time-series IMU sensor readings first pass through the classification section, where workout activities are recognized as exercises being performed, and non-workout activities are filtered out. Classification is performed using a sliding windows technique with 50% overlapping and window length 4s, SVM algorithm, and a vector of 243 features, already detail explained in subchapter 3.2.5.

After classification, repetitions counting and segmentation can be performed using either the method with or without domain knowledge. The metrics section then conducts a quantitative analysis using equation (25) and a qualitative analysis using equation (24) and generates an output assessment.

5.2 Results

5.2.1 Counting and Segmentation

The process of counting and segmentation was accomplished through a method without domain knowledge, solely utilizing input data from an accelerometer (*AVM*). Difference between the observed number of repetition counts and the number of detected movement counts were quantified by an error count. The impact of the number and placement of nodes on the accuracy of the proposed approach was evaluated through experimentation with one (Figure 56), two (Figure 57), and three (Figure 58) IMUs.

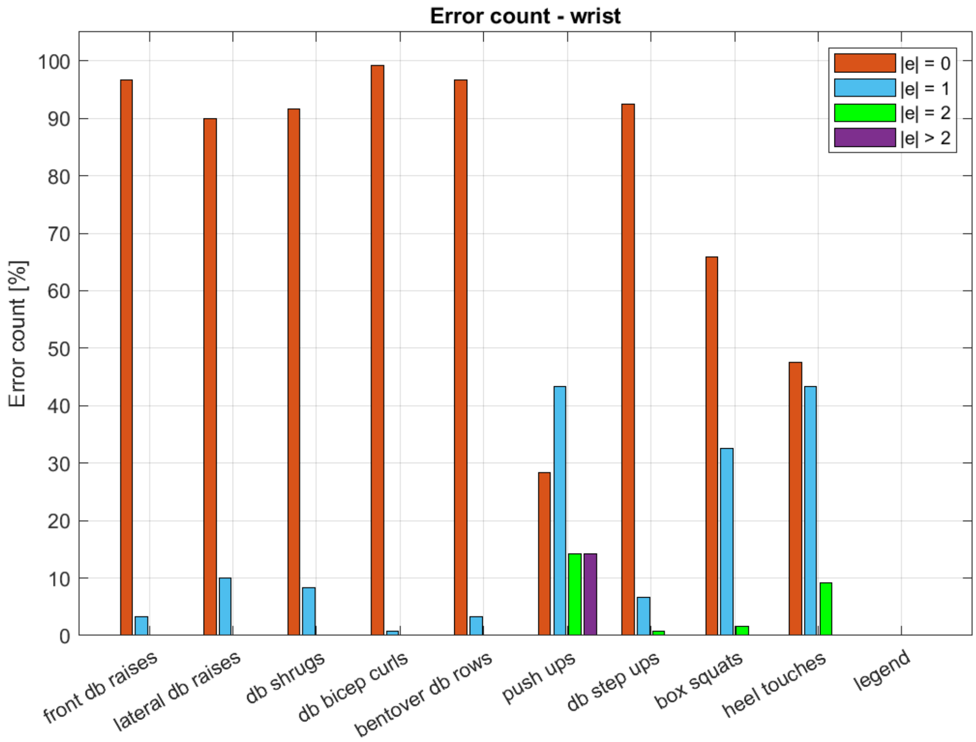


Figure 56 Repetition counting performance with 1 IMU. Position – wrist

The utilization of an IMU placed on the wrist resulted in an overall repetition counting performance of 78.70% for all exercises. The inclusion of the possibility of a single error within the set increases the performance to 95.56%. However, accuracy is notably diminished during the execution of push ups, box squats, and heel touches. Excluding these three exercises, the accuracy without any errors increases to 94.44%, or 99.86% when accounting for the possibility of a single error within the set.

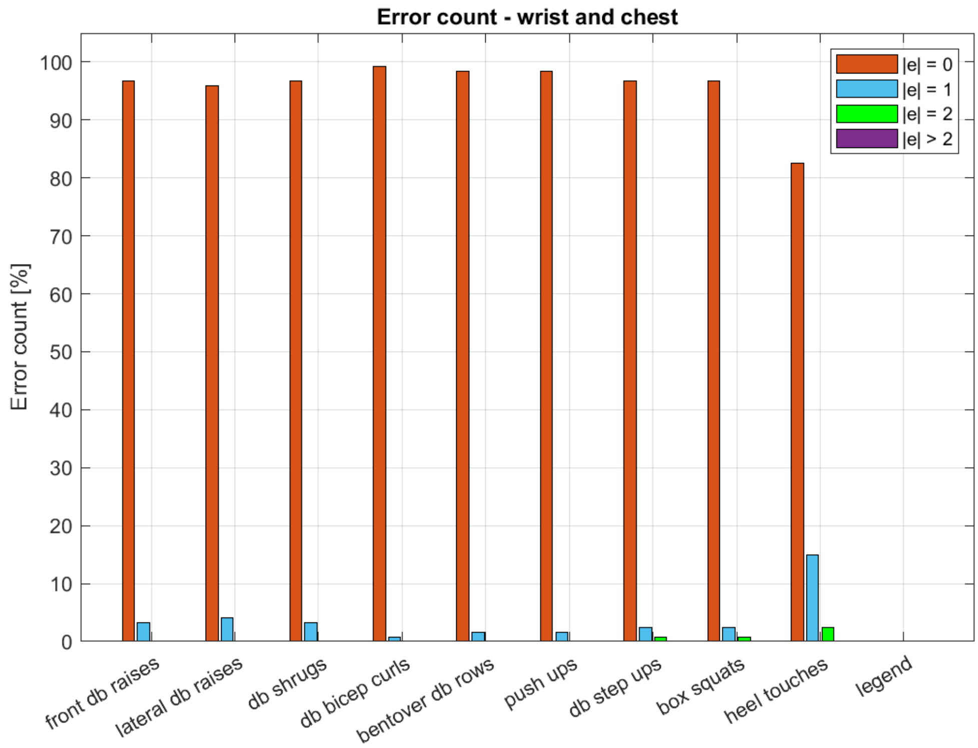


Figure 57 Repetition counting performance with 2 different IMUs. Position – wrist and chest

The integration of IMUs on both the wrist and chest yielded an overall repetition counting performance of 95% for all exercises. When accounting for the possibility of a single error within the set, the performance increases to 99.54%. Notably, the exercise without a single error accuracy below 95.85% was heel touches, while the accuracy for the remaining exercises exceeded this threshold.

Employing three IMUs, placed on the wrist, chest, and thigh, resulted in a modest improvement in repetition counting performance. Without any errors, the performance increased to 95.65%. The inclusion of the possibility of a single error within the set resulted in a performance of 99.54%.

The results of segmentation are in a correlation with repetition counting performance, as explicated in the previous subchapter 3.2.4.1.

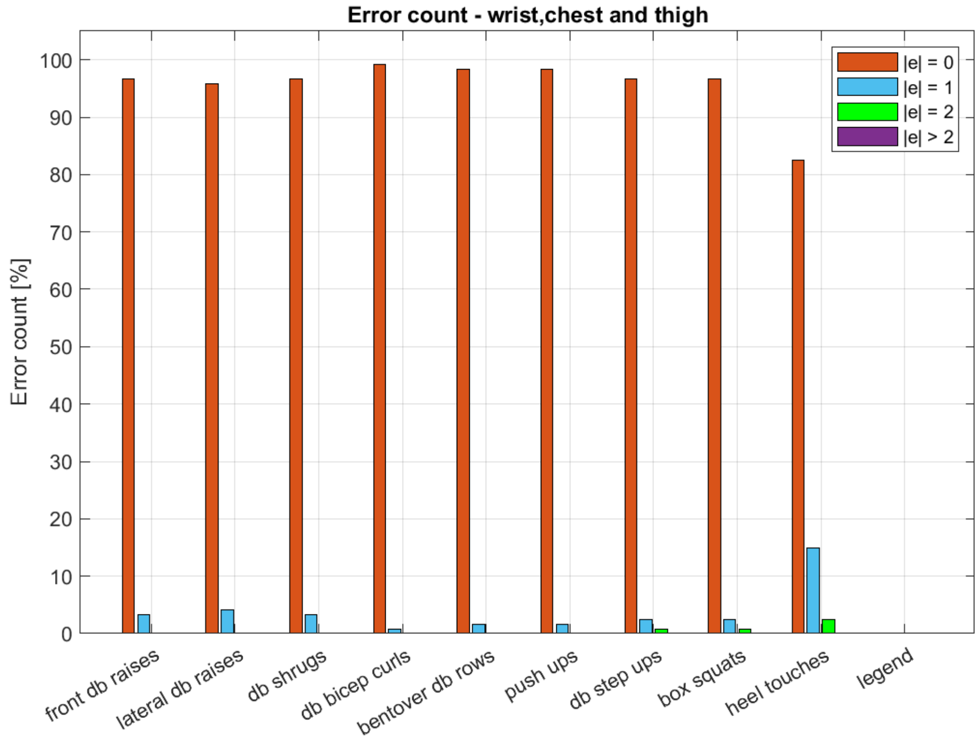


Figure 58 Repetition counting performance with 3 different IMUs. Position – wrist, chest and thigh

5.2.2 Classification – Exercise Recognition

Depending on the chosen procedure for monitoring and evaluating human movements, three distinct approaches to exercise recognition can be identified.

The first approach entails the application of a low-pass filter to the IMU data obtained during the workout, which must subsequently be segmented into labeled time intervals to enable further signal processing. Activities performed during the workout are classified into ten distinct categories utilizing a support vector machine (SVM) and a sliding window technique with a window length of 4 seconds and a 50% overlap. These categories include: 0 - other, 1 - Standing Front Dumbbell Raise, 2 - Standing Dumbbell Lateral Raise with Arms Straight, 3 - Standing Side Dumbbell Shrug, 4 - Standing Dumbbell Curl with Rotation, 5 - Bent-over Dumbbell Row, 6 - Push-up, 7 - Dumbbell Step-up, 8 - Box Squat, and 9 - Heel Touch. The overall results are presented in Table 7 (with the label All Activity – AA), and more detail results in Figure 59 and Figure 60. Results indicate that there is no notable difference, approximately 1%, in utilizing one or three IMUs, or solely utilizing input data from the accelerometer.

Table 7 Comparison of overall 5-fold cross validation test accuracy for different combination of input data and IMUs. AA – All Activity (pause between sets included), AD – Activity Detection (pause between sets excluded), ADW – Activity Defined Window

Input Data	Wrist, w=4s (AA)	W+C+T, w=4s (AA)	Wrist, w=4s (AD)	W+C+T, w=4s (AD)	Wrist, ADW (AD)	W+C+T, ADW (AD)
Acceleration Angular velocity Euler angles	Acc = 95.9%	Acc = 96.1%	Acc=99.4%	Acc=99.4%	Acc =98.6%	Acc = 99.7%
Acceleration	Acc = 94.7%	Acc = 95.3%	Acc=98.0%	Acc=99.2%	Acc = 97.3%	Acc = 99.4%

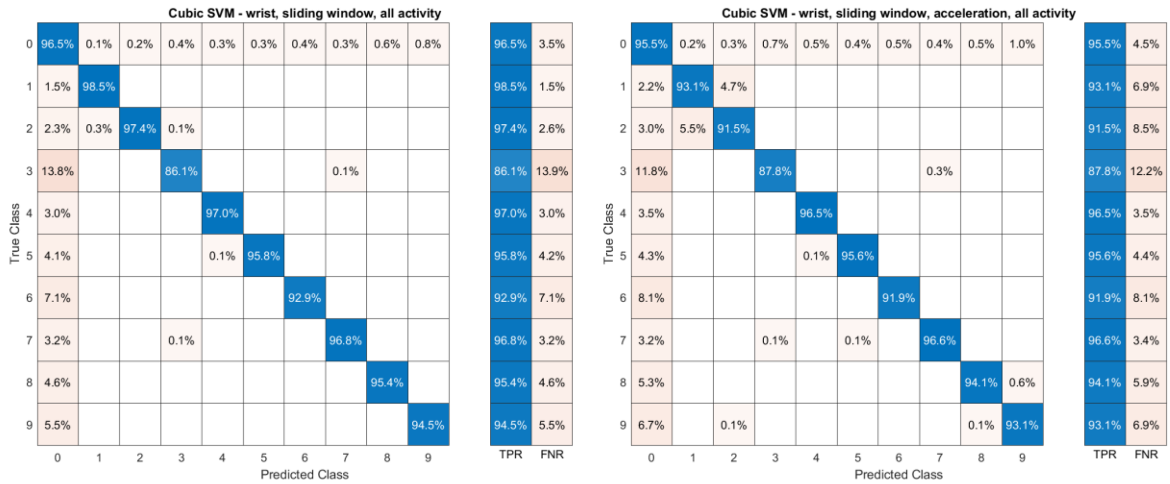


Figure 59 Activity classification with SVM, sliding window 4s with 50% overlapping (AA). IMU position – wrist. Input data – acceleration, angular velocity, Euler angles (left); acceleration (right)

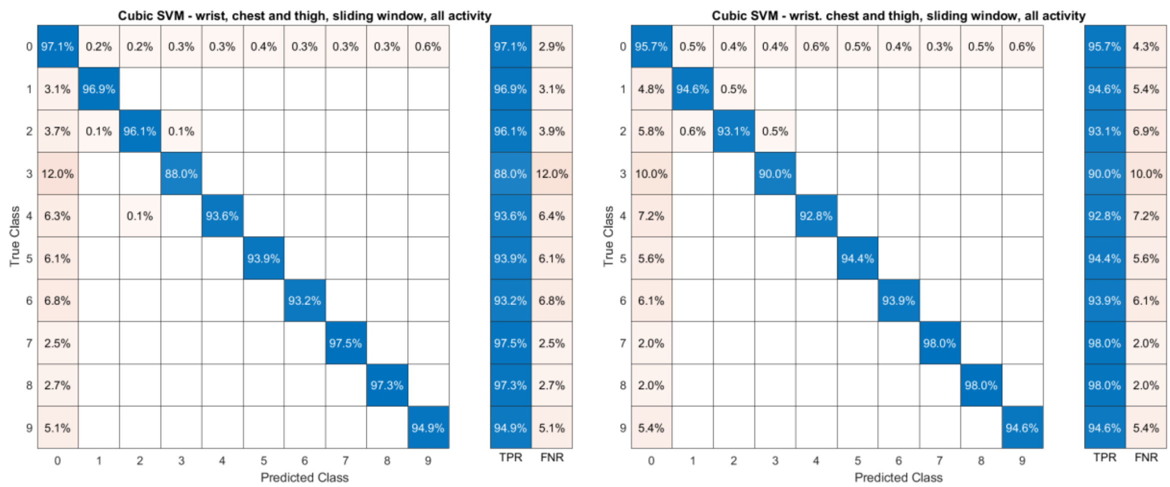


Figure 60 Activity classification with SVM, sliding window 4s with 50% overlapping (AA). IMU position – wrist, chest and thigh. Input data – acceleration, angular velocity, Euler angles (left); acceleration (right)

The second approach assumes that the segmentation of activities and non-activities has been performed by an expert beforehand, as described in section 5.1.1.4. In this scenario, nine distinct classes are presented, excluding the "other" class. Exercise classification is executed using a SVM in combination with two different windowing techniques: sliding window (with a window length of 4 seconds and a 50% overlap) and activity-defined window. The overall results are presented in Table 7 (labeled as Activity Detection – AD), with further detailed outcomes exhibited in Figure 61, Figure 62, Figure 63 and Figure 64. Higher accuracy outcomes were achieved compared to the first approach, around 99%, but there is no significant difference between utilizing one or three IMUs, nor is there a significant difference in performance when utilizing acceleration, angular velocity, and Euler angles as input data versus solely utilizing acceleration.

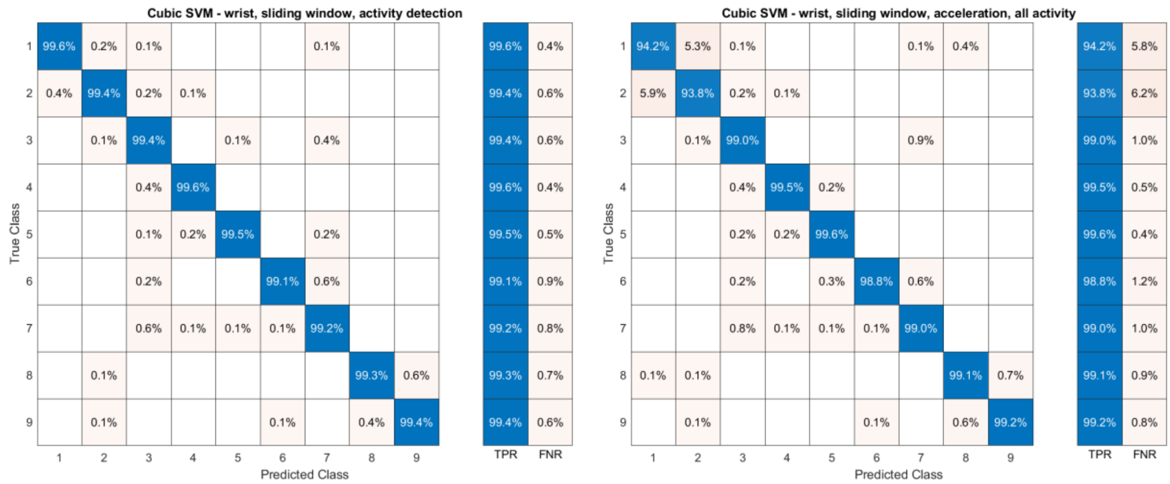


Figure 61 Exercise classification with SVM, sliding window 4s with 50% overlapping (AD). IMU position – wrist. Input data – acceleration, angular velocity, Euler angles (left); acceleration (right)

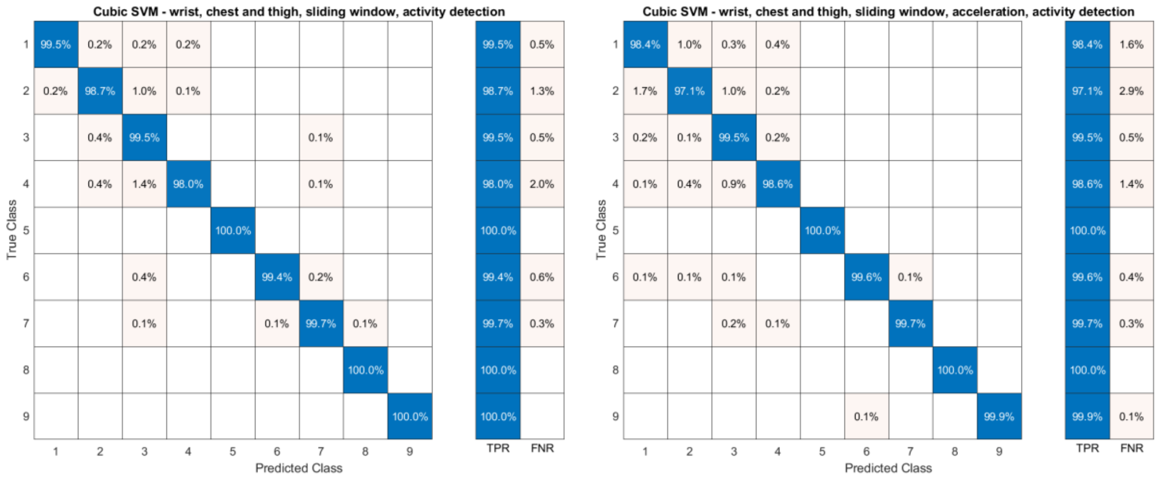


Figure 62 Exercise classification with SVM, sliding window 4s with 50% overlapping (AD). IMU position – wrist, chest and thigh. Input data – acceleration, angular velocity, Euler angles (left); acceleration(right)

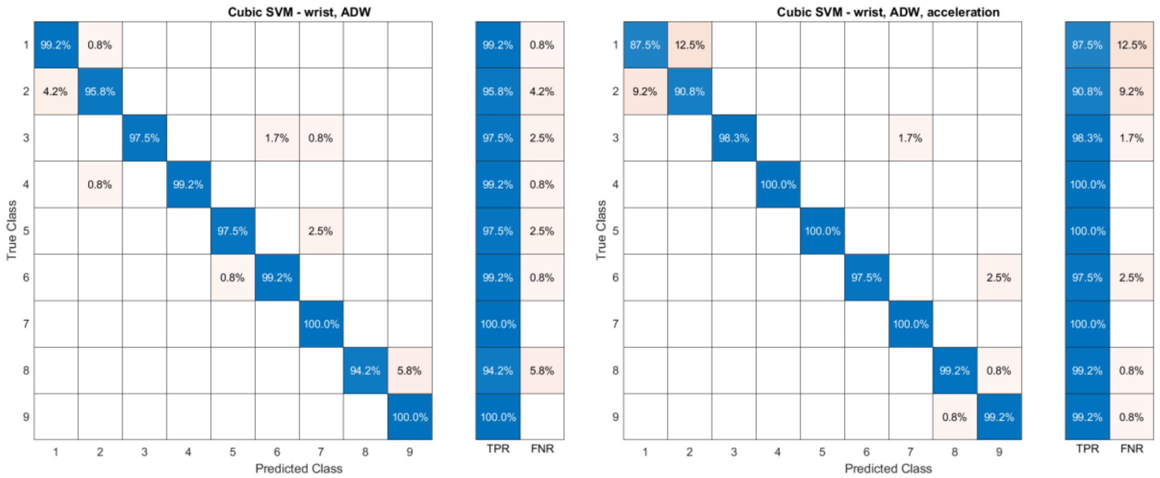


Figure 63 Exercise classification with SVM, ADW (AD). IMU position – wrist. Input data – acceleration, angular velocity, Euler angles (left); acceleration (right)

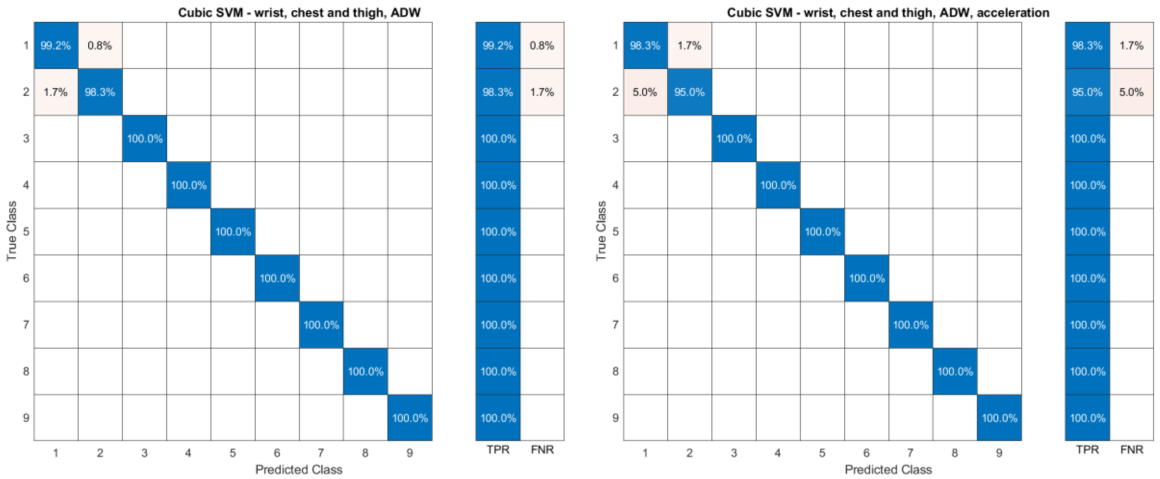


Figure 64 Exercise classification with SVM, ADW (AD). IMU position – wrist, chest and thigh. Input data – acceleration, angular velocity, Euler angles (left); acceleration (right)

The third approach assumes that individual human movements have been segmented utilizing a method without domain knowledge based on autocorrelation, as presented in subchapter 3.2.4.1. Multiple commonly utilized machine learning algorithms, such as SVM, KNN, Ensemble, and Naïve Bayes, were employed to determine the exercise to which a given movement corresponds. Additionally, to reduce the number of features that enter the machine learning algorithm the use of Maximum Relevance Minimum Redundancy (MRMR) was also explored, along with the influence of IMU position on classification accuracy (Figure 65 - Figure 71). When utilizing all features, the classification accuracy consistently exhibited a high level, nearly reaching 100%. However, as the number of features decreased, the classification accuracy also experienced a noticeable decline, except in the case of IMU position on the wrist, where accuracy remained high, around 99%. Further detailed results with the impact of reduction are provided in the Appendix section through Receiver Operating Characteristic (ROC) curves (Figure A 1 - Figure A 6). Furthermore, a list of the chosen features and their respective rankings can be found in Figure A 7 - Figure A 12.

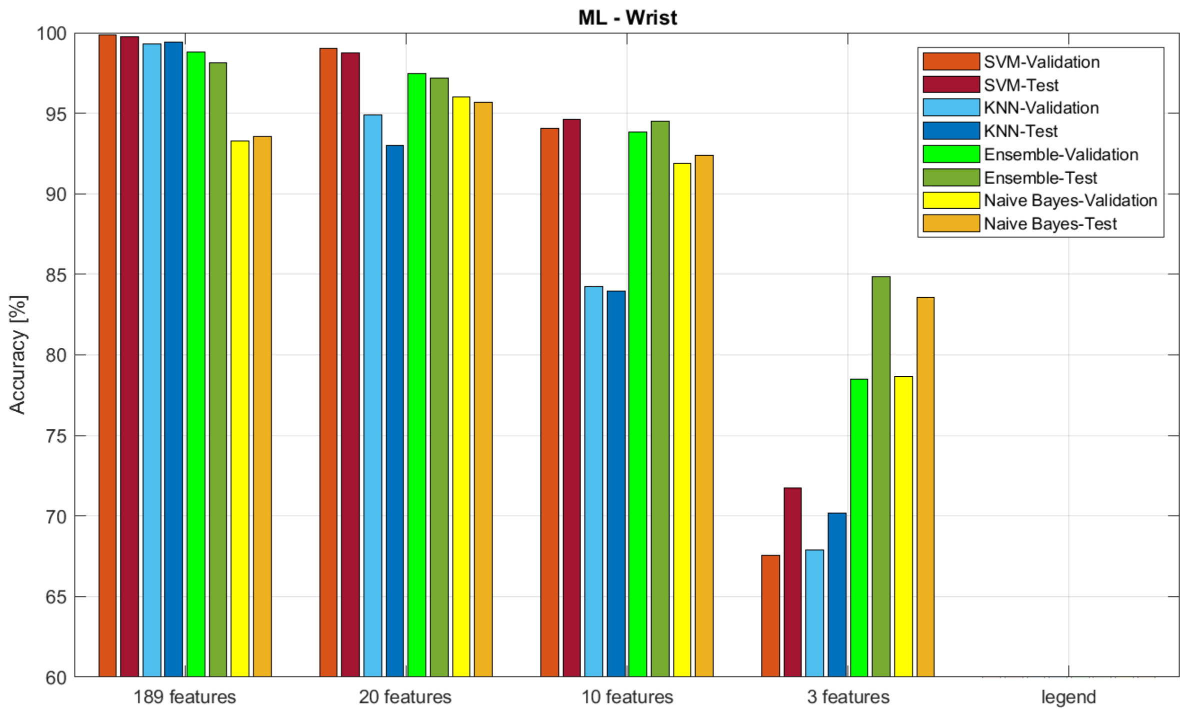


Figure 65 Score comparison for different ML model types and number of selected features. IMU position – wrist

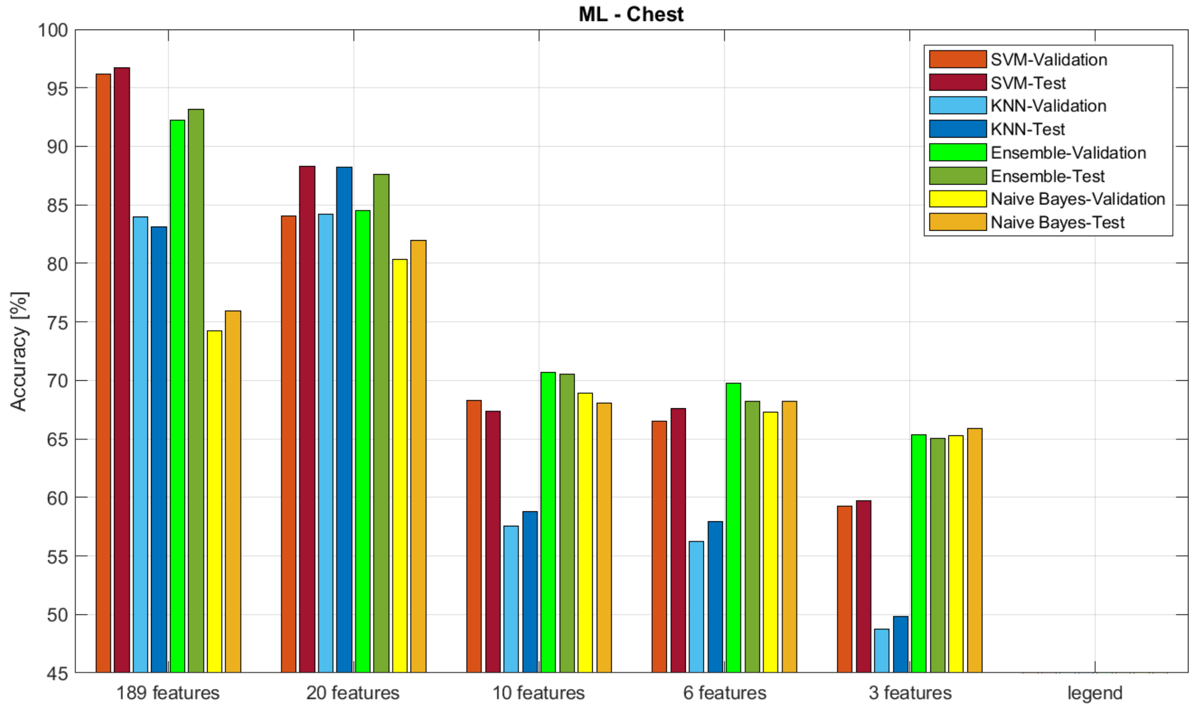


Figure 66 Score comparison for different ML model types and number of selected features. IMU position – chest

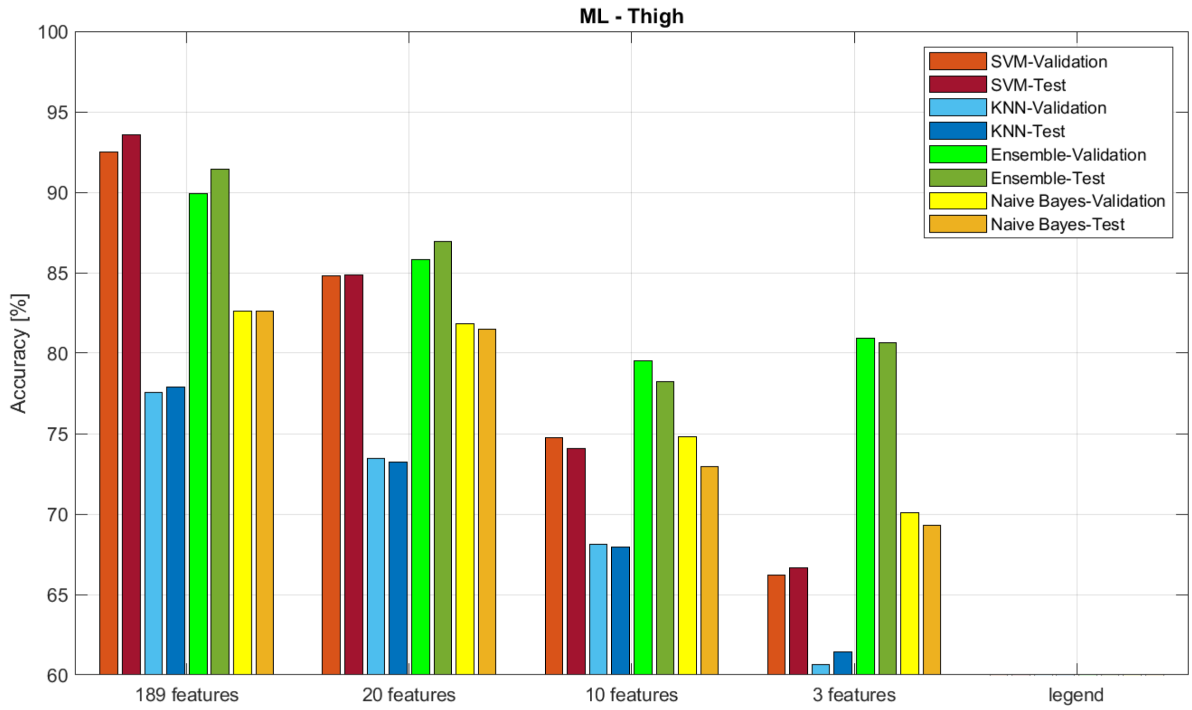


Figure 67 Score comparison for different ML model types and number of selected features. IMU position – thigh

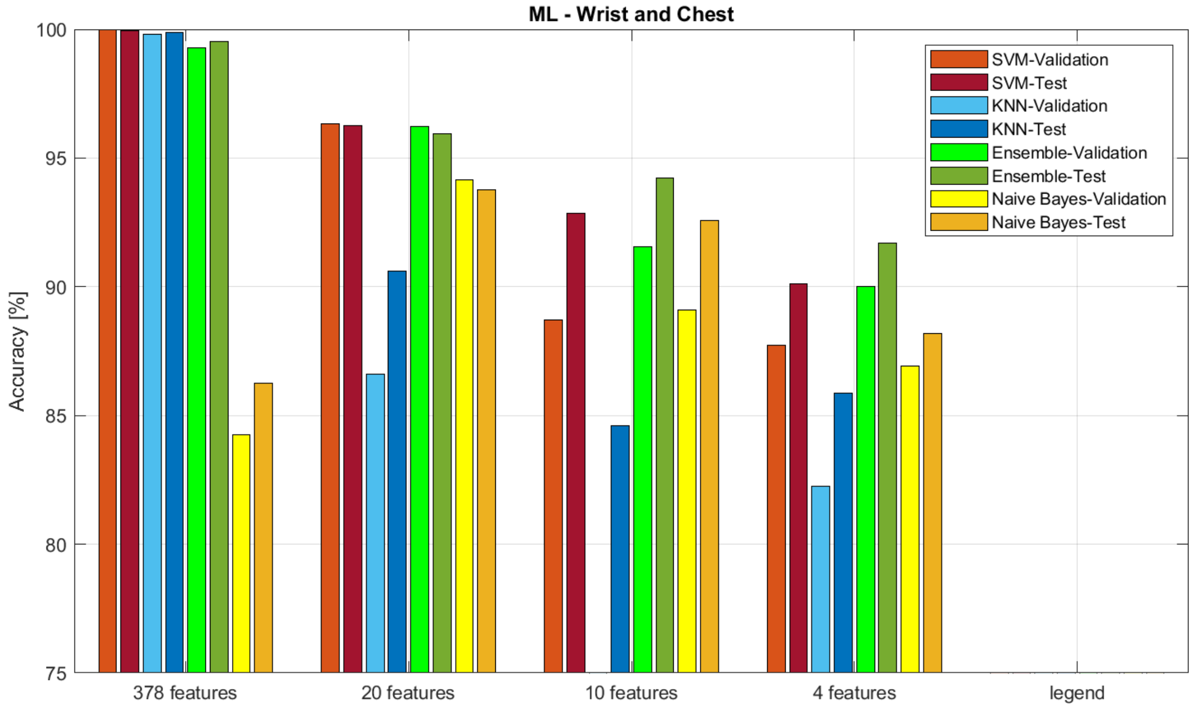


Figure 68 Score comparison for different ML model types and number of selected features. IMU position – wrist and chest

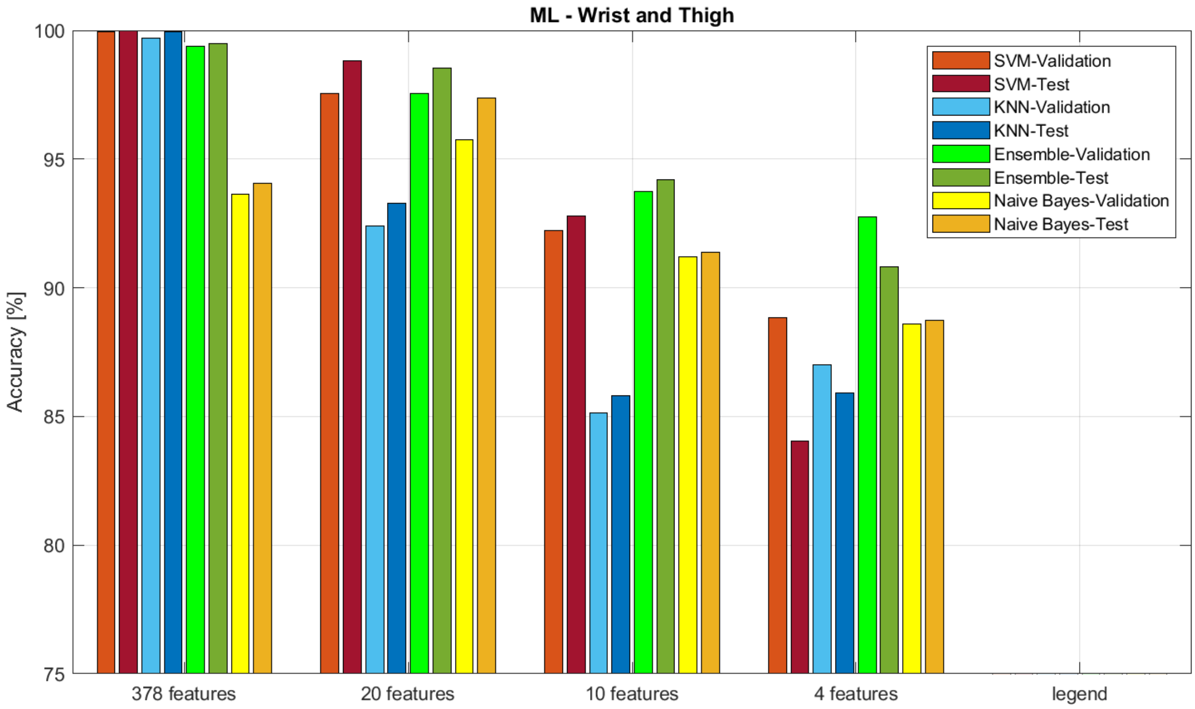


Figure 69 Score comparison for different ML model types and number of selected features. IMU position – wrist and thigh

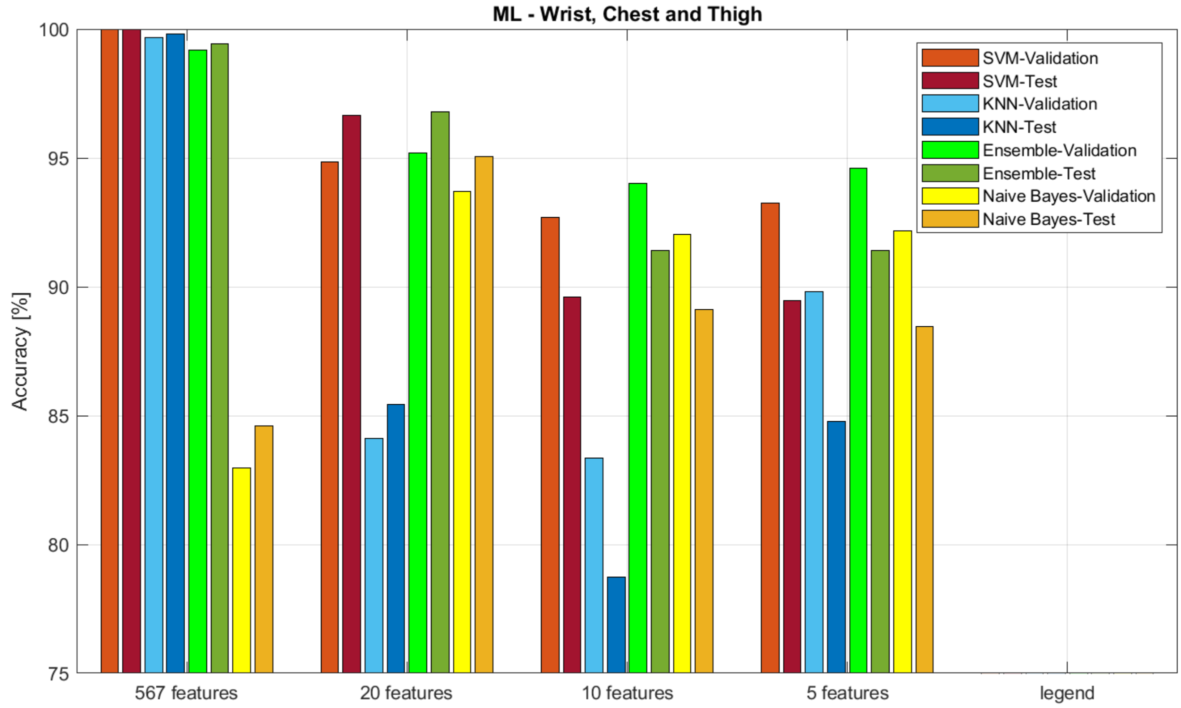


Figure 70 Score comparison for different ML model types and number of selected features. IMU position – wrist, chest and thigh

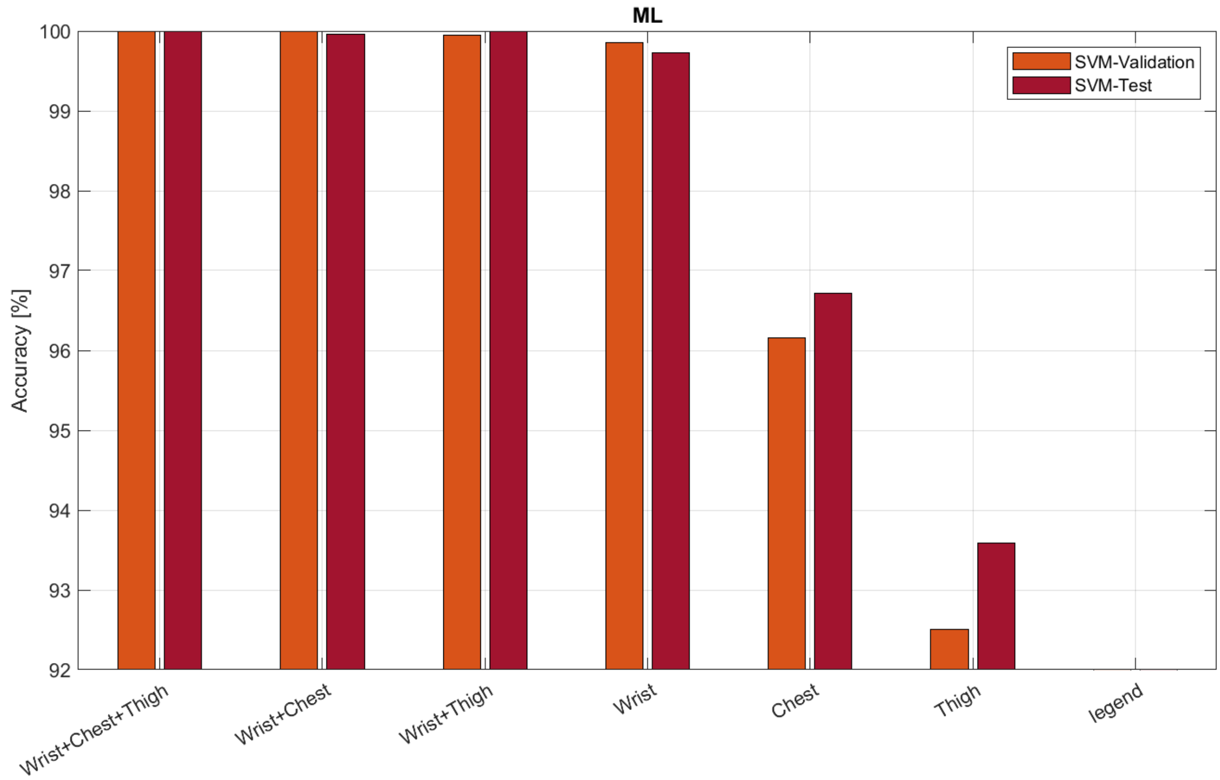


Figure 71 Score comparison for SVM and maximum features. IMU position – all combination

5.2.3 Assessment

The evaluation of workout performance is presented using either quantitative (25) or qualitative (24) metrics. In this study, a personal metric was utilized for each subject, which is further detailed in subchapter 4.1. The exercises in the workout were predominantly executed in three sets of eight repetitions each, and thus, the personal metric was calculated as the median value obtained from the eight repetitions in the initial set and then extended to the repetitions in the subsequent two sets. Poor repetitions can be easily identified as outliers, as depicted in Figure 72.

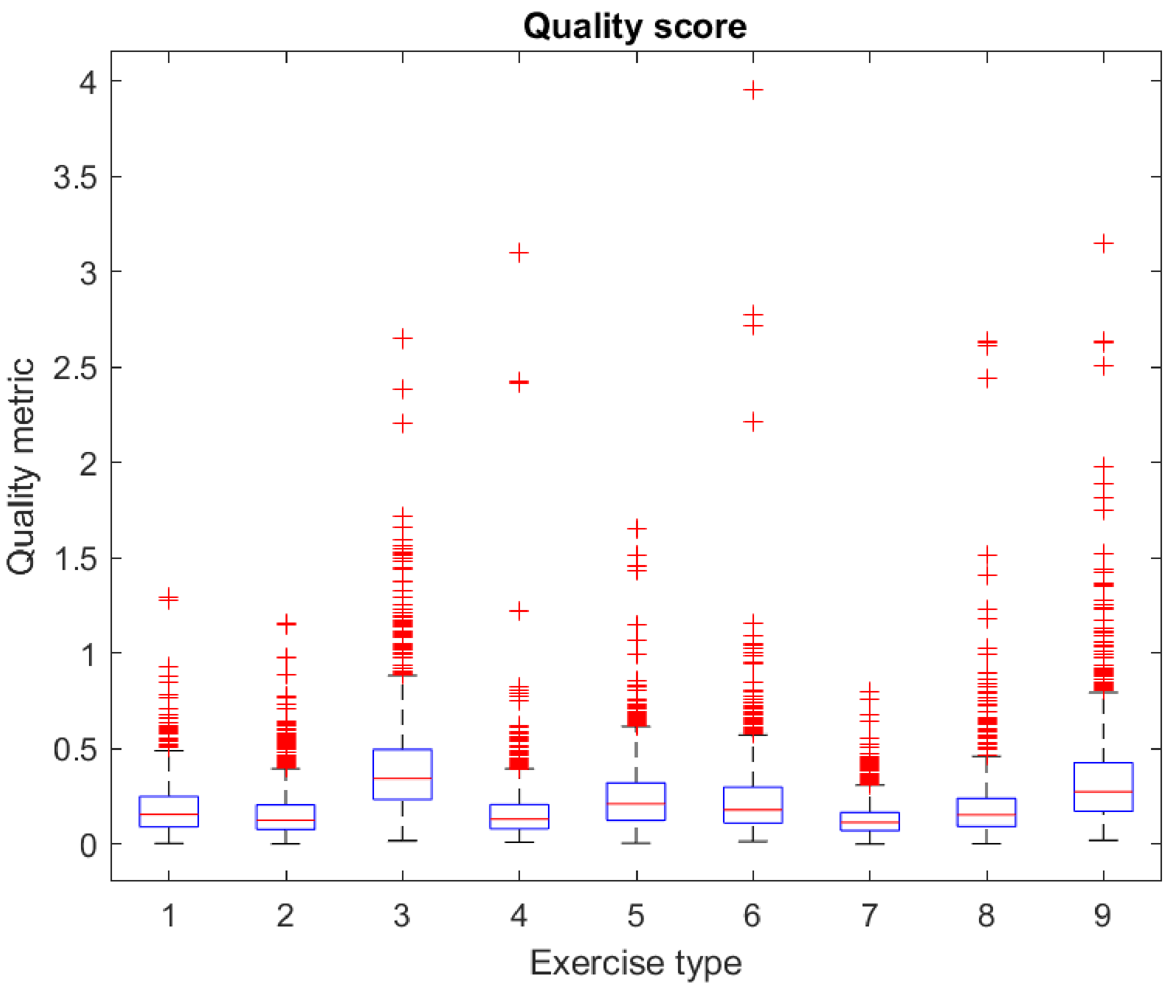


Figure 72 Quality score for all subjects and 9 exercises

Furthermore, the utilization of non-parametric statistical method exposed a pronounced discrepancy in the attained quality scores of inexperienced and experienced subjects (Table 8). The predetermined level of statistical significance was set at 5%, employing the Wilcoxon rank sum test. In the Wilcoxon rank sum test, the p-value is a measure of the strength of evidence against the null hypothesis of no difference between the two populations being compared. If the p-value is less than the predetermined level of significance, then the null hypothesis is rejected and the difference between the populations is statistically significant.

Table 8 Wilcoxon rank sum test for quality score for 9 exercises between experienced and inexperienced subjects

	Ex.1	Ex.2	Ex.3	Ex.4	Ex.5	Ex.6	Ex.7	Ex.8	Ex.9
p	0.2081	0.0383	<0.0001	0.0228	0.0204	0.0126	0.0010	<0.0001	0.3774
h	0	1	1	1	1	1	1	1	0

The performance of the algorithm was further assessed by comparison with the comprehensive evaluation conducted by the exercise expert who was physically present during the workout sessions. The evaluation was categorized into three scores, representing the highest performance rating (score 3), middle (score 2), and lowest (score 1). According to the results of the Wilcoxon rank sum test, a substantial variation was observed for most exercises in the quality scores associated with the highest rating when compared with those of the middle (Table 9) or lowest ratings (Table 10). However, no statistically significant differences were identified between the middle and lowest ratings (Table 11).

Table 9 Wilcoxon rank sum test for quality score for 9 exercises between subjects with assessment score 3 and 2 (score given by expert)

	Ex.1	Ex.2	Ex.3	Ex.4	Ex.5	Ex.6	Ex.7	Ex.8	Ex.9
p	0.0071	0.0071	0.0002	0.0406	0.6265	0.0433	0.3406	0.0220	0.0002
h	1	1	1	1	0	1	0	1	1

Table 10 Wilcoxon rank sum test for quality score for 9 exercises between subjects with assessment score 3 and 1 (score given by expert)

	Ex.1	Ex.2	Ex.3	Ex.4	Ex.5	Ex.6	Ex.7	Ex.8	Ex.9
p	0.1645	0.1226	0.0082	0.0197	0.9929	0.0099	0.0284	0.0022	0.0130
h	0	0	1	1	0	1	1	1	1

Table 11 Wilcoxon rank sum test for quality score for 9 exercises between subjects with assessment score 2 and 1 (score given by expert)

	Ex.1	Ex.2	Ex.3	Ex.4	Ex.5	Ex.6	Ex.7	Ex.8	Ex.9
p	0.1549	0.1602	0.2270	0.8050	0.5745	0.3678	0.0014	0.4504	0.2545
h	0	0	0	0	0	0	1	0	0

In addition to assessing quality and quantity through IMU sensors, heart rate (HR) monitoring was conducted during exercising. The movement and behavior of HR during exercise can be observed in the accompanying Figure 73 and Figure 74. HR parameters typically monitored during workouts, such as maximum HR (HR_{max}), HR at the beginning (HR_{beg}) and end (HR_{end}) of the workout, were compared between two groups of subjects - active and inactive (Figure 75). Using the Wilcoxon rank sum test (Table 12), it was established that there is a significant distinction in HR levels between physically active and inactive individuals for both, HR_{beg} and HR_{max}, while no significant difference was observed in the ratio $\frac{(HR_{max}-HR_{end})}{HR_{max}}$ and $\frac{(HR_{max}-HR_{beg})}{HR_{max}}$.

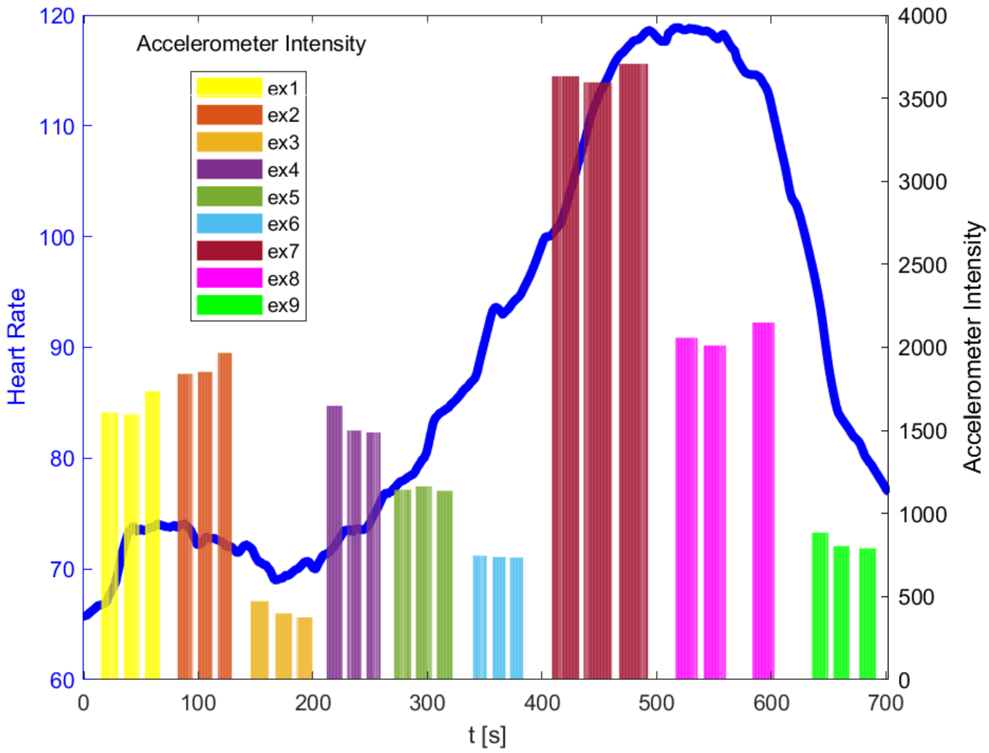


Figure 73 Heart rate during workout with accelerometer intensity for every exercise

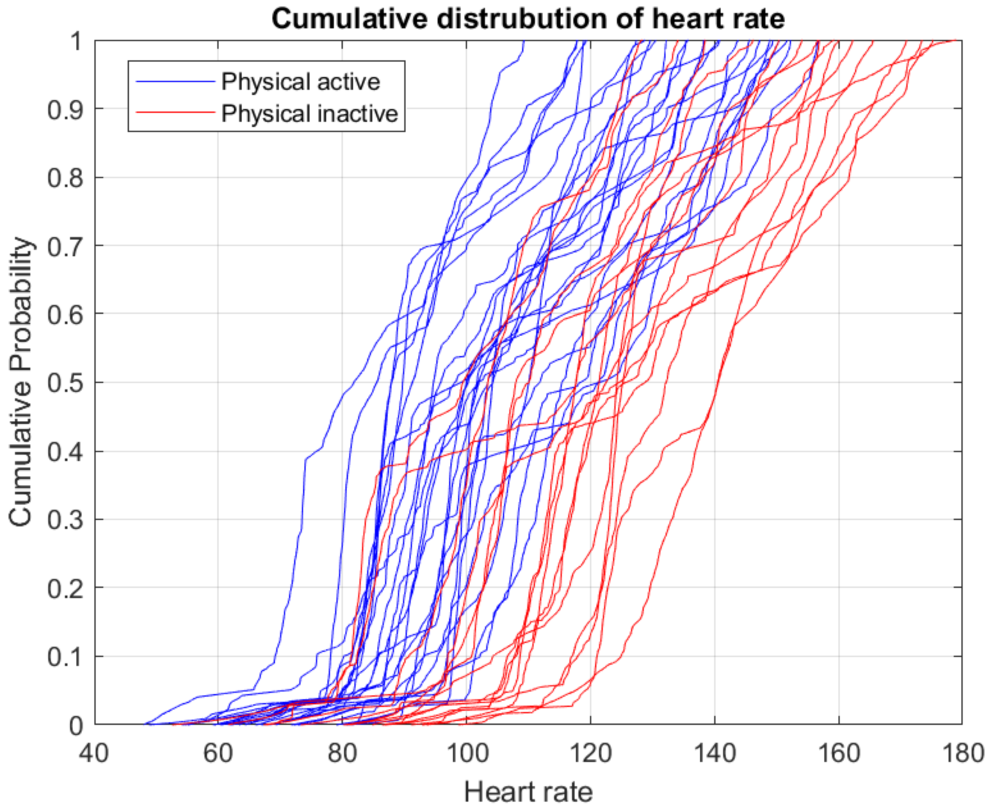


Figure 74 Cumulative distribution of heart rate for all subject

Table 12 Wilcoxon rank sum test for different heart rate parameters between physical active and inactive subjects

	HR_{beg}	HR_{max}	HR_{end}	$\frac{(HR_{max} - HR_{end})}{HR_{max}}$	$\frac{(HR_{max} - HR_{beg})}{HR_{max}}$
p	0.0002	0.0009	0.0523	0.5095	0.1178
h	1	1	0	0	0

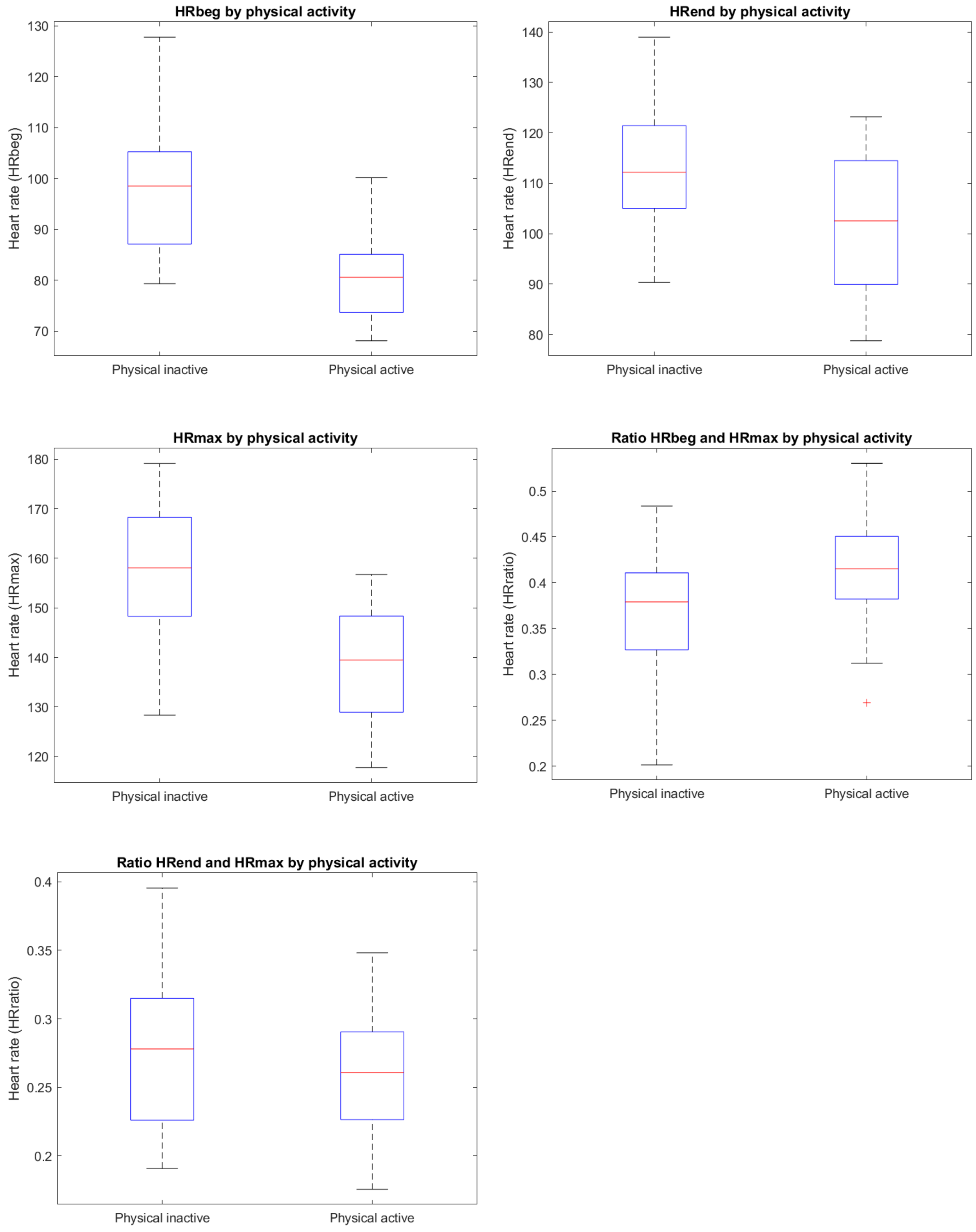


Figure 75 Heart rate differences between physical active and inactive subjects

5.3 Discussion

With the aim to develop a wearable system that would make it easier for professional expert to monitor a person who performs exercise or enable people to train independently with good form quality and motivation, it is necessary that the system has satisfactory feedback to the user [3][6][7][101][114]. In the development of a system feedback, where workout consists primarily of strength exercises, it is possible to take advantage of the fact that human movements are repetitive. The form of feedback in this case should contain two important parameters, quantitative and qualitative, i.e. the number of performed repetitions of a particular exercise and the quality of the performed repetitions [98][102]. For successful counting and assessment of repetition quality, repetition must first be detected and isolated (segmented), and then identified (classified) to which exercise it belongs [81]. Only after the segmentation and classification of repetitions has been done, it is possible to start the quality assessment [115].

The main objective of this research was to proposed detail procedure for quantitative and qualitative monitoring of exercise performance. The concepts of quantity and quality of motion are explained, and a developed algorithm that enables this is presented. The structure of the algorithm consists of: activity segmentation, repetition detection and segmentation, feature extraction, exercise recognition, and assessment. Assessment is the most interesting information for the end user, which can be observed at a lower (individual exercise) or higher (entire workout) level over time and possibly react in a timely manner to prevent poor performance and thus the possibility of injury. The number of subjects who were included in the research as volunteers was 40 (28 men and 12 women). The data was acquired in the same way and same sensors sensitivity and positions as described in Chapter 3.

During the counting of repetitions of an individual exercise using only the IMU on the wrist, a repetition performance without a single error is 78.70%, or 95.56% if the possibility of one error within the set is included. Smaller accuracy occurs with push-ups, squats and heel touches exercises, but by adding the IMU sensor on the chest, the accuracy increases to 95% without a single error, or to 99.54% if the possibility of one error within the set is included. By including the third IMU (thigh), a repetition performance increased slightly, without a single error is 95.65%, or 99.54% if the possibility of one error within the set is included.

The recognition of exercises performed was carried out using SVM classifier, employing a 4 sec sliding window with a 50% overlap. By utilizing input data from the accelerometer, gyroscope, and magnetometer of the IMU positioned on the wrist, chest, and thigh, an accuracy of 99.4% is achieved, which is comparable to using only the wrist IMU. Furthermore, using input data solely from the accelerometer resulted in accuracy of 99.2%, and 98%, respectively. The SVM classifier was also applied to windows determined based on activities, yielding higher accuracy on a larger dataset compared to Chapter 3. The obtained data are comparable with the sliding window approach. Utilizing input data from the accelerometer, gyroscope, and magnetometer of the IMU positioned on the wrist, chest, and thigh resulted in accuracies of 99.7% and 98.6% using only the wrist IMU. Moreover, using input data solely from the accelerometer resulted in accuracy of 99.4%, and 97.3%, respectively.

In addition to the recognition of the entire exercise, the classification of the segmented individual movement of each exercise was also done. Validation was done using 5-fold, and the test was done in a ratio of 70/30. Using the SVM method with IMU data from: a) the wrist - validation accuracy is 98.85% and test accuracy is 99.73%, b) for IMU combination of wrist and thigh - validation accuracy is 99.95% and test accuracy is 100%, and c) for IMUs from wrist, chest, and thigh - validation accuracy is 100% and test accuracy is 100%. To reduce the number of features that enter the machine learning algorithm without significantly affecting accuracy, using Maximum Relevance Minimum Redundancy (MRMR) characteristic features were selected and tested.

At the level of performing the entire workout, in addition to the processed data from the IMU sensors, the change in heart rate was also monitored. Although the heart rate is mostly associated with cardio exercises, it also proved to be a useful parameter when performing strength exercises and determining the rhythm of execution depending on the current physical fitness level of the individual. An uncontrolled and large increase in heart rate can put the exerciser in a situation where, due to excessive efforts, he cannot influence the quality of the movement i.e. the performed exercise. Using Wilcoxon rank sum test for different heart rate parameters the results showed that there is a significant difference between people who are physically active and inactive for the HR at the beginning of the exercise (HR_{beg}) as well as the maximum HR (HR_{max}), while there is not a significant difference in ratio between HR_{beg} and HR_{max}, or HR_{end} and HR_{max}.

The metric proposed in Chapter 4 was applied to all subjects. Using Wilcoxon rank sum test results showed that there is a significant difference in achieved score between experienced and inexperienced subjects. Also, the achieved results of the algorithm were compared with the overall assessment of the performance of the expert who was with the subjects during the workout session. The Wilcoxon rank sum test results indicated a significant difference for most exercises between the highest performance rating (score 3) and the middle (score 2) or lowest rating (score 1). Conversely, no statistically significant differences were observed between the middle and lowest ratings.

6 CONCLUSIONS

Wearable devices equipped with inertial and magnetic sensors are increasingly being employed for the monitoring and assessment of physical activity. The affordability, accuracy, and portability of such devices enable real-time monitoring of human movement during exercise, without requiring direct supervision by a trained professional. Furthermore, the data collected by these devices can be analyzed over time, providing valuable insights into an individual's patterns of physical activity and progress. The advent of such technology has the potential to revolutionize the field of physical activity monitoring and assessment and may play a crucial role in promoting health and well-being.

The use of wearable devices especially for monitoring and assessment during strength exercises involves several key steps. Firstly, the wearable devices must be properly positioned on the body of the individual performing the exercises, in order to obtain accurate and reliable data. Next, the signals from the sensors are processed to detect and separate the individual repetitions of the exercise (segmentation), as well as to recognize which exercise is being performed based on the sensor data (classification). Once the repetitions have been segmented and classified, quantitative information such as the number of repetitions performed can be obtained. In addition to obtaining quantitative data, there is often a need to analyze the quality of each individual repetition. This can be achieved by calculating various parameters such as linear acceleration, angle, and duration, which describe the movement trajectory. Finally, the qualitative and quantitative information is combined to generate an overall assessment of the exercise performance, which can be used to monitor progress and identify areas for improvement.

This doctoral thesis presents a comprehensive procedure for quantitative and qualitative monitoring of exercise performance using wearable sensor nodes with inertial and magnetic sensors, along with a measurement method for assessing human movement variability during exercise and movement execution metrics. The procedure was developed to achieve high accuracy in tracking movement while maintaining low cost and energy autonomy of the monitoring system. Validation of the procedure, method, and metrics was first done in controlled conditions and on a reduced number of subjects, followed by validation in real conditions on a larger scale of subjects.

The proposed method for measuring the variability of human movement during strength exercises was developed to detect, count, and segment repetitive movements without domain knowledge of the exercise being performed. The method was tested on a smaller group of subjects using one, two, or three IMUs (chapter 3). The results demonstrated that for workouts that include whole body activation and a wider range of exercises, an accuracy of approximately 99% in exercise recognition can be achieved using only accelerometer data from the IMU located on the wrist. However, for accurate repetition counting and segmentation, a minimum of two IMUs, one on the wrist and one on the chest, is needed. When only IMU on the wrist was used, the largest errors in repetition counting and segmentation were observed in exercises such as push-ups, squats, and heel touches.

Chapter 5 of the thesis present research conducted on a larger group of subjects using sensor nodes equipped with inertial and magnetic sensors, alongside heart rate measurements. The study aims to design a procedure for monitoring exercise performance through the selection of significant features from the obtained data and testing various machine learning algorithms with different IMU locations. Results indicate that the support vector machine algorithm has the most favorable characteristics for the given conditions. Furthermore, in addition to detecting incorrect repetitions during strength training exercises, the newly developed movement execution metric is also capable of distinguishing between experienced and inexperienced subjects. The proposed metric enables the generation of an overall performance assessment utilizing data from all three IMUs, located on the wrist, chest, and thigh.

6.1 Limitations and future work

Several limitations have been identified at the conclusion of this research work that warrant attention in future research.

Firstly, a more extensive dataset encompassing a wider range of subjects would enhance variability and allow for a more comprehensive analysis. This should include individuals with current or recent musculoskeletal injuries that may impede their exercise performance.

Moreover, it would be valuable to validate the assumptions stated in this research across diverse environments and real-world scenarios. Rigorous testing under such conditions would provide further insights and enhance the applicability of the findings.

Regarding quality assessment, a more detailed annotation process is essential, encompassing individual movements rather than providing a general rating for specific exercises. This would facilitate a thorough examination of metrics and algorithms, potentially enabling the recognition of multiple classes rather than solely distinguishing between experienced and inexperienced subjects.

In terms of heart rate analysis, additional information beyond measurements taken during the workout session is required. It would be advantageous to gather data on resting heart rate, commonly known as baseline heart rate, as well as the time required for the heart rate to return to baseline after exercise.

Furthermore, it is recommended to conduct a more comprehensive assessment of the subjects' fitness and activity levels prior to their participation in the research. This can be accomplished by employing adapted questionnaires or, preferably, integrating specific activity monitoring techniques to gather precise and accurate data.

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APPENDIX

Table A 1 Repetition detection performance metrics for 6 subjects using autocorrelation method, IMU position – wrist

Exercise	Method	Position	Sensitivity	Precision	F-score
Front db. raises	Autocor	Wrist	1.0000	1.0000	1.0000
Lateral db. raises	Autocor	Wrist	1.0000	1.0000	1.0000
Db. shrugs	Autocor	Wrist	0.9722	1.0000	0.9859
Db. bicep curls	Autocor	Wrist	1.0000	0.9931	0.9965
Bentover db. rows	Autocor	Wrist	1.0000	0.9931	0.9965
Push ups	Autocor	Wrist	0.7639	0.9910	0.8627
Db. step ups	Autocor	Wrist	1.0000	0.9114	0.9536
Box squats	Autocor	Wrist	1.0000	0.9730	0.9863
Heel touches	Autocor	Wrist	0.9236	0.9852	0.9534

Table A 2 Repetition detection performance metrics for 6 subjects using modified autocorrelation method, IMU position – wrist

Exercise	Method	Position	Sensitivity	Precision	F-score
Front db. raises	M Autocor	Wrist	1.0000	1.0000	1.0000
Lateral db. raises	M Autocor	Wrist	1.0000	1.0000	1.0000
Db. shrugs	M Autocor	Wrist	1.0000	1.0000	1.0000
Db. bicep curls	M Autocor	Wrist	1.0000	1.0000	1.0000
Bentover db. rows	M Autocor	Wrist	1.0000	0.9931	0.9965
Push ups	M Autocor	Wrist	0.8056	1.0000	0.8923
Db. step ups	M Autocor	Wrist	1.0000	1.0000	1.0000
Box squats	M Autocor	Wrist	1.0000	0.9730	0.9863
Heel touches	M Autocor	Wrist	0.9444	0.9927	0.9680

Table A 3 Repetition detection performance metrics for 6 subjects using energy method with raw AVM, IMU position – wrist

Exercise	Method	Position	Sensitivity	Precision	F-score
Front db. raises	Raw AVM	Wrist	0.9861	0.9861	0.9861
Lateral db. raises	Raw AVM	Wrist	0.9861	1.0000	0.9930
Db. shrugs	Raw AVM	Wrist	0.9028	1.0000	0.9489
Db. bicep curls	Raw AVM	Wrist	0.9792	0.9463	0.9625
Bentover db. rows	Raw AVM	Wrist	0.9653	1.0000	0.9823
Push ups	Raw AVM	Wrist	0.8750	0.9265	0.9000
Db. step ups	Raw AVM	Wrist	0.9861	1.0000	0.9930
Box squats	Raw AVM	Wrist	0.9028	0.9924	0.9455
Heel touches	Raw AVM	Wrist	0.8264	0.9917	0.9015

Table A 4 Repetition detection performance metrics for 6 subjects using energy method with linear AVM, IMU position – wrist

Exercise	Method	Position	Sensitivity	Precision	F-score
Front db. raises	Lin AVM	Wrist	0.9861	0.9861	0.9861
Lateral db. raises	Lin AVM	Wrist	0.9931	0.9795	0.9862
Db. shrugs	Lin AVM	Wrist	0.8889	1.0000	0.9412
Db. bicep curls	Lin AVM	Wrist	0.9931	0.9470	0.9695
Bentover db. rows	Lin AVM	Wrist	0.9722	1.0000	0.9859
Push ups	Lin AVM	Wrist	0.8611	0.9612	0.9084
Db. step ups	Lin AVM	Wrist	0.9861	1.0000	0.9930
Box squats	Lin AVM	Wrist	0.8750	0.9921	0.9299
Heel touches	Lin AVM	Wrist	0.7986	0.9664	0.8745

Table A 5 Repetition detection performance metrics for 6 subjects using energy method with AVVM. IMU position – wrist

Exercise	Method	Position	Sensitivity	Precision	F-score
Front db. raises	AVVM	Wrist	1.0000	0.9931	0.9965
Lateral db. raises	AVVM	Wrist	0.9792	1.0000	0.9895
Db. shrugs	AVVM	Wrist	0.7708	0.9823	0.8638
Db. bicep curls	AVVM	Wrist	0.9861	0.9404	0.9627
Bentover db. rows	AVVM	Wrist	0.9444	0.9927	0.9680
Push ups	AVVM	Wrist	0.9931	1.0000	0.9965
Db. step ups	AVVM	Wrist	0.8264	1.0000	0.9049
Box squats	AVVM	Wrist	0.8611	0.9841	0.9185
Heel touches	AVVM	Wrist	0.8264	0.9917	0.9015

Table A 6 Repetition detection performance metrics for 6 subjects using autocorrelation method, IMU position – chest

Exercise	Method	Position	Sensitivity	Precision	F-score
Front db. raises	Autocor	Chest	0.9861	1.0000	0.9930
Lateral db. raises	Autocor	Chest	0.9444	1.0000	0.9714
Db. shrugs	Autocor	Chest	0.8958	1.0000	0.9451
Db. bicep curls	Autocor	Chest	0.9097	0.9357	0.9225
Bentover db. rows	Autocor	Chest	0.8750	0.9618	0.9164
Push ups	Autocor	Chest	1.0000	1.0000	1.0000
Db. step ups	Autocor	Chest	0.9792	0.9038	0.9400
Box squats	Autocor	Chest	1.0000	1.0000	1.0000
Heel touches	Autocor	Chest	0.9931	0.9108	0.9502

Table A 7 Repetition detection performance metrics for 6 subjects using modified autocorrelation method, IMU position – chest

Exercise	Method	Position	Sensitivity	Precision	F-score
Front db. raises	M Autocor	Chest	0.9583	1.0000	0.9787
Lateral db. raises	M Autocor	Chest	0.9931	1.0000	0.9965
Db. shrugs	M Autocor	Chest	0.9861	1.0000	0.9930
Db. bicep curls	M Autocor	Chest	0.9444	0.9927	0.9680
Bentover db. rows	M Autocor	Chest	0.9792	0.9930	0.9860
Push ups	M Autocor	Chest	1.0000	1.0000	1.0000
Db. step ups	M Autocor	Chest	0.9792	1.0000	0.9895
Box squats	M Autocor	Chest	1.0000	1.0000	1.0000
Heel touches	M Autocor	Chest	0.9653	1.0000	0.9823

Table A 8 Repetition detection performance metrics for 6 subjects using autocorrelation method, IMU position – thigh

Exercise	Method	Position	Sensitivity	Precision	F-score
Front db. raises	Autocor	Thigh	0.9444	0.9577	0.9510
Lateral db. raises	Autocor	Thigh	0.7847	0.8496	0.8159
Db. shrugs	Autocor	Thigh	0.7569	0.8258	0.7899
Db. bicep curls	Autocor	Thigh	0.8750	0.8129	0.8428
Bentover db. rows	Autocor	Thigh	0.8264	0.9225	0.8718
Push ups	Autocor	Thigh	1.0000	1.0000	1.0000
Db. step ups	Autocor	Thigh	0.9653	1.0000	0.9823
Box squats	Autocor	Thigh	1.0000	0.9730	0.9863
Heel touches	Autocor	Thigh	0.9167	0.9103	0.9135

Table A 9 Repetition detection performance metrics for 6 subjects using modified autocorrelation method, IMU position – thigh

Exercise	Method	Position	Sensitivity	Precision	F-score
Front db. raises	M Autocor	Thigh	0.9236	0.9925	0.9568
Lateral db. raises	M Autocor	Thigh	0.8611	0.9688	0.9118
Db. shrugs	M Autocor	Thigh	0.8611	0.9688	0.9118
Db. bicep curls	M Autocor	Thigh	0.9236	0.9779	0.9500
Bentover db. rows	M Autocor	Thigh	0.8889	0.9922	0.9377
Push ups	M Autocor	Thigh	1.0000	1.0000	1.0000
Db. step ups	M Autocor	Thigh	0.9653	1.0000	0.9823
Box squats	M Autocor	Thigh	1.0000	1.0000	1.0000
Heel touches	M Autocor	Thigh	0.9514	0.9856	0.9682

Table A 10 Repetition counting performance using autocorrelation method. IMU position – wrist

Exercise	Total set no.	Error count							
		|e| = 0	[%]	|e| = 1	[%]	|e| = 2	[%]	|e| > 2	[%]
Front db. raises	18	18	100.00	0	0.00	0	0.00	0	0.00
Lateral db. raises	18	18	100.00	0	0.00	0	0.00	0	0.00
Db. shrugs	18	17	94.44	0	0.00	0	0.00	1	5.56
Db. bicep curls	18	17	94.44	1	5.56	0	0.00	0	0.00
Bentover db. rows	18	17	94.44	1	5.56	0	0.00	0	0.00
Push ups	18	7	38.89	6	33.33	0	0.00	5	27.78
Db. step ups	18	16	88.89	0	0.00	0	0.00	2	11.11
Box squats	18	14	77.78	4	22.22	0	0.00	0	0.00
Heel touches	18	12	66.67	3	16.67	1	5.56	2	11.11

Table A 11 Repetition counting performance using modified autocorrelation method. IMU position – wrist

Exercise	Total set no.	Error count							
		|e| = 0	[%]	|e| = 1	[%]	|e| = 2	[%]	|e| > 2	[%]
Front db. raises	18	18	100.00	0	0.00	0	0.00	0	0.00
Lateral db. raises	18	18	100.00	0	0.00	0	0.00	0	0.00
Db. shrugs	18	18	100.00	0	0.00	0	0.00	0	0.00
Db. bicep curls	18	18	100.00	0	0.00	0	0.00	0	0.00
Bentover db. rows	18	17	94.44	1	5.56	0	0.00	0	0.00
Push ups	18	8	44.44	4	22.22	4	22.22	2	11.11
Db. step ups	18	18	100.00	0	0.00	0	0.00	0	0.00
Box squats	18	14	77.78	4	22.22	0	0.00	0	0.00
Heel touches	18	11	61.11	5	27.78	2	11.11	0	0.00

Table A 12 Repetition counting performance using energy method with raw AVM. IMU position – wrist

Exercise	Total set no.	Error count							
		|e| = 0	[%]	|e| = 1	[%]	|e| = 2	[%]	|e| > 2	[%]
Front db. raises	18	14	77.78	4	22.22	0	0.00	0	0.00
Lateral db. raises	18	16	88.89	2	11.11	0	0.00	0	0.00
Db. shrugs	18	8	44.44	8	44.44	0	0.00	2	11.11
Db. bicep curls	18	8	44.44	9	50.00	1	5.56	0	0.00
Bentover db. rows	18	13	72.22	5	27.78	0	0.00	0	0.00
Push ups	18	4	22.22	8	44.44	2	11.11	4	22.22
Db. step ups	18	16	88.89	2	11.11	0	0.00	0	0.00
Box squats	18	10	55.56	5	27.78	2	11.11	1	5.56
Heel touches	18	3	16.67	8	44.44	4	22.22	3	16.67

Table A 13 Repetition counting performance using energy method with linear AVM. IMU position – wrist

Exercise	Total set no.	Error count							
		|e| = 0	[%]	|e| = 1	[%]	|e| = 2	[%]	|e| > 2	[%]
Front db. raises	18	14	77.78	4	22.22	0	0.00	0	0.00
Lateral db. raises	18	14	77.78	4	22.22	0	0.00	0	0.00
Db. shrugs	18	8	44.44	6	33.33	2	11.11	2	11.11
Db. bicep curls	18	10	55.56	7	38.89	1	5.56	0	0.00
Bentover db. rows	18	15	83.33	2	11.11	1	5.56	0	0.00
Push ups	18	5	27.78	6	33.33	5	27.78	2	11.11
Db. step ups	18	16	88.89	2	11.11	0	0.00	0	0.00
Box squats	18	10	55.56	3	16.67	3	16.67	2	11.11
Heel touches	18	0	0.00	7	38.89	8	44.44	3	16.67

Table A 14 Repetition counting performance using energy method with AVVM. IMU position – wrist

Exercise	Total set no.	Error count							
		|e| = 0	[%]	|e| = 1	[%]	|e| = 2	[%]	|e| > 2	[%]
Front db. raises	18	17	94.44	1	5.56	0	0.00	0	0.00
Lateral db. raises	18	15	83.33	3	16.67	0	0.00	0	0.00
Db. shrugs	18	0	0.00	6	33.33	9	50.00	3	16.67
Db. bicep curls	18	8	44.44	9	50.00	1	5.56	0	0.00
Bentover db. rows	18	9	50.00	9	50.00	0	0.00	0	0.00
Push ups	18	17	94.44	1	5.56	0	0.00	0	0.00
Db. step ups	18	3	16.67	9	50.00	2	11.11	4	22.22
Box squats	18	5	27.78	7	38.89	4	22.22	2	11.11
Heel touches	18	7	38.89	4	22.22	3	16.67	4	22.22

Table A 15 Repetition counting performance using modified autocorrelation method. IMU position – chest

Exercise	Total set no.	Error count							
		|e| = 0	[%]	|e| = 1	[%]	|e| = 2	[%]	|e| > 2	[%]
Front db. raises	18	12	66.67	6	33.33	0	0.00	0	0.00
Lateral db. raises	18	17	94.44	1	5.56	0	0.00	0	0.00
Db. shrugs	18	16	88.89	2	11.11	0	0.00	0	0.00
Db. bicep curls	18	10	55.56	7	38.89	1	5.56	0	0.00
Bentover db. rows	18	14	77.78	4	22.22	0	0.00	0	0.00
Push ups	18	18	100.00	0	0.00	0	0.00	0	0.00
Db. step ups	18	15	83.33	3	16.67	0	0.00	0	0.00
Box squats	18	18	100.00	0	0.00	0	0.00	0	0.00
Heel touches	18	13	72.22	5	27.78	0	0.00	0	0.00

Table A 16 Repetition counting performance using modified autocorrelation method. IMU position – thigh

Exercise	Total set no.	Error count							
		|e| = 0	[%]	|e| = 1	[%]	|e| = 2	[%]	|e| > 2	[%]
Front db. raises	18	8	44.44	8	44.44	2	11.11	0	0.00
Lateral db. raises	18	6	33.33	6	33.33	4	22.22	2	11.11
Db. shrugs	18	7	38.89	6	33.33	2	11.11	3	16.67
Db. bicep curls	18	8	44.44	7	38.89	2	11.11	1	5.56
Bentover db. rows	18	5	27.78	10	55.56	2	11.11	1	5.56
Push ups	18	18	100.00	0	0.00	0	0.00	0	0.00
Db. step ups	18	13	72.22	5	27.78	0	0.00	0	0.00
Box squats	18	18	100.00	0	0.00	0	0.00	0	0.00
Heel touches	18	11	61.11	5	27.78	2	11.11	0	0.00

Table A 17 Score comparison for different model types and number of selected features. IMU position – wrist

Model Type	Accuracy % (Validation)	Accuracy % (Test)	Prediction Speed (obs/sec)	Training Time (sec)	Selected Features	Feature Ranking Algorithm
SVM	99.85	99.73	2774.01	84.96	189/189	None
KNN	99.29	99.42	632.00	158.68	189/189	None
Ensemble	98.83	98.11	8184.12	218.39	189/189	None
Naive Bayes	93.28	93.55	44.72	855.81	189/189	None
SVM	99.04	98.73	7420.11	65.63	20/189	MRMR
KNN	94.92	92.97	16125.79	20.62	20/189	MRMR
Ensemble	97.49	97.18	13722.54	36.79	20/189	MRMR
Naive Bayes	96.00	95.68	391.45	99.01	20/189	MRMR
SVM	94.04	94.59	9152.18	51.25	10/189	MRMR
KNN	84.25	83.98	9440.72	47.84	10/189	MRMR
Ensemble	93.86	94.48	10622.97	58.75	10/189	MRMR
Naive Bayes	91.89	92.39	577.64	81.75	10/189	MRMR
SVM	67.57	71.74	20110.23	396.25	3/189	MRMR
KNN	67.92	70.19	18104.65	33.59	3/189	MRMR
Ensemble	78.47	84.83	12159.83	33.84	3/189	MRMR
Naive Bayes	78.64	83.59	2804.01	43.21	3/189	MRMR

Table A 18 Score comparison for different model types and number of selected features. IMU position – thigh

Model Type	Accuracy % (Validation)	Accuracy % (Test)	Prediction Speed (obs/sec)	Training Time (sec)	Selected Features	Feature Ranking Algorithm
SVM	99.85	99.73	2774.01	84.96	189/189	None
KNN	99.29	99.42	632.00	158.68	189/189	None
Ensemble	98.83	98.11	8184.12	218.39	189/189	None
Naive Bayes	93.28	93.55	44.72	855.81	189/189	None
SVM	99.04	98.73	7420.11	65.63	20/189	MRMR
KNN	94.92	92.97	16125.79	20.62	20/189	MRMR
Ensemble	97.49	97.18	13722.54	36.79	20/189	MRMR
Naive Bayes	96.00	95.68	391.45	99.01	20/189	MRMR
SVM	94.04	94.59	9152.18	51.25	10/189	MRMR
KNN	84.25	83.98	9440.72	47.84	10/189	MRMR
Ensemble	93.86	94.48	10622.97	58.75	10/189	MRMR
Naive Bayes	91.89	92.39	577.64	81.75	10/189	MRMR
SVM	67.57	71.74	20110.23	396.25	3/189	MRMR
KNN	67.92	70.19	18104.65	33.59	3/189	MRMR
Ensemble	78.47	84.83	12159.83	33.84	3/189	MRMR
Naive Bayes	78.64	83.59	2804.01	43.21	3/189	MRMR

Table A 19 Score comparison for different model types and number of selected features. IMU position – chest

Model Type	Accuracy % (Validation)	Accuracy % (Test)	Prediction Speed (obs/sec)	Training Time (sec)	Selected Features	Feature Ranking Algorithm
SVM	96.16	96.72	3124.35	25.36	189/189	None
KNN	84.00	83.09	1533.45	19.90	189/189	None
Ensemble	92.27	93.13	12358.53	91.51	189/189	None
Naive Bayes	74.21	75.91	46.98	578.24	189/189	None
SVM	84.07	88.26	6614.01	53.72	20/189	MRMR
KNN	84.22	88.19	7767.45	97.94	20/189	MRMR
Ensemble	84.55	87.61	8028.98	85.35	20/189	MRMR
Naive Bayes	80.36	81.97	266.18	139.48	20/189	MRMR
SVM	68.30	67.34	6403.45	130.38	10/189	MRMR
KNN	57.56	58.80	12825.73	120.91	10/189	MRMR
Ensemble	70.67	70.54	7097.04	81.70	10/189	MRMR
Naive Bayes	68.91	68.07	472.49	95.22	10/189	MRMR
SVM	66.55	67.61	18618.41	306.55	6/189	MRMR
KNN	56.22	57.92	18066.03	91.40	6/189	MRMR
Ensemble	69.74	68.19	9392.61	62.43	6/189	MRMR
Naive Bayes	67.26	68.19	725.91	70.41	6/189	MRMR
SVM	59.25	59.73	12943.02	555.73	3/189	MRMR
KNN	48.74	49.85	15302.08	92.55	3/189	MRMR
Ensemble	65.39	65.06	8379.60	104.94	3/189	MRMR
Naive Bayes	65.30	65.87	2090.71	67.00	3/189	MRMR

Table A 20 Score comparison for different model types and number of selected features. IMU position – wrist and thigh

Model Type	Accuracy % (Validation)	Accuracy % (Test)	Prediction Speed (obs/sec)	Training Time (sec)	Selected Features	Feature Ranking Algorithm
SVM	99.95	100.00	1462.88	247.32	378/378	None
KNN	99.69	99.96	385.23	253.26	378/378	None
Ensemble	99.37	99.50	5199.28	566.74	378/378	None
Naive Bayes	93.65	94.05	18.01	1558.41	378/378	None
SVM	97.53	98.80	4207.92	575.40	20/378	MRMR
KNN	92.39	93.28	5906.22	327.87	20/378	MRMR
Ensemble	97.53	98.53	4145.60	513.12	20/378	MRMR
Naive Bayes	95.76	97.37	285.24	419.53	20/378	MRMR
SVM	92.22	92.78	4384.10	653.47	10/378	MRMR
KNN	85.14	85.79	4268.33	682.62	10/378	MRMR
Ensemble	93.75	94.21	3360.95	857.74	10/378	MRMR
Naive Bayes	91.21	91.39	555.52	676.65	10/378	MRMR
SVM	88.85	84.05	5410.08	969.23	4/378	MRMR
KNN	87.01	85.91	4989.21	987.87	4/378	MRMR
Ensemble	92.74	90.81	3773.67	998.44	4/378	MRMR
Naive Bayes	88.60	88.73	1412.76	821.52	4/378	MRMR

Table A 21 Score comparison for different model types and number of selected features. IMU position – wrist and chest

Model Type	Accuracy % (Validation)	Accuracy % (Test)	Prediction Speed (obs/sec)	Training Time (sec)	Selected Features	Feature Ranking Algorithm
SVM	100.00	99.96	1933.63	35.94	378/378	None
KNN	99.80	99.88	1016.24	31.09	378/378	None
Ensemble	99.27	99.54	8034.50	139.26	378/378	None
Naive Bayes	84.25	86.25	20.63	1241.76	378/378	None
SVM	96.33	96.25	6180.80	192.44	20/378	MRMR
KNN	86.61	90.62	5317.60	176.29	20/378	MRMR
Ensemble	96.23	95.95	7374.08	349.39	20/378	MRMR
Naive Bayes	94.16	93.78	251.97	264.33	20/378	MRMR
SVM	88.70	92.86	6830.85	281.40	10/378	MRMR
KNN	74.34	84.59	7241.85	374.77	10/378	MRMR
Ensemble	91.55	94.21	7420.98	455.44	10/378	MRMR
Naive Bayes	89.10	92.59	549.61	277.33	10/378	MRMR
SVM	87.74	90.12	7285.18	590.24	4/378	MRMR
KNN	82.26	85.87	9258.78	481.39	4/378	MRMR
Ensemble	90.01	91.70	6068.21	516.73	4/378	MRMR
Naive Bayes	86.93	88.19	1804.33	354.89	4/378	MRMR

Table A 22 Score comparison for different model types and number of selected features. IMU position – wrist, thigh and chest

Model Type	Accuracy % (Validation)	Accuracy % (Test)	Prediction Speed (obs/sec)	Training Time (sec)	Selected Features	Feature Ranking Algorithm
SVM	100	100	0	0	567/567	None
KNN	99.66909	99.80695	0	0	567/567	None
Ensemble	99.17273	99.42085	0	0	567/567	None
Naive Bayes	82.97485	84.59459	0	0	567/567	None
SVM	94.8544	96.64093	0	0	20/567	MRMR
KNN	84.11648	85.44402	0	0	20/567	MRMR
Ensemble	95.20185	96.79537	0	0	20/567	MRMR
Naive Bayes	93.69623	95.05792	0	0	20/567	MRMR
SVM	92.68696	89.6139	0	0	10/567	MRMR
KNN	83.35539	78.72587	0	0	10/567	MRMR
Ensemble	94.01059	91.38996	0	0	10/567	MRMR
Naive Bayes	92.02515	89.11197	0	0	10/567	MRMR
SVM	93.23296	89.45946	0	0	5/567	MRMR
KNN	89.80807	84.78764	0	0	5/567	MRMR
Ensemble	94.58968	91.38996	0	0	5/567	MRMR
Naive Bayes	92.15751	88.4556	0	0	5/567	MRMR

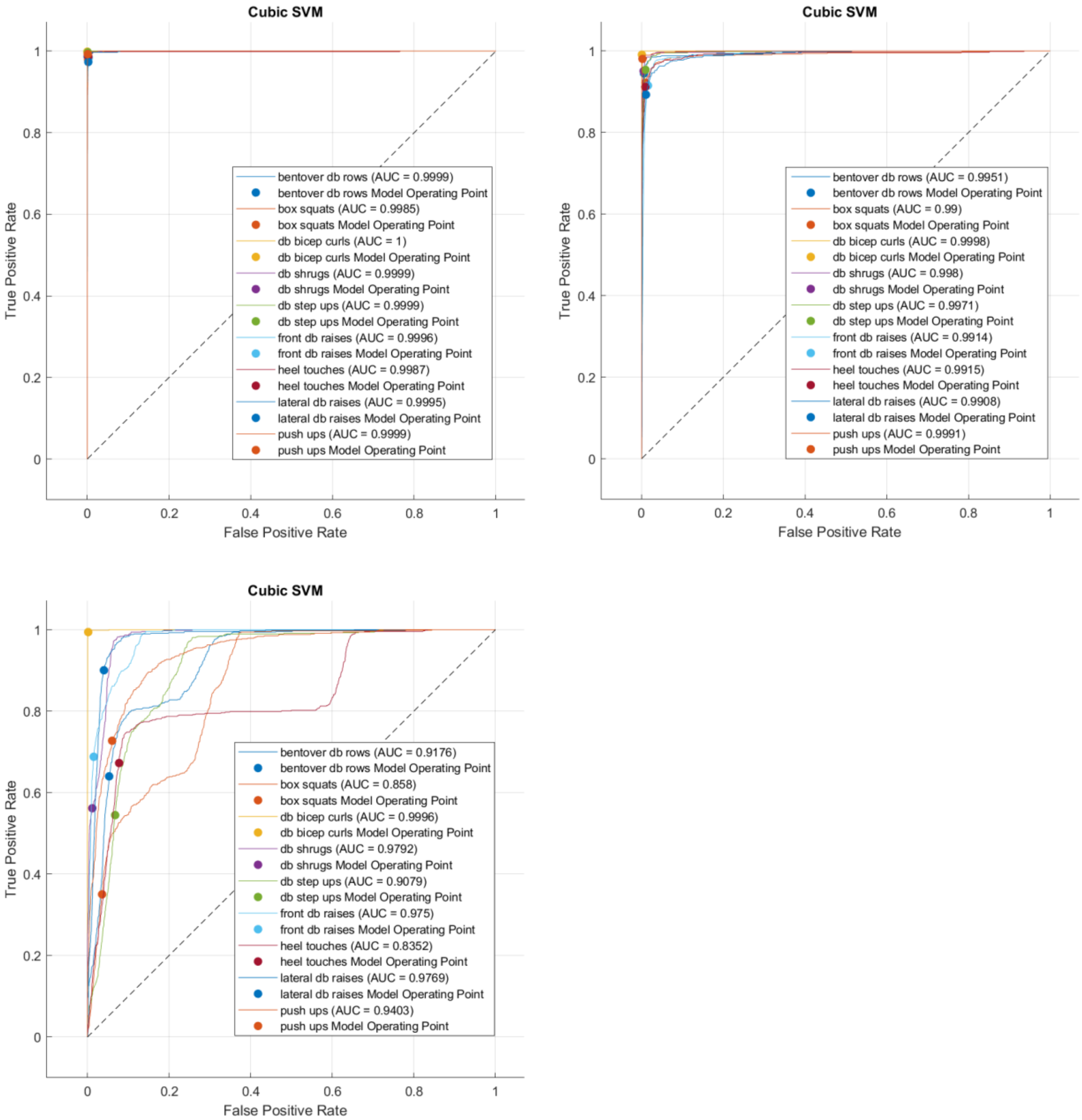

Figure A 1 ROC curve: 20 features (upper left), 10 features (upper right) and 3 features (down). IMU position – wrist

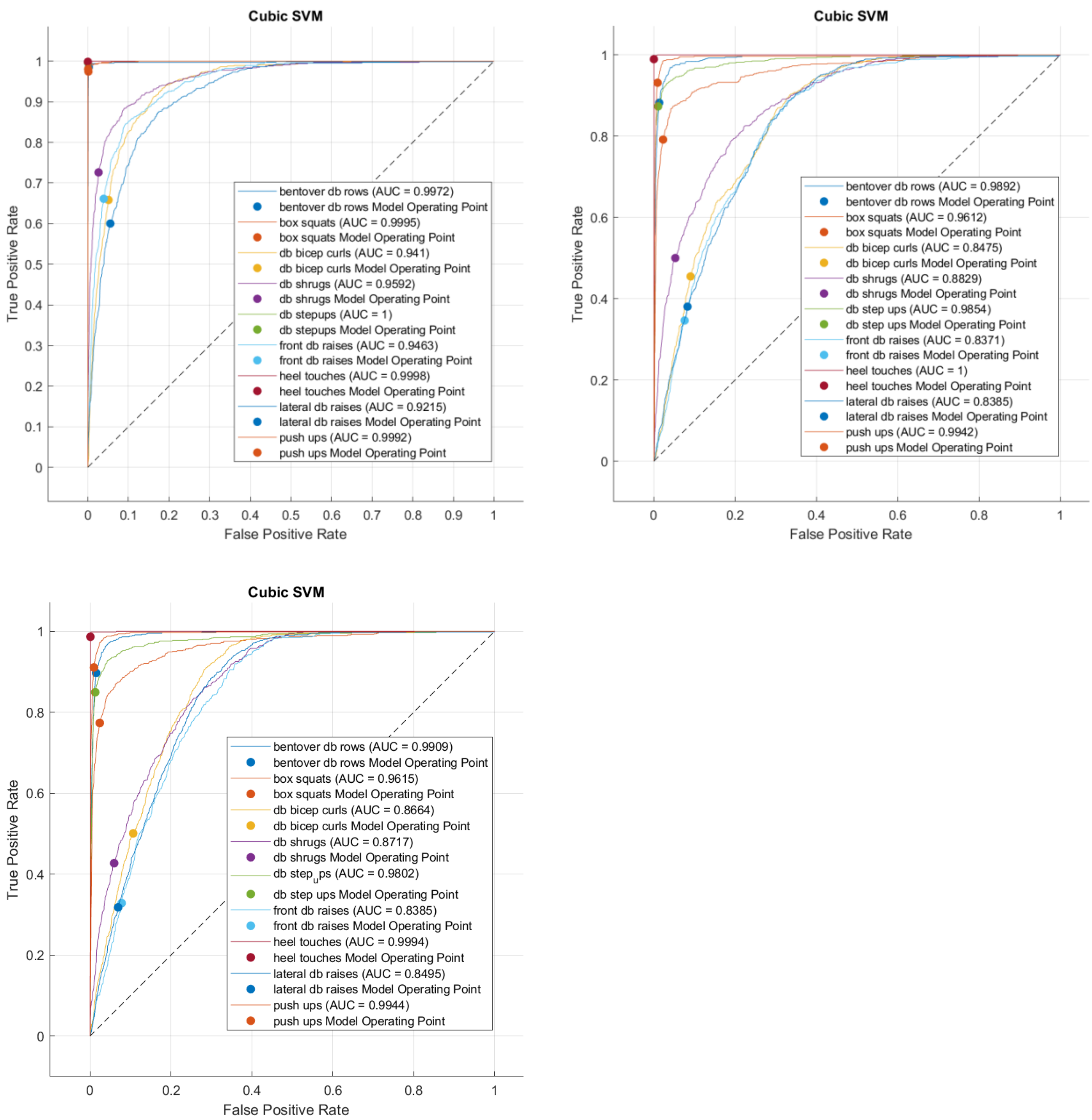

Figure A 2 ROC curve: 20 features (upper left), 10 features (upper right) and 6 features (down). IMU position – chest

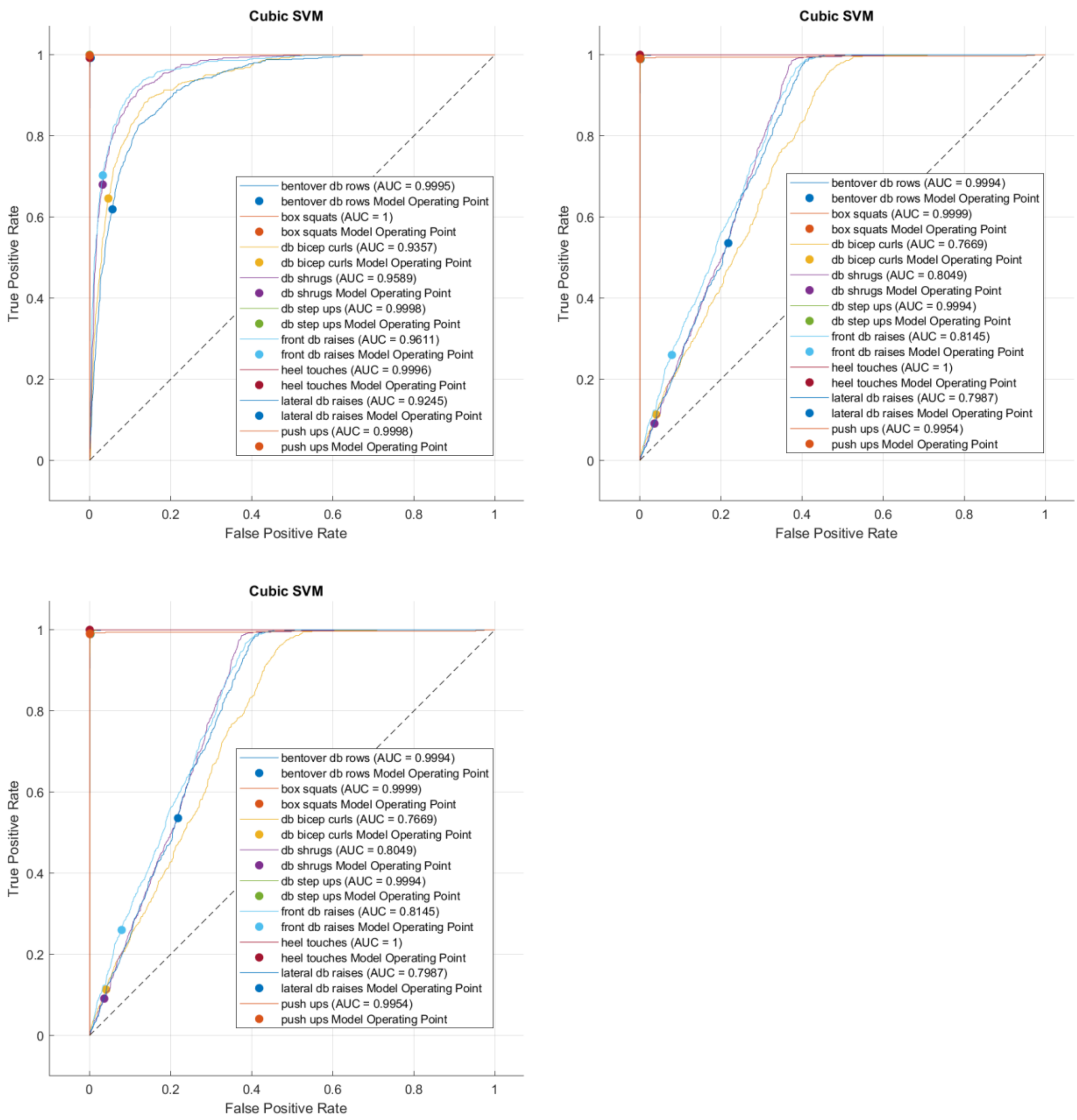

Figure A 3 ROC curve: 20 features (upper left), 10 features (upper right) and 3 features (down). IMU position – thigh

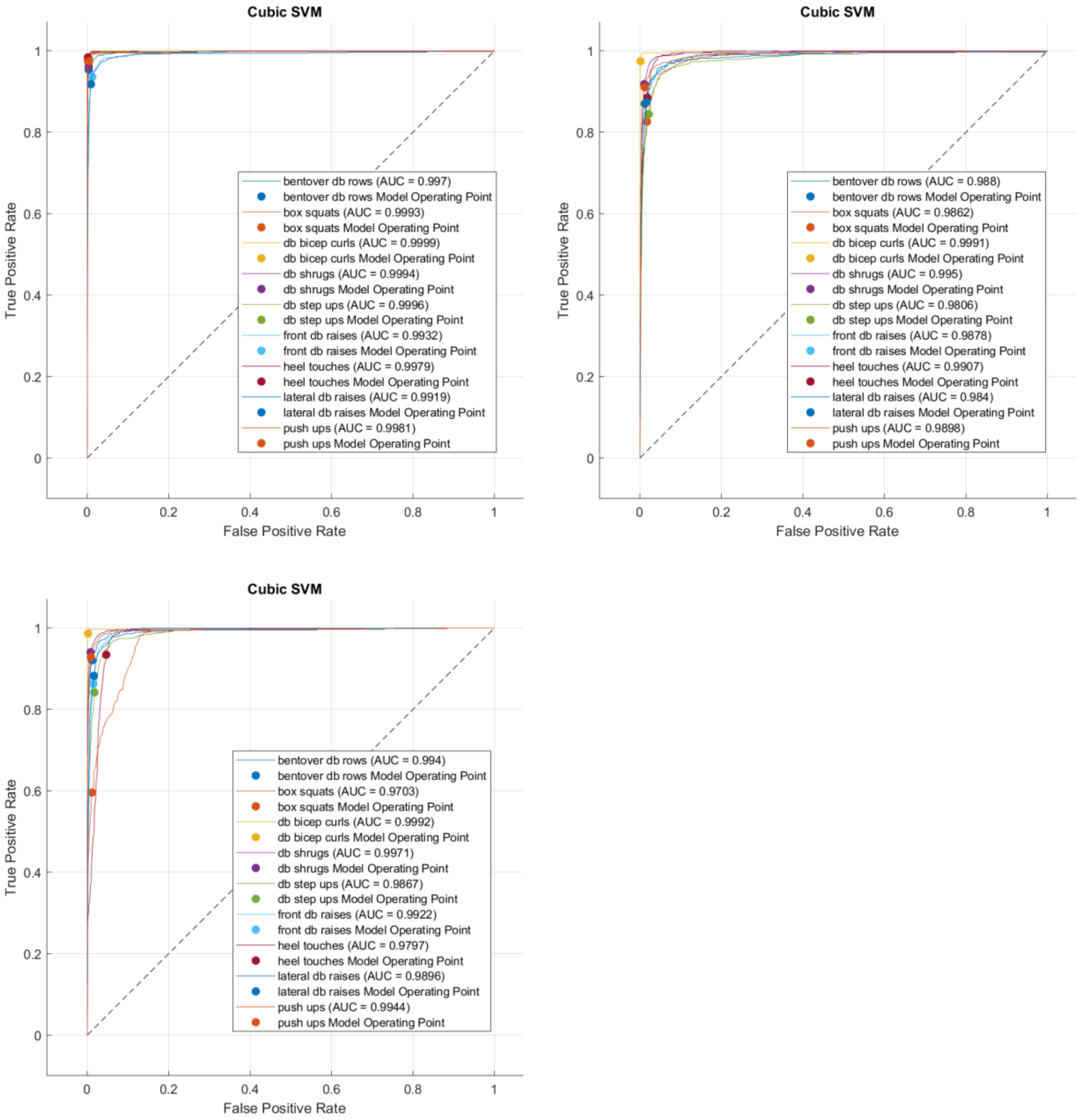

Figure A 4 ROC curve: 20 features (upper left), 10 features (upper right) and 4 features (down). IMU position – wrist and chest

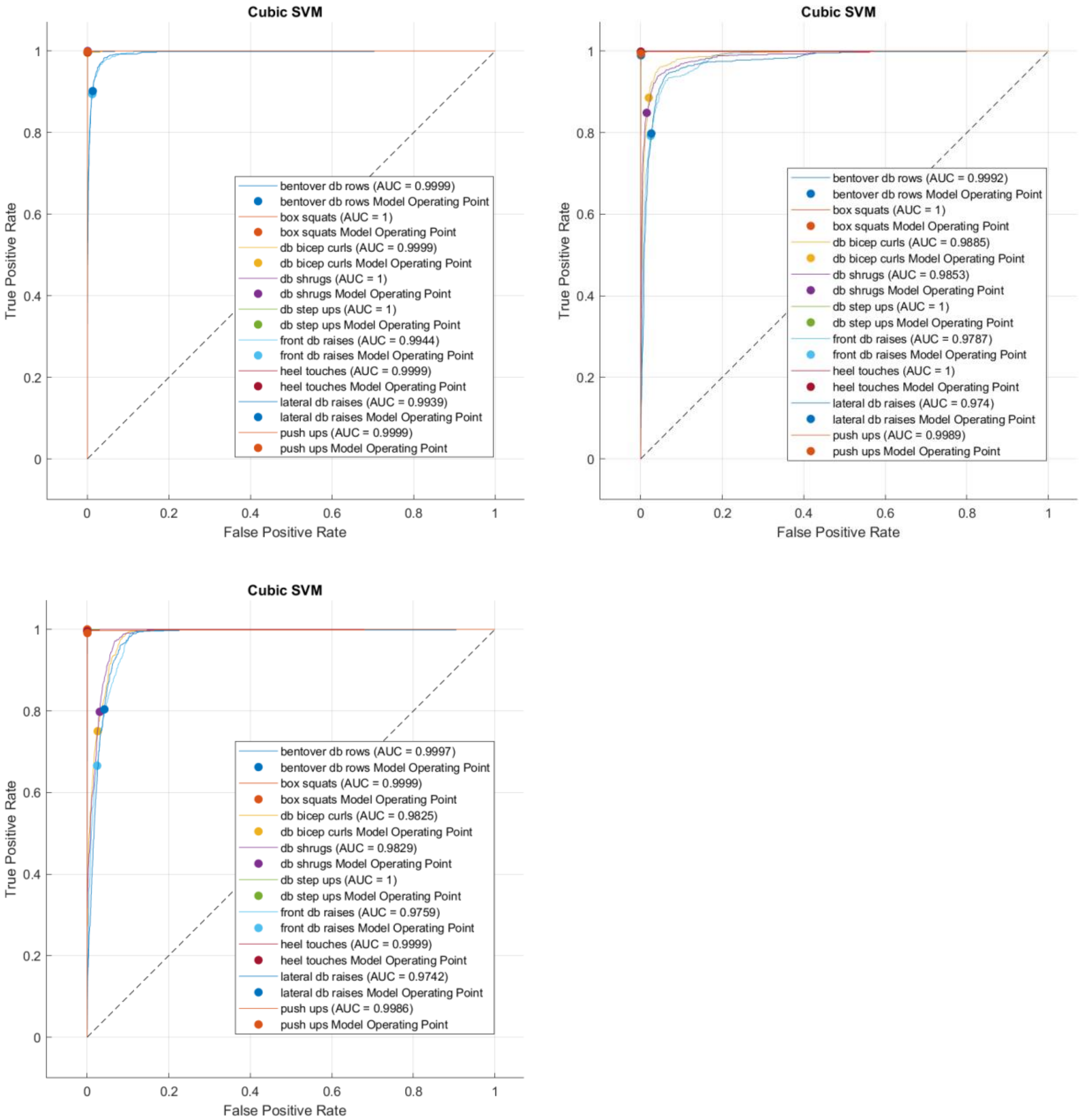

Figure A 5 ROC curve: 20 features (upper left), 10 features (upper right) and 4 features (down). IMU position – wrist and thigh

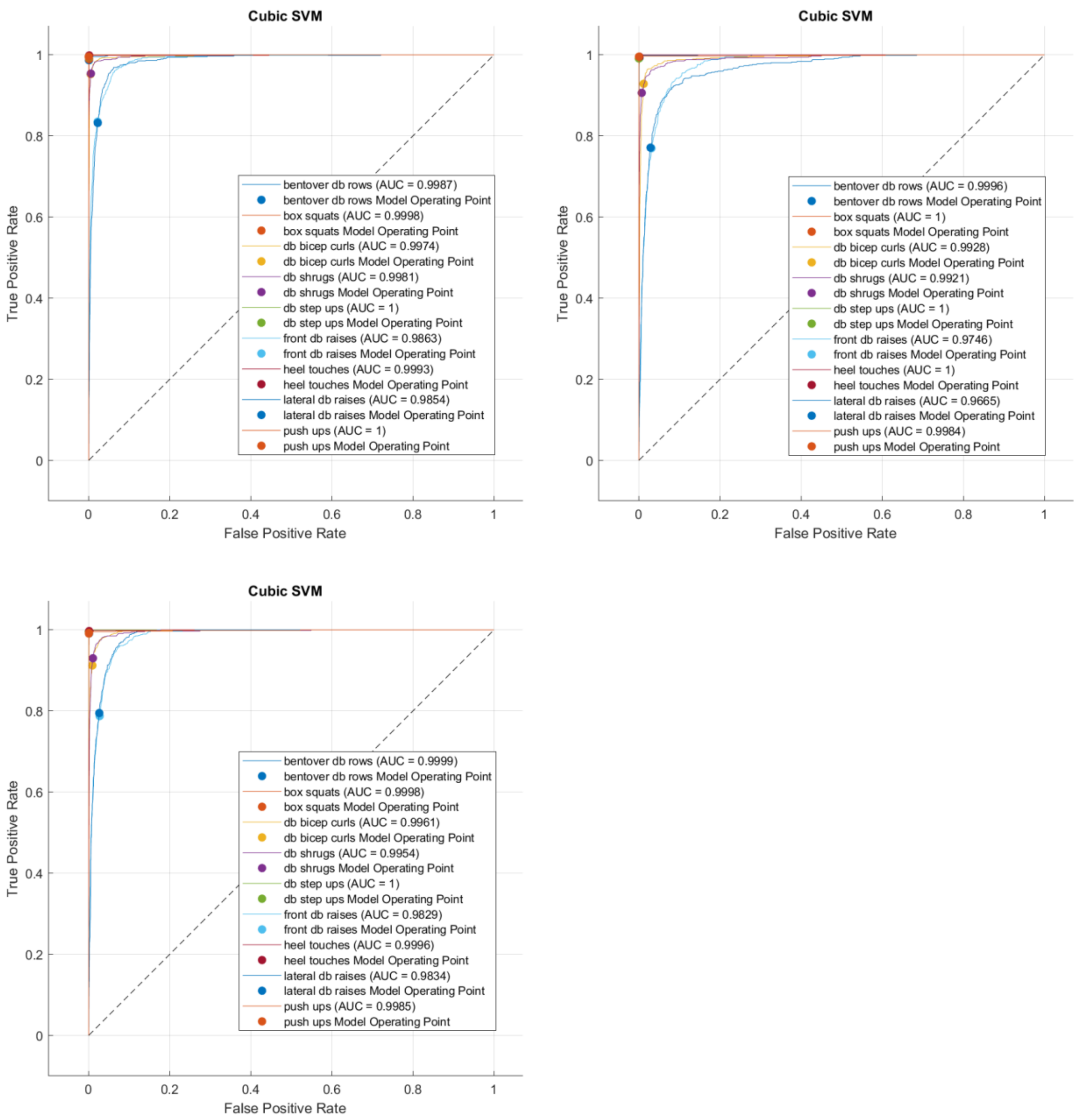

Figure A 6 ROC curve: 20 features (upper left), 10 features (upper right) and 5 features (down). IMU position – wrist, chest and thigh

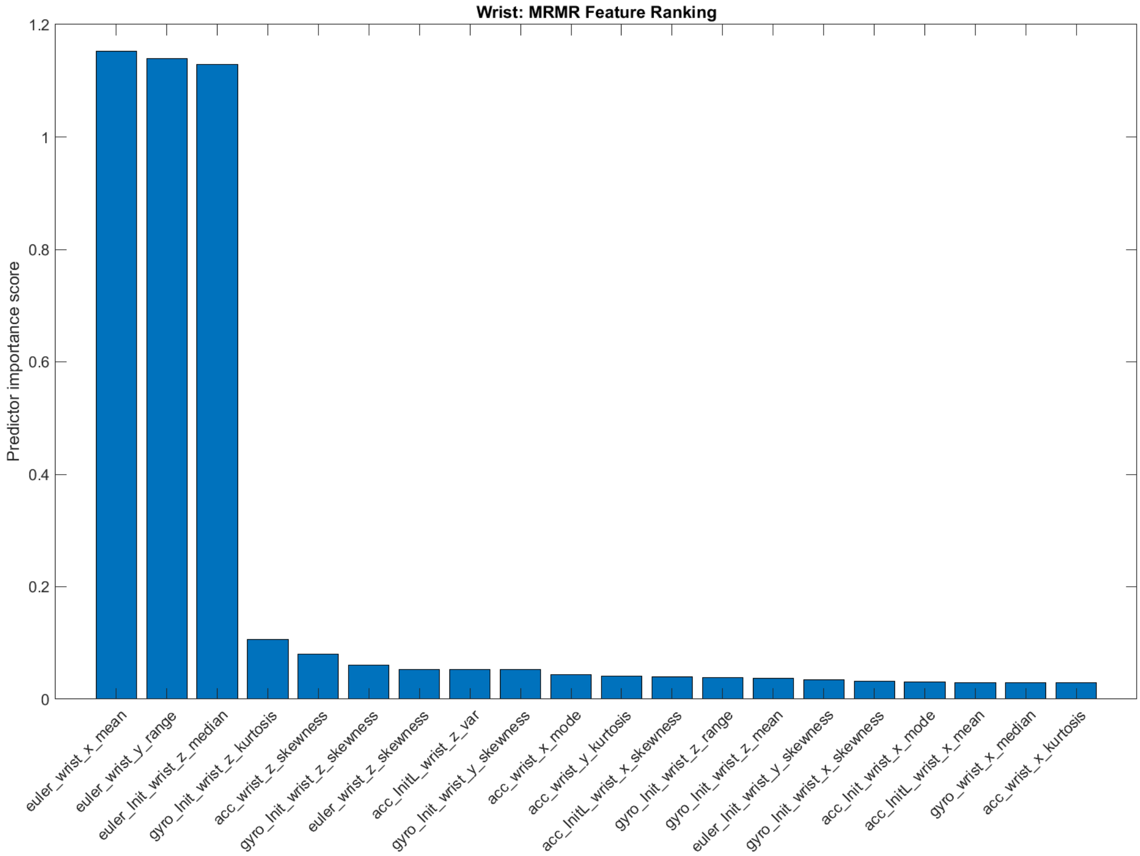

Figure A 7 MRMR feature ranking. IMU position – wrist

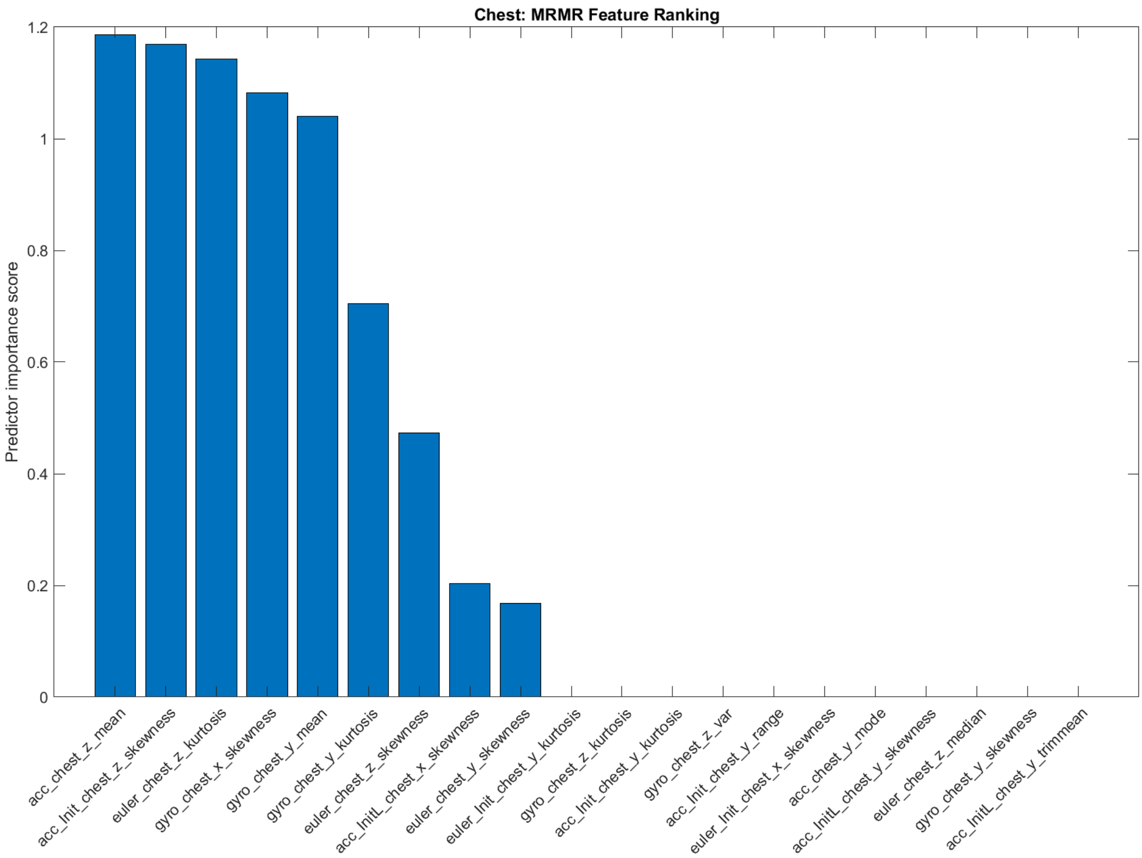

Figure A 8 MRMR feature ranking. IMU position – chest

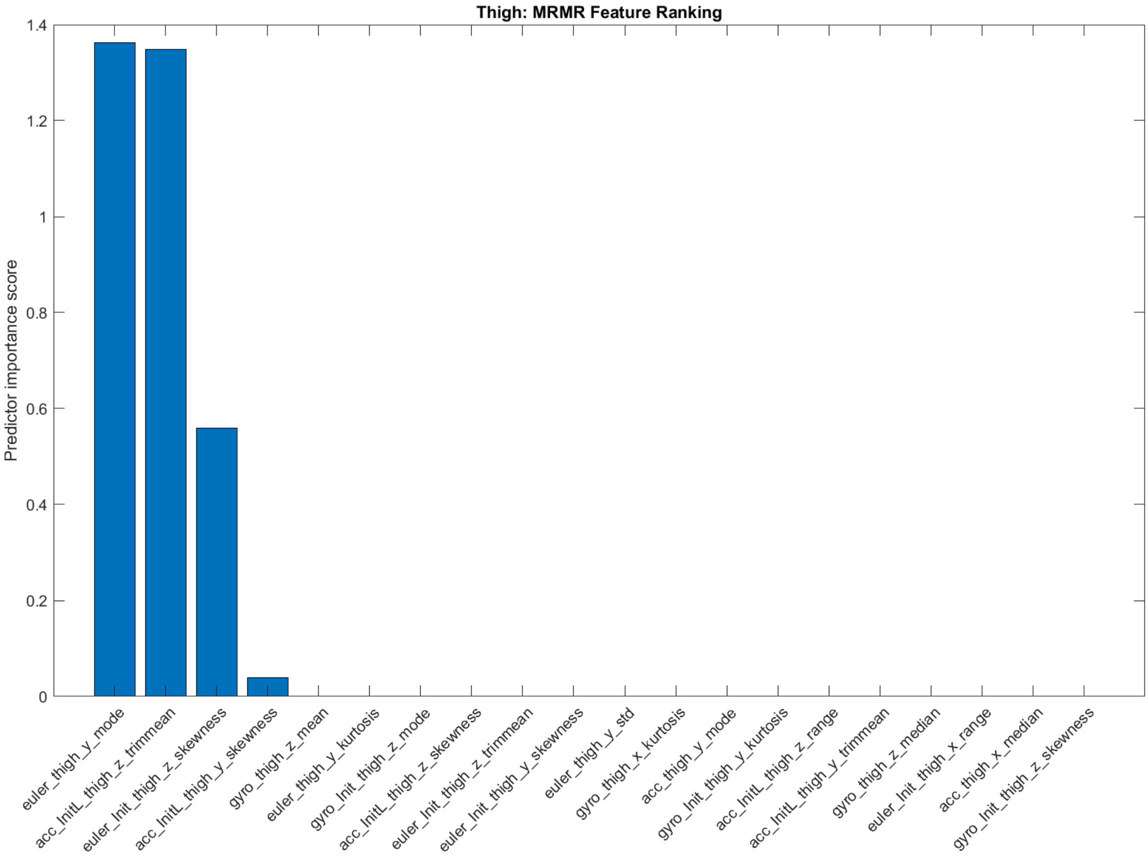

Figure A 9 MRMR feature ranking. IMU position – thigh

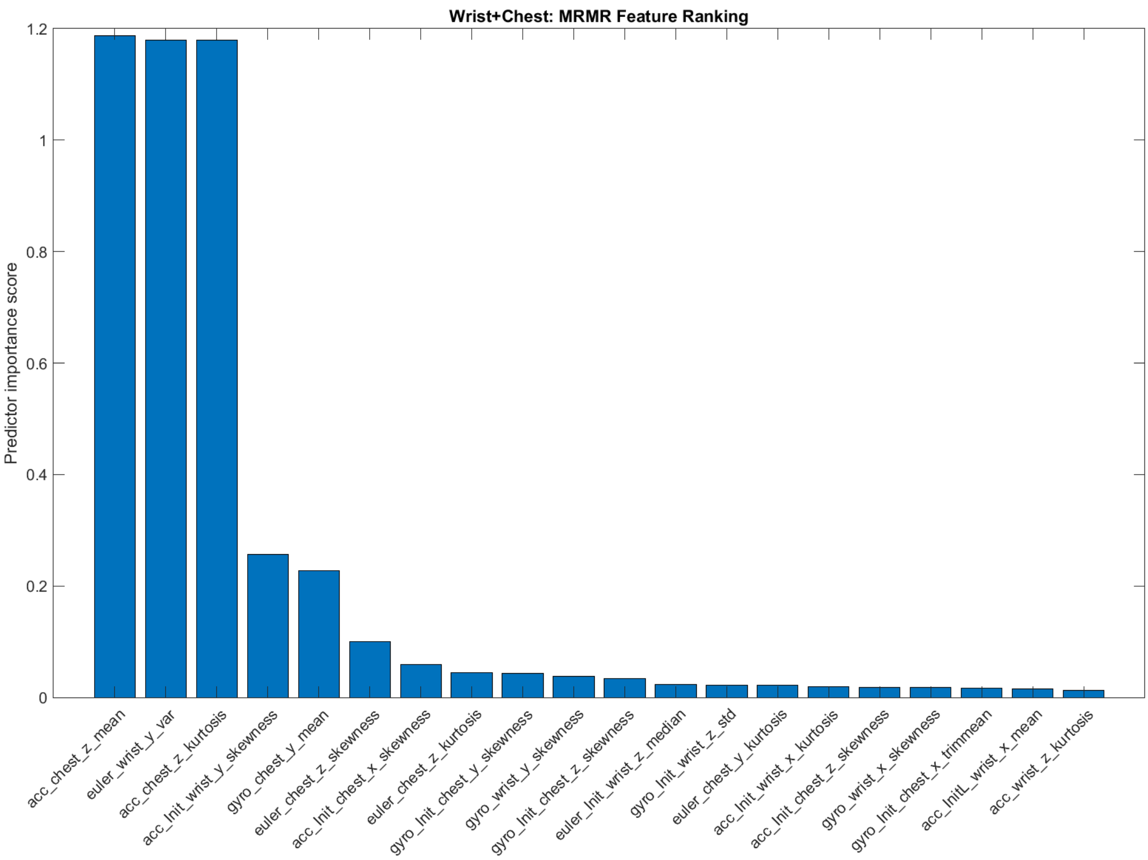

Figure A 10 MRMR feature ranking. IMU position – wrist and chest

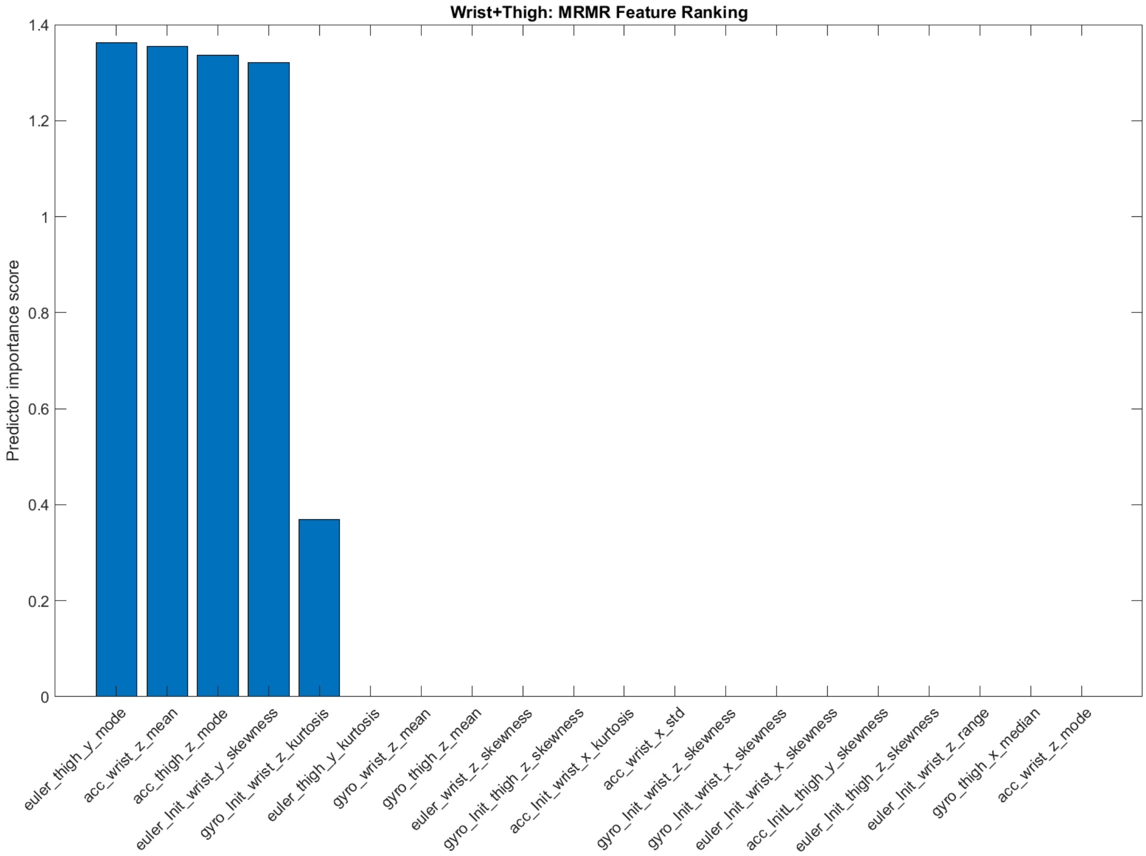

Figure A 11 MRMR feature ranking. IMU position – wrist and thigh

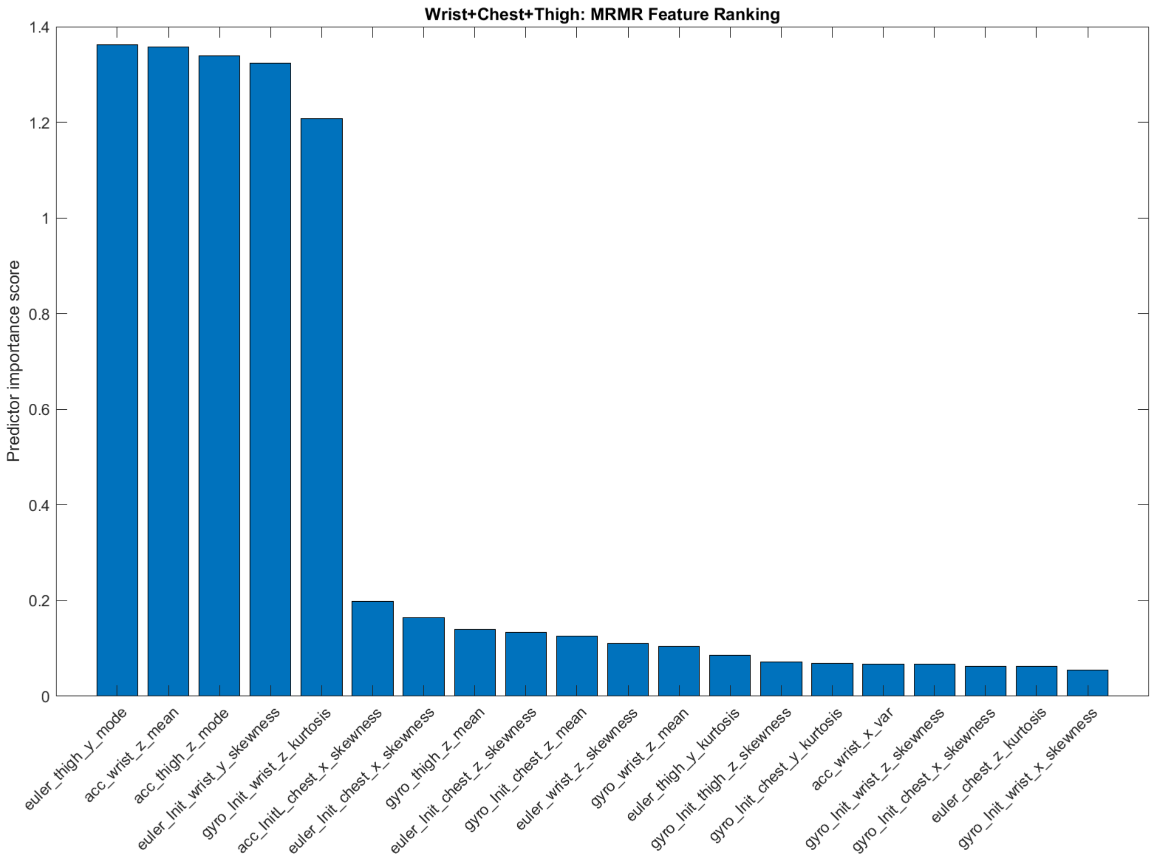

Figure A 12 MRMR feature ranking. IMU position – wrist, chest and thigh

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Biography

Dominik Džaja was born on July 29th, 1989 in Zagreb, Croatia. He completed his primary and secondary education in Zagreb. He received the B.S. and M.S degrees from the University of Zagreb, Faculty of Electrical Engineering and Computing in 2011 and 2013, respectively. In March 2014, he enrolled in the postgraduate doctoral study of electrical engineering at the same faculty.

From the end of 2013 until the end of 2021, he has been employed at the Faculty of Electrical Engineering and Computing, first as a research fellow and then as an assistant funded by the Croatian Science Foundation. During his employment he participated in the work of several international and domestic projects: “Advanced Solutions for Supporting Cardiac Patients in Rehabilitation” – HeartWays (FP7-SME-2012, Research for SMEs), “Tehnološka platforma za nove ICT strategije u terapiji i kontroli dijabetesa” – diabICT, “Napredne tehnologije u elektroenergetskim postrojenjima i tračnim vozilima” – FER KIET, “Wrist and Arm Sensing Technologies for Cardiac Arrhythmias Detection in Long Term Monitoring” - WASTCArD (Research and Innovation Staff Exchange Call: H2020-MSCA-RISE-2014) and “Istraživanje i razvoj sustava za prepoznavanje umora i distrakcije vozača” - DFDM. His tasks were related to the application of inertial and magnetic sensors for human motion tracking and included: programming user applications, development of algorithms and writing technical documentation.

At the Department of Electronic Systems and Information Processing he was enrolled as a teaching assistant on the courses: Electronic Equipment Design, Electronical Measurements and Components, Laboratory of Electronical and Computer Engineering 1/2, Biomedical Instrumentation and Technology in Medicine. Additionally, he was involved in supervision of students in the preparation of Bachelor and Master thesis.

He is a member of the Croatian Society of Biomedical Engineering and Medical Physics (HDBIMF) and International Federation for Medical and Biological Engineering

(IFMBE). His research interests include wireless body area networks and algorithms for biomedical signal processing.

Publications:

Journal Articles

1. D. Džaja, M. Čibarić, G. Šeketa, and R. Magjarević, “Accelerometer-based algorithm for the segmentation and classification of repetitive human movements during workouts,” Automatika, pp. 1–14, Sep. 2022.
2. G. Šeketa, L. Pavlaković, D. Džaja, I. Lacković, and R. Magjarević, “Event-centered data segmentation in accelerometer-based fall detection algorithms,” Sensors, vol. 21, no. 13, p. 4335, Jun. 2021.

Conference Proceedings

1. L. Celić, M. Varga, T. Pozaić, S. Žulj, D. Džaja, and R. Magjarević, “WBAN for physical activity monitoring in health care and wellness,” IFMBE Proc., vol. 39 IFMBE, pp. 2228–2231, 2013.
2. T. Pozaic, M. Varga, D. Dzaja, and S. Zulj, “Closed-loop system for assisted strength exercising,” in 2013 36th International Convention on Information and Communication Technology, Electronics and Microelectronics, MIPRO 2013 - Proceedings, 2013.
3. T. Pozaić et al., “Quantitative and qualitative assessment of assisted strength exercising,” IFMBE Proc., vol. 42, pp. 71–75, 2014.
4. D. Džaja et al., “System for assisted exercising and qualitative exercise assessment,” IFMBE Proc., vol. 45, pp. 682–686, 2015.
5. S. Žulj, G. Šeketa, D. Džaja, L. Celić, and R. Magjarević, “Virtual reality system for assisted exercising using wban,” IFMBE Proc., vol. 45, pp. 721–722, 2015.
6. G. Šeketa, D. Džaja, S. Žulj, L. Celić, I. Lacković, and R. Magjarević, “Real-time evaluation of repetitive physical exercise using orientation estimation from inertial and magnetic sensors,” IFMBE Proc., vol. 50, pp. 11–15, 2015.
7. S. Zulj et al., “Supporting diabetic patients with a remote patient monitoring systems,” IFMBE Proc., vol. 60, pp. 577–580, 2017.

8. G. Šeketa, L. Pavlaković, S. Žulj, D. Džaja, I. Lacković, and R. Magjarević, "Comparison of Human Fall Acceleration Signals Among Different Datasets," IFMBE Proc., vol. 74, pp. 413–419, 2020.
9. S. Zulj, G. Seketa, D. Dzaja, L. Celic, I. Lackovic, and R. Magjarevic, "Empowering Diabetic Patients Using Gadgets and Mobile App," IFMBE Proc., vol. 76, pp. 891–897, 2020.

ŽIVOTOPIS

Dominik Džaja rođen je 29.7.1989. u Zagrebu. Osnovno i srednjoškolsko obrazovanje završava u Zagrebu i 2008. upisuje Fakultet elektrotehnike i računarstva (FER) u Zagrebu. Diplomski studij završava 2013. godine, a 2014. upisuje poslijediplomski studij elektrotehnike i računarstva na istom fakultetu.

Od kraja 2013. do kraja 2021. godine zaposlen je na FER-u, prvo na radnom mjestu zavodskog suradnika, a zatim kao HRZZ asistent. Sudjeluje u provedbi nekoliko međunarodnih i domaćih projekata: *„Advanced Solutions for Supporting Cardiac Patients in Rehabilitation“ – HeartWays (FP7-SME-2012, Research for SMEs*), „Tehnološka platforma za nove ICT strategije u terapiji i kontroli dijabetesa“ – diabICT, „Napredne tehnologije u elektroenergetskim postrojenjima i tračnim vozilima“ – FER KIET, *„Wrist and Arm Sensing Technologies for Cardiac Arrhythmias Detection in Long Term Monitoring“ - WASTCArD (Research and Innovation Staff Exchange Call: H2020-MSCA-RISE-2014)* i „Istraživanje i razvoj sustava za prepoznavanje umora i distrakcije vozača“ - DFDM. Kroz navedene projekte primarno se bavio primjenom inercijskih i magnetskih senzora za praćenje ljudskih pokreta.

Na Zavodu za elektroničke sustave i obradbu informacija sudjeluje kao asistent u izvođenju nastave na predmetima Konstrukcija elektroničkih uređaja, Elektronička mjerenja i komponente, Laboratorij elektroničkog i računalnog inženjerstva 1/2, Biomedicinska instrumentacija i Tehnologija u medicini. Uz to, radi i kao neposredni voditelj studenata pri izradi Završnih i Diplomskih radova.

Član je Hrvatskog društva za medicinsku i biološku tehniku (HDBIMF) i međunarodne federacije medicinskog i biološkog inženjerstva (eng. *International Federation for Medical and Biological Engineering* - IFMBE). Njegovi interesi istraživanja vezani su uz bežične mreže, algoritme i programske podrške za praćenje ljudskih pokreta.