

# Sara Manuel Leitão Vinagre Piteira dos Santos

Bachelor of Science in Biomedical Engineering

# Explaining the Ergonomic Assessment of Human Movement in Industrial Contexts

Dissertation submitted in partial fulfillment of the requirements for the degree of

Master of Science in **Biomedical Engineering** 

Adviser: Prof. Dr. Hugo Filipe Silveira Gamboa, Assistant Professor, NOVA School of Science and Technology, NOVA University of Lisbon

**Examination Committee** 

Chairperson:Prof. Dr. Paulo António Martins Ferreira RibeiroRaporteur:Prof. Dr. Cláudia Regina Pereira QuaresmaMember:Prof. Dr. Hugo Filipe Silveira Gamboa



FACULDADE DE CIÊNCIAS E TECNOLOGIA= UNIVERSIDADE NOVA DE LISBOA

November, 2019

# Explaining the Ergonomic Assessment of Human Movement in Industrial Contexts

Copyright © Sara Manuel Leitão Vinagre Piteira dos Santos, Faculty of Sciences and Technology, NOVA University Lisbon.

The Faculty of Sciences and Technology and the NOVA University Lisbon have the right, perpetual and without geographical boundaries, to file and publish this dissertation through printed copies reproduced on paper or on digital form, or by any other means known or that may be invented, and to disseminate through scientific repositories and admit its copying and distribution for non-commercial, educational or research purposes, as long as credit is given to the author and editor.

This document was created using the (pdf) LTEX processor, based in the "novathesis" template[1], developed at the Dep. Informática of FCT-NOVA [2]. [1] https://github.com/joaomlourenco/novathesis [2] http://www.di.fct.unl.pt

## ACKNOWLEDGEMENTS

While accomplishing this extraordinary academic and personal moment, I would like to acknowledge a group of people who certainly contributed throughout this journey.

My first word of gratitude goes to my academic supervisor, Professor Hugo Gamboa, for all his guidance and support throughout the project. Thank you for the good advises and the contagious enthusiasm towards data science. I owe you my scientific growth.

I must thank the ergonomist Carlos Fujão, the person behind this projects' success at the assembly lines. Thank you for unveiling me the ergonomics world and its inherent challenges. Thanks also to João and Nafiseh for all the suggestions.

A word of appreciation to all members of Fraunhofer AICOS, particularly to everyone in the Lisbon office, for the warm welcome and for the opportunity of pursuing my research in an amazing work environment. My deepest gratitude to Duarte Folgado, for the unconditional support and infinite patience. The brainstorming sessions were undoubtedly valuable. I am eternally grateful. Thanks also to Ricardo Leonardo, for having an eagle eye for code mistakes. To the master students, with whom I shared these past months, a giant thank you. A special thank you to the Space Team for the companionship, shared-knowledge and daily fun.

To my college friends, I would also like to express my sincere gratitude. This five-year journey would certainly not be the same without you. Special thanks to Mariana, Joana, Pedro and Ricardo - you are the definition of awesomeness. Thank you for your true friendship and legendary moments.

To Luís, my unsuccessful manager of time, thank you for your understanding and motivation. I owe you many dinners.

Finally, I am truly thankful to my family, for their patience and understanding. Especially to my Mom for her endless love and support. You are a source of inspiration. To my big brother, for all the silliness during Sunday' lunches and for carefully watching all my steps, not yet realising I'm no longer 13. To my grandparents, the gentlest souls, for the constant support and for lighting up candles whenever needed. A big thank you, I owe you my heart.

You cannot answer a question that you cannot ask, and you cannot ask a question that you have no words for.

— Judea Pearl, The Book of Why: The New Science of Cause and Effect

## ABSTRACT

Manufacturing processes are based on human labour and the symbiosis between human operators and machines. The operators are required to follow predefined sequences of movements. The operations carried out at assembly lines are repetitive, being identified as a risk factor for the onset of musculoskeletal disorders.

Ergonomics plays a big role in preventing occupational diseases. Ergonomic risk scores measure the overall risk exposure of operators however these methods still present challenges: the scores are often associated to a given workstation, being agnostic to the variability among operators. Observation methods are most often employed yet require a significant amount of effort, preventing an accurate and continuous ergonomic evaluation to the entire population of operators. Finally, the risk's results are rendered as index scores, hindering a more comprehensive interpretation by occupational physicians.

This dissertation developed a solution for automatic operator risk exposure in assembly lines. Three main contributions were presented: (1) an upper limb and torso motion tracking algorithm which relies on inertial sensors to estimate the orientation of anatomical joints; (2) an adjusted ergonomic risk score; (3) an ergonomic risk explanation approach based on the analysis of the angular risk factors. Throughout the research, two experimental assessments were conducted: laboratory validation and field evaluation. The laboratory tests enabled the creation of a movements' dataset and used an optical motion capture system as reference. The field evaluation dataset was acquired on an automotive assembly line and serve as the basis for an ergonomic risk evaluation study. The experimental results revealed that the proposed solution has the potential to be applied in a real environment. Through direct measures, the ergonomic feedback is fastened, and consequently, the evaluation can be extended to more operators, ultimately preventing, in long-term, work-related injuries.

**Keywords:** Ergonomics, Industry, Musculoskeletal disorders, Inertial sensors, Motion capture, Risk score.

## Resumo

Os processos de manufatura são baseados no trabalho humano e na simbiose entre operários e máquinas. Os operários devem seguir sequências predefinidas de movimentos. As operações realizadas nas linhas de montagem são repetitivas, constituindo um fator de risco para o desenvolvimento de lesões musculoesqueléticas.

A ergonomia desempenha um papel fulcral na prevenção de doenças ocupacionais. Os índices de risco ergonómico medem a exposição geral dos operários, contudo, ainda apresentam desafios: os índices de risco são associados às estações de trabalho, sendo agnósticos à variabilidade entre os operários. Os métodos observacionais, embora empregues mais frequentemente, exigem uma quantidade significativa de esforço, impedindo uma avaliação precisa e contínua para todos os trabalhadores. Por fim, os resultados do risco são apresentados como índices, dificultando a interpretação de médicos do trabalho.

Esta dissertação desenvolveu uma solução para avaliação automática da exposição ao risco ergonómico do operário em linhas de montagem. Três contribuições são apresentadas: (1) um algoritmo de monitorização do membro superior e do tronco que se baseia em sensores inerciais para estimar a orientação das articulações anatómicas; (2) uma pontuação de risco ergonómico ajustado; (3) uma abordagem explicativa do risco ergonómico baseada na análise dos fatores de risco angulares. Ao longo desta investigação foram realizadas duas avaliações experimentais: validação laboratorial e avaliação de campo. Os testes de laboratório criaram um conjunto de dados de movimentos e utilizou um sistema ótico de captura de movimento como referência. O conjunto de dados de avaliação de campo foi adquirido numa linha de montagem automóvel e serve de base para um estudo de avaliação de risco ergonómico. Os resultados revelaram que a solução proposta tem potencial para ser aplicada em ambiente real. Através de medidas diretas, a resposta ergonómica é acelerada e, consequentemente, a avaliação pode ser estendida a mais operários, prevenindo a longo prazo lesões relacionadas com o trabalho.

**Palavras-chave:** Ergonomia, Indústria, Lesões musculoesqueléticas, Sensores inerciais, Captura de movimento, Pontuação de risco.

# Contents

Li	List of Figures xv							
Li	List of Tables xxi							
Ac	rony	ms x	xiii					
1	Intr	oduction	1					
	1.1	Context	1					
	1.2	Motivation	3					
	1.3	Literature Review	4					
		1.3.1 Ergonomic Risk Assessment	4					
		1.3.2 Current Available Commercial Solutions	8					
	1.4	Summary	8					
	1.5	Objectives	9					
	1.6	Structure	10					
2	The	oretical Background	13					
	2.1	Ergonomics	13					
		2.1.1 Musculoskeletal Disorders	14					
		2.1.2 Ergonomic Risk Assessment Tools	14					
		2.1.3 Risk Factors	16					
	2.2	Modelling Human Movement	18					
		2.2.1 Human Joints and Movements	18					
	2.3	Motion Capture	22					
		2.3.1 Inertial Motion Capture	22					
		2.3.2 Marker-based motion capture	24					
		2.3.3 Markerless motion capture	24					
	2.4	Attitude Representation	25					
		2.4.1 Quaternion Algebra	26					
	2.5	Sensor Fusion for Orientation Estimation	30					
		2.5.1 Complementary Filter	31					

3	Motion	Tracker	Framework
---	--------	---------	-----------

33

	3.1	System	n Overview	33	
3.2 Kinematic Model					
	3.3	Signal	Pre-Processing	35	
		3.3.1	Temporal Synchronisation	35	
		3.3.2	Noise Reduction	37	
		3.3.3	Data Normalisation	37	
	3.4	Orient	ation Estimation	37	
		3.4.1	Algebraic Method	38	
		3.4.2	Quaternion Based Complementary Filter	39	
	3.5	Angula	ar Trajectory Reconstruction	40	
		3.5.1	Pronation and Supination	41	
4	Res	ults		45	
	4.1	Inertia	l Signal Acquisition	45	
	4.2	Labora	atory Validation	47	
		4.2.1	Equipment and Placement	48	
		4.2.2	Dataset Overview	50	
		4.2.3	Motion tracking performance	51	
		4.2.4	Summary	61	
	4.3	Indust	rial Assessment	62	
		4.3.1	Equipment and Placement	63	
		4.3.2	Dataset Overview	63	
		4.3.3	Ergonomic Evaluation and Explanation	64	
		4.3.4	Workers relation with sensors	71	
		4.3.5	Summary	72	
5	Con	clusion	and Future Work	75	
	5.1	Main (	Conclusions	75	
	5.2	Future	Work	77	
Bi	bliog	raphy		79	
A	Info	ormed C	onsent to Participants, Portuguese Version	89	
			in the full of full of full of the second seco	05	
B	Part	icipant	's questionnaire, Portuguese Version	91	
С	Vali	dation	Protocol, Portuguese Version	93	
D	Sens	sor fusi	on algorithms Results	97	
	D.1	Madgv	vick	97	
	D.2	Mahor	ny	98	
	D.3	AGCF		99	

I Rapid Upper Limb Assessment

101

# List of Figures

1.1	Distribution of people (aged 15-64), from European Union countries, report-	
	ing work-related health problems by type of problem, in 2013	1
1.2	Industrial revolutions: the 1st Industrial Revolution was steam engine-driven;	
	the 2nd involved innovations from Henry Ford's assembly line; the 3rd ap-	
	plied microelectronics and computer power on factories; the 4th applies cyber-	
	physical systems.	2
1.3	Motion tracking overview.	10
1.4	Dissertation structure.	11
2.1	Diagram to obtain the final RULA score	15
2.2	U-shaped model - health risks associated with postures and movements	18
2.3	Human anatomical planes: frontal, sagittal and transverse plane (left to right).	19
2.4	Simplified arm's movements. Shoulder abduction, adduction, flexion, exten-	
	sion, medial and lateral rotation (left to right)	21
2.5	Simplified forearm's movements. Elbow flexion, extension, pronation and	
	supination	21
2.6	Wrist complex movements and respective range of motion. Wrist flexion,	
	extension, radial deviation and ulnar deviation (left to right).	22
2.7	Representation of Vicon setup - 10 Vicon cameras, capture volume, synchro-	
	nisation box and computer	25
2.8	OpenPose skeleton representation.	26
2.9	Coordinate systems.	26
2.10	Frame B orientation is obtained through a rotation of angle $\theta$ around the axis	
	$A_{\mathbf{r}}$	28
2.11	Representation of quaternions classes. Example of a pure and a rotation	
	quaternions (left to right).	30
2.12	Sensor fusion is applied to get the best attitude estimation.	31
3.1	The anatomical segments of the proposed framework: thorax, upper arm,	
	forearm and hand	34
3.2	Motion tracker system pipeline.	34
3.3	Temporal synchronisation stages.	36

3.4	Synchronisation at the device level. The synchronisation events are repre- sented by red vertical lines.	36
3.5	Block diagram of QCF approach.	38
3.6	Quaternion based complementary filter architecture.	39
3.7	Example of angular reconstruction of abduction and adduction movement. Movement description: five seconds in a neutral pose; abduction reaching shoulder line; pose sustained for five seconds; full abduction; pose sustained for five seconds; adduction until shoulder line; pose sustained for five seconds;	
	full adduction until neutral pose; pose sustained for five seconds	41
3.8	Vector considerations for angular reconstruction.	42
3.9	Supination and pronation movements (left to right).	42
3.10	Method to identify pronation and supination movements. The acceleration is represented by acc. Top to bottom: normalised acceleration, z-axis, with movements identification; normalised acceleration, z-axis, after applying the convolution-based and the median filters; signal derivative where minimums	10
	represent supination and maximums represent pronation.	43
4.1	The IoTiP device is composed of a triaxial accelerometer, gyroscope and a	
	magnetometer.	46
4.2	Screenshots of Recorder application. From left to right: Recorder's home interface; sensors and devices selection; subject and sensors position; selection	
	of desired workstation; acquisition interface with annotations panel	46
4.3	Placement of the IMU devices: three units on the upper limb and one unit on the torse. The devices were commonly aligned with V axis pointing up	47
1 1	Vicen Upper Limb Model marker placement. Front and rear view. The adopted	47
4.4	model did not consider the RBAK marker	49
4.5	Screeshot from Vicon Nexus right upper limb model. Frame example. Markers are represented as spheres and anatomical segments are depicted connecting	17
	the markers.	49
4.6	Side-view subject with inertial devices and optical markers attached.	50
4.7	Angular reconstruction of Set 1 arm's exercises. Comparison of different sensor	
	fusion methods.	52
4.8	Cumulative distribution function for the absolute error for each considered	
	algorithm across different segments - static evaluation	53
4.9	Cumulative distribution function for the absolute error for each considered	
	algorithm across different segments - dynamic evaluation	54
4.10	Sequence of hand movements and respective angular reconstruction using	
	Vicon software. A - rest position; B - Wrist extension; C - Wrist flexion	56
4.11	Angular reconstruction of Set 1 arm's exercises. QCF, Vicon and OpenPose	
	results.	58

4.12	Cumulative distribution function for the absolute error of OpenPose and QCF across different segments - Set 1.	58
4.13	Cumulative distribution function for the absolute error of OpenPose and OCF	
1.10	across different segments - dynamic evaluation.	59
4.14	Left - calibration positions: N-pose and T-pose. Right- A worker performing	
	and one on the thorax	63
4 1 5	Fromomic risk evaluation and explanation	64
4.16	Comparison of RULA and AdRULA methods. Studied body regions, posture	υı
1.10	selection and posture capture	65
4.17	Liftgate. Fender and Doors workstation analysis. Mean score distribution for	00
1.17	each workstation.	66
4.18	Representation of operator's average flexion and extension movements from	00
	Liftgate. Fender and Doors workstations with AdRULA score thresholds.	67
4.19	Comparison of average flexion and extension movements distribution from	0.
	four different subjects while performing Liftgate's tasks, with AdRULA score	
	thresholds. Right side - subjects' characteristics.	68
4.20	A participants cycle score comparison with the average score of the workstation.	69
4.21	Time dependent AdRULA scoring. Representation of one work cycle per-	
	formed by subject 1 from Liftgate workstation. Green: score 1-2; Yellow: score	
	3-4; Orange: score 4-5; Red: score 6+	70
4.22	Temporal analysis of seconds 42 to 45 from a subject performing Liftgate's	
	tasks. Arm, forearm, hand and trunk flexion/extension movements along	
	with the correspondent AdRULA score.	71
4.24	Radar chart with the average opinion of 12 subjects' on using IMU devices in	
	an industrial context. Agreement scale: 1 (totally disagree) - 5 (fully agree).	72
4.23	Detailed information on a subject's movement over a work cycle. Percentage	
	of time spent in each pose.	73

# LIST OF TABLES

1.1	Comparison of ergonomics studies applied to the industry relying on direct	
	measurements	7
2.1	Relevant body regions considered by each ergonomic assessment tools	14
2.2	Comparison between coverage across different ergonomic risk assessment tool.	16
4.1	Subjects' characteristic. m: male; f: female; $\overline{yr}$ : average years; r: ratio	48
4.2	Validation protocol. Considered sets, for static and dynamic evaluations, with	
	respective anatomical segments	48
4.3	Studied actions for static evaluation.	50
4.4	Studied actions for dynamic evaluation.	50
4.5	Mean absolute error regarding QCF method for each anatomical segment in-	
	cluding all static sets.	54
4.6	Root mean square error regarding QCF method for each anatomical segment	
	including all static sets.	55
4.7	Mean absolute error regarding QCF method for each anatomical segment in-	
	cluding all dynamic sets.	56
4.8	Root mean square error regarding QCF method for each anatomical segment	
	including all dynamic sets.	56
4.9	Pronation and supination identification.	57
4.10	Mean absolute error regarding QCF method for each anatomical segment in-	
	clude static Set 1	60
4.11	Mean absolute error regarding OpenPose method for each anatomical segment	
	include static Set 1.	60
4.12	Root mean square error regarding QCF method for each anatomical segment	
	include static Set 1	60
4.13	Root mean square error regarding OpenPose method for each anatomical seg-	
	ment include static Set 1	60
4.14	Mean absolute error regarding OpenPose method for each anatomical segment	
	including all dynamic sets.	61
4.15	Root mean square error regarding OpenPose method for each anatomical seg-	
	ment including all dynamic sets.	61

4.16	Industrial assessment subjects' characteristics. m: male; f: female; $\overline{yr}$ : average years; $\overline{h}$ : average height in cm; r: ratio.	62
D.1	Mean absolute error regarding Madgwick method for each anatomical segment	
	including all static sets	97
D.2	Root mean square error regarding Madgwick method for each anatomical seg- ment including all static sets.	97
D 3	Mean absolute error regarding Madgwick method for each anatomical segment	
D.5	including all dynamic sets	98
D 4	Root mean square error regarding Madgwick method for each anatomical seg-	70
D.1	most including all dynamic sets	08
D 5	Mean absolute error regarding Mahony method for each anatomical segment	70
D.J	including all static sots	08
D 6	Poot mean square error regarding Mahany method for each anatomical seg	90
D.0	mont including all static sets	08
D 7	Mean absolute error regarding Mahany method for each anotomical segment	90
D.7	in alle din a all demonstration acts	00
	Including all dynamic sets.	99
D.8	Root mean square error regarding Mahony method for each anatomical seg-	0.0
DO	ment including all dynamic sets.	99
D.9	Mean absolute error regarding AGCF method for each anatomical segment	
_	including all static sets.	99
D.10	Root mean square error regarding AGCF method for each anatomical segment	
	including all static sets	99
D.11	Mean absolute error regarding AGCF method for each anatomical segment	
	including all dynamic sets.	100
D.12	Root mean square error regarding AGCF method for each anatomical segment	
	including all dynamic sets.	100

# ACRONYMS

- AdRULA Adjusted Rapid Upper Limb Assessment.
- AGCF Accelerometer Gyroscope Complementary Filter.
- CDF Cumulative Distribution Function.
- CNN Convolutional Neural Network.
- DoF Degrees of Freedom.
- EAWS Ergonomic Assessment Work-Sheet.
- EMG Electromyography.
- ENU East-North-Up.
- Gonio Goniometer.
- IMU Inertial Measurement Unit.
- IoT Internet of Things.
- IoTiP Internet of Things in Packages.
- LI Lifting Index.
- MAE Mean Absolute Error.
- Mocap Motion Capture.

#### ACRONYMS

- MSDs Musculoskeletal Disorders.
- OCRA Occupational Repetitive Actions.
- OMC Optical Motion Capture.
- OWAS Ovako Working Posture. Analysis System.
- PAFs Part Affinity Fields.
- QCF Quaternion-based Complementary Filter.
- REBA Rapid Entire Body Assessment.
- RMSE Root-Mean-Square Error.
- ROM Range of Motion.
- RULA Rapid Upper Limb Assessment.
- SI The Strain Index.
- SLERP Spherical Linear Interpolation.
- WMSDs Work-related Musculoskeletal Disorders.



# INTRODUCTION

#### 1.1 Context

Work-related Musculoskeletal Disorders (WMSDs) prevail as the most common occupational disease in the European Union, impacting employees from different working sectors [1]. According to the World Health Organization, musculoskeletal conditions are the second largest contributor to disability worldwide and they are predicted to rise as the global population ages [2]. Due to the growth of case reports and its impact on production the interest in this type of injuries has increased thus, becoming one of the main concerns for workers health and safety [3]. In 2013, it was estimated that musculoskeletal injuries covered about 60% of the total occupational diseases [4], as shown in Figure 1.1.



Figure 1.1: Distribution of people (aged 15-64), from European Union countries, reporting work-related health problems by type of problem, in 2013. Data source [4].

Work-related musculoskeletal injuries are often due to trauma resulting from extreme movements or positions. Additionally, upper limb disorders account for 20% to 45% of WMSDs. Within these, elbow diseases are the most prevailing [5, 6].

For prevention, it is necessary to monitor field activities and properly address workers' concerns about the conditions of the work environment. This motivated researchers to explore different methods to collect work-related data and to identify the potential hazards from the collected information [7]. With the arrival of the fourth Industrial Revolution, shown in Figure 1.2, manufacturing business are integrating robots, automation and other technologies into their workflows.

Industry 4.0, a subset of the fourth Industrial Revolution, describes the trend towards smart and intelligent machines, 3D technology, the Internet of Things (IoT), factory virtualisation, and many other emerging technologies [8]. Companies are launching pilot projects in which they try to embed these technologies in their current manufacturing process [8, 9].



Figure 1.2: Industrial revolutions: the 1st Industrial Revolution was steam engine-driven; the 2nd involved innovations from Henry Ford's assembly line; the 3rd applied microelectronics and computer power on factories; the 4th applies cyber-physical systems. Adapted from [10].

Although robots are becoming more common in manufacturing environments, operators are still essential. However, the concept of an operator is undergoing a paradigm shift through the new generation of operators coming entitled as "Operator 4.0". These new smart and skilled workers will have super-strength provided by exoskeletons, smarter decision capabilities supported by artificial intelligence, and able to age healthily at work supported by a set of wearable body monitoring devices [11].

Over the last years, those wearable devices have captured high levels of interest in industrial environments. By using inertial motion capture system, data can be collected, and several parameters can be assessed, e.g. postural angles, making these fundamental for ergonomics studies [12].

## 1.2 Motivation

Manufacturing industries are a valuable portion of European Economy by securing 50 million direct jobs. Particularly, in Portugal, the sector employs about 23% of active workers [11]. For maintaining their position and growth, industry uphold digital transformation processes. In some industry sectors, e.g., textile and automotive, production processes are typically based on human effort and/or cooperation between the employee and machines. Although being well-defined and intended to guarantee that people abide by best practices, the operation methods carried out by workers can be repetitive. Nevertheless, musculoskeletal lesions' risk is increased due to repetitive tasks, which may lead not only to absenteeism but also early retirement and loss of productivity [13, 14]. In Great Britain, it is estimated that about 3.9 million working days were lost due to work-related musculoskeletal injuries during 2016-2017 [5].

Companies are realising that investing in ergonomics will bring advantages to both employees and employers – ergonomics reduce costs, improves productivity and quality and creates a better safety culture. Additionally, older workers tend to be the company's most experienced workers, but also, the most exposed to injuries [15].

On large industrial environments, there are dedicated occupational health and ergonomics teams who work towards a continuous ergonomic risk evaluation of operators. However, there are still some unsolved challenges which prevent a more effective ergonomic assessment at work.

During the design of a work process (or method), which often comprises a set of motions, manufacturing industries rely on a series of predefined ergonomic risk scores for each motion. The global risk score, for a given task, is calculated taking into account all local scores, an approach which is widely adopted across diverse manufacturing contexts, but it has inherent flaws. Firstly, the predefined scores are based on an average worker, meaning that they do not take into account the variability among operators such as anthropometric variations that may exist at the manufacturing plant population, operator's age and work experience. A shorter operator might have a higher ergonomic risk performing a given task than a taller operator and this fact might become unnoticeable as the design standards only take into consideration an "average worker". Secondly, ergonomic teams might still rely on observational methods, which involve dedicated personnel to observe or video record operators at work for posterior analysis. Although, due to the high workload involved in this process, it becomes unfeasible to employ observational methods across the complete manufacturing population. Finally, the outcome of the ergonomic risk assessment often results in a number which quantifies the associated risk yet, when occupational doctors receive their patients and ask for the tracking history of the assigned workstations and associated ergonomic risk, they only have access to a score to describe the risk, lacking a more comprehensive analysis of the risk factors which contributed to the resulting score.

Hereupon, this research focuses on tackling the aforementioned open challenges in ergonomic risk assessment on manufacturing industries. This research encompasses a solution to establish quantitative direct measurements of posture and movement using inertial sensors for the upper limb and torso. Those measurements will be able to continuously monitor operators individually producing also more comprehensive reports with explanations, concerning the most contributing factors for the calculated risk scores. It is expected that in long-term this solution will help in the prevention of upper limb WMSDs arising from repetitive tasks.

#### **1.3 Literature Review**

This section will introduce a literature review describing emerging methods to conduct the ergonomic risk assessment. In this context, relevant academic works and commercial solutions are presented. At last, it will be highlighted how this project goes beyond the state-of-the-art.

#### 1.3.1 Ergonomic Risk Assessment

It is possible to prevent musculoskeletal injuries by designing a task, workplace and/or equipment in such way that a worker does not put much physical stress on his/her body [16]. To prevent and control work related injuries, illnesses, and fatalities it is required to former identify the risk factors. For that matter, work-related data must be adequately collected and subsequently used in a risk assessment framework.

In literature, there are essentially three different data collection approaches that have been practised for identifying ergonomic risk assessment: self-assessment, observation-based measurement and direct measurement [3, 7, 17–19].

In the first method, data are collected, on both physical and psychosocial factors through interviews and questionnaires, on written records. This method has relative advantages of having low initial cost, being straightforward to use and applicable to wide range of workplace situations. However, researchers have revealed that workers' self-assessments on exposure level are often imprecise and unreliable [17].

The second technique, observation-based measurement, consists of visual analysis of recording observations with the help of predefined ergonomic risk sheets. Simpler observational methods can assess various exposure factors. While some permit only postural analysis of several body segments, others assess critical physical exposure factors. Some of these methods enable overall indices (or scores) for the combination of exposure factors to be determined. They aim to establish acceptable exposure limits for workers or at least settle priorities for intervention across a range of tasks, having the advantage of being inexpensive and practical for a wide range of activities and workplaces. However, they are subjected to intra- and inter-observer variability and are more suitable to assess static or repetitive jobs [3, 17, 20]. The Rapid Upper Limb Assessment (RULA) index is one of the most cited ergonomic risk assessment tools. It is based on the observation of postures during a certain task and outputs biomechanical and postural load values on the whole body with particular attention to the neck, trunk and upper limbs [7, 18, 21].

At last, direct measurement relies on sensors that are attached directly to the subject for the measurement of variables at work. Despite the fact that this technique can provide large quantities of highly accurate data on a range of exposure variables, the wearables require the employment of trained and skilled technical staff to ensure their effective operation [17, 22].

By comparison of techniques, previous works have revealed that the direct measurement approach provides the most valid analysis of risk factors [23]. Improvements in sensor technology seem to offer the potential for regular industrial use in contrast with other tracking devices, such as range cameras or magnetic sensors which are more effective in virtual environments [7, 24]. Consequently, low-cost wearable sensors, such as Inertial Measurement Unit (IMU)s, have gained relevance for data collection.

Capturing and monitoring human motion through inertial sensors has gained attention in diverse fields, e.g. film-making, video game developing and ergonomics. This fact is mainly explained by the technological advances which allowed mass production at reduced costs and, consequently, the sensors proliferation in various contexts [25].

By using several IMUs simultaneously connected, biomechanical models can be developed to capture a wide range of movements [7]. To reconstruct the upper limb segments, joints and movements an upper limb model is required. Some authors [26, 27], assume that the human arm motion could be approximated to an articulated motion of rigid body parts, characterising the human arm as two rigid segments, the upper arm and the lower arm. Each of the segments can only rotate about its preceding joints, the shoulder joint or the elbow joint. Moreover, it states that human arm motions can be represented by kinematic chains.

Table 1.1 represents a general overview of the main ergonomics studies based on direct observation methods applied to the industrial field.

Throughout the last years, the necessity to perform pose-related industrial studies has been identified. Table 1.1 shows that researches mainly focus on the upper body and combine multiple devices, namely electromyography, goniometers and IMUs. Studies lack to describe the employed biomechanical model and if any calibration procedure was adopted and in general, the cost/effective for sensors number is high. Furthermore, few studies have included a system validation trial, providing no error estimate on tracking angular motion. At last, the previous studies have focused on using direct measurement to automatically retrieve local or global scores of different ergonomic risk assessment methods, and did not include more consolidated methods to explain the most contributing factors for each score.

Table 1.1:	Comparison of	ergonomics	studies applie	d to the ind	ustry relying	on direct me	asurements.	N/A - Not A	Applicable; N	JM - Not
Mentioned	ł									

Study	Body Region	Sensors	Model (DoF)	Calibration	Validation	Output
Cabeças. (2007) [28]	Forearm	EMG <sup>1</sup> (1000 Hz)	N/A	Maximum Isomet- ric tests	NM	Modified SI <sup>2</sup>
Bleser et al. (2011) [29]	Upper Limbs	5 x IMUs (100 Hz); Camera marker	5	Static n-pose, back- bent	OMC <sup>3</sup>	Wrist position
Ray and Teizer. (2012) [24]	Full body	Range Camera	N/A	NM	NM	Pose classification; Pose estimation; ergonomic analysis.
Vignais et al. (2013) [7]	Upper Limbs	21 x IMU (100 Hz); 2 x Gonio <sup>4</sup> (100 Hz)	20	N-pose, back-bent	Study-group Vs control-group	Execution time; RULA <sup>5</sup>
Battini et al. (2014) [19]	Full body	17 x IMU (500 Hz)	NM	NM	NM	RULA <sup>5</sup> , OWAS <sup>6</sup> , OCRA <sup>7</sup> LI <sup>8</sup>
Peppoloni et al. (2016) [3]	Upper Limbs	3 x IMU; EMG (100 Hz)	7	N-pose, T-pose	10 manual Vs 10 auto	RULA <sup>5</sup> , SI <sup>2</sup>
Yan et al. (2017) [30]	Head; Trunk	2 x IMU (10 Hz)	NM	N-pose	Lab Vs field exper- iment	Ergonomic analysis with thresholds
Viganis et al. (2017) [18]	Upper Limbs; Head; Pelvis	7 x IMU (64 Hz); 2 x Gonio <sup>4</sup> (32 Hz); 2 x Video system	20	N-pose (begin) N- pose (end)	NM	RULA <sup>5</sup>
Bauters et al. (2018) [31]	Full body	Video system	N/A	NM	NM	Performance indica- tors
Caputo et al. (2019) [12]	Upper limbs; Trunk; Pelvis	4 x IMU	NM	NM	NM	OWAS; OCRA; EAWS9

 $\mathbf{n}$ 

<sup>1</sup> Electromyography. <sup>2</sup> The Strain Index. <sup>3</sup> Optical Motion Capture. <sup>4</sup> Goniometer. <sup>5</sup> Rapid Upper Limb Assessment. <sup>6</sup> Ovako Working Posture. Analysis System. <sup>7</sup> Occupational Repetitive Actions. <sup>8</sup> Lifting Index. <sup>9</sup> Ergonomic Assessment Work-Sheet.

#### 1.3.2 Current Available Commercial Solutions

In recent years, the combination of Information Technologies and Operational Technologies has been reforming Industry, bringing not only higher production levels, but also moderating employees' work while generating more income [32]. Furthermore, to promote physical comfort, productivity and efficiency ergonomics studies are being performed, which explains the increasing number of solution providers, offering the ability to automatic monitoring human motion and environmental conditions.

ViveLab Ergo, IBM Maximo Worker Insights and Soter Analytics are three examples of established platform solutions:

- The **ViveLab Ergo** service performs an ergonomic analysis through a digital humanmodel based software and has a major advantage of being a cloud-based system. The service was released in 2015 and relies on Xsens Motion Capture system to collect movement data. However, in terms of setup time, invasiveness and hardware complexity it has a high cost [33].
- **IBM Maximo Worker Insights** solution combines wearable data from environmental sensors with advanced analytics, allowing real-time feedback. Nonetheless, it fails to provide detailed and generalised metrics from movement data [34].
- The Soter Spine, developed by **Soter Analytics**, uses a combination of wearable sensors for measuring the activities of industrial workforces and analytics for predicting and preventing work-related musculoskeletal disorders [35].

## 1.4 Summary

The dissemination of Industry 4.0 promotes a trend towards IoT solutions and, as reviewed, academic works and commercial solutions which use direct measurements to apply ergonomic principles are emerging. Nevertheless, the solutions often require subjects to wear an extensive amount of devices or depend on complex systems. Additionally, current methods lack explanatory reasoning.

Specifically, Vivelab Ergo solution offers ergonomic analysis through the development of low-level metrics yet, depends on complex hardware. The Soter Spine solution only develops high-level metrics, failing in characterising angular details.

This research aims not only to present a cost-effective ergonomic technique but also intends to provide an ergonomic risk explanation approach based on the comprehensive analysis of the angular risk factors.

# 1.5 Objectives

When planning a direct system for an ergonomic assessment, there are typically three design considerations: explainability, invasiveness and scalability.

Explainability relates to the degree of information that a setup's evaluation can report. Invasiveness is related to the operator's discomfort level, when using the solution, and also to the impact on the operator's performance due to the setup. Scalability establishes how many subjects can, simultaneously, use the setup, depending on invasiveness and cost.

This project was intended to design a system which allowed to extract information at an intermediate level, i.e., calculating low-level metrics of ergonomic risk and not demanding a large number of sensors. Thus, it is expected that the system has an average level of scalability, explainability and invasiveness.

When the results of a traditional ergonomic assessment, in the form of an index score, are delivered to occupational medicine, they may not be explanatory and may compromise the acceptance, implementation and effectiveness of the system.

Herewith, this research seeks to answer the following main research question: How to continuously measure and explain the ergonomic risk of industrial workers using inertial sensors?

The main research question is approached through four additional research questions: Which workstation has a higher ergonomic risk score across the plant? Which operators' movements contribute to workstation's ergonomic risk? Do subjects antropomethric characteristics influence their risk? How does ergonomic risk vary in a work cycle? Accordingly, it is intended to extract knowledge from Human motion, during the execution of repetitive tasks, using wearable sensors technology. This will allow later delivery of recommendations through the conception of a complete report.

The main goals of this dissertation are the following: (1) develop an upper limb and torso tracking technique using wearable sensors; (2) perform a laboratory assessment, based on Human motion, to validate the developed method; (3) conduct a feasibility test focused on the ergonomic risk assessment on real manufacturing environments; (4) generate reports explaining the outcome of an ergonomic assessment.

An idealised system is organised under the architecture represented on Figure 1.3.



Figure 1.3: Motion tracking overview.

In the acquisition module, the worker wears motion sensors on the upper limb and torso which will be integrated in a smartphone or other equipment to collect the data. Then, in the processing stage noise reduction, sensors synchronisation and cycle segmentation are addressed. The visualisation module summarises processing outputs by creating human interpretable data, information and knowledge visualisations which are akin to system user's mental models, to enable quick and effective response from decision-makers over the collected and processed data. Thus, the system must provide fast and accurate tree-dimensional angular motion tracking as a supporting tool to create optimal working environments and work methods across different industrial contexts.

Using employees to gather requirements and evaluate new technologies, as a new data-driven industry 4.0 system, may introduce tensions for bringing consequences to employees. In this context, a project which commits to good practice guidelines must consider research ethics, ensuring that employees do not experience any negative effects from participating in the research.

The developed method should never be considered as a tool to prejudice any worker. It is expected to act as: (1) a technique to assure that the worker is not overly exposed when performing a selected task; (2) a way to cover a larger number of employees and give feedback in lesser time, as the instrumentation phase is fairly simple.

#### 1.6 Structure

This dissertation is composed by four elements and it is divided into five chapters, three appendices and an annex, as schematised in Figure 1.4.



Figure 1.4: Dissertation structure.

The present chapter introduced the context and motivation which lead to the development of this project. Additionally, a review of the literature and the main objectives were also presented. Chapter 2 provides the theoretical background concepts and principles. These two chapters form the basis for the development of the dissertation.

The methods used in this research are introduced in Chapter 3 which thoroughly presents and explains the developed upper limb and torso motion tracker.

Chapter 4 summarises a description, results and discussion of two main studies conducted during this dissertation: laboratory and field assessments.

Finally, Chapter 5 highlights the more relevant conclusions and points to future work directions.
Снартек

# THEORETICAL BACKGROUND

In this Chapter, a review of the fundamental topics on ergonomics, motion capture techniques and orientation representation are presented. Firstly, concepts regarding ergonomics and risk assessment methods are described. Then, considerations on modelling the upper limb and torso are provided. Relevant motion capture methods are then introduced and representation in coordinate frames is followed after. Lastly, quaternion algebra and sensor fusion methods are approached.

## 2.1 Ergonomics

Ergonomics is the scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data and methods to design in order to optimise human well-being and overall system performance [36].

The concept of ergonomics, which derives from the Greek *ergon* (work) and *nomos* (laws), was originally proposed and defined in 1857 by the Polish scientist B. W. Jastrzebowski as the scientific discipline that covers all aspects of human activity [37]. Contemporary ergonomics studies human behaviour, abilities, limitations and other characteristics in order to design tools, machines, systems tasks, jobs and environments for productive, safe, comfortable, and effective human use [38–40]. In this context, the ergonomics professionals study how a product/workplace/system should be designed to serve the people who need to use it, complementing people's strengths and minimising their limitations [2, 36]. The establishment of a balance between the requirements of the work and the capacity of the working person is a major concern in ergonomic studies.

### 2.1.1 Musculoskeletal Disorders

Musculoskeletal Disorders (MSDs) are inflammatory and degenerative diseases, of the locomotor system, i.e. of muscles, tendons, the skeleton, cartilage, ligaments and nerves [2]. According to the World Health Organization, the most common MSDs are osteoarthritis, back and neck pain, fractures associated with bone fragility, injuries and systemic inflammatory conditions such as rheumatoid arthritis [41].

Such disorders are supposed to be caused or intensified by work. Thus, the injuries that are consequence of the action of professional risk factors are denominated as Work-related Musculoskeletal Disorders (WMSDs). Most often, WMSDs are located in the upper limb and spine. However, there may be other locations, e.g. knees or ankles, depending on the activity developed by the worker [13].

To address WMSDs hazards, safety and health principles are employed in an ergonomic process, which should be viewed as an ongoing function rather than as an individual project [42].

#### 2.1.2 Ergonomic Risk Assessment Tools

The influence of postures adopted at the workplace has been a major concern. The goal of assessment methods is to recognise ergonomic risk factors, quantify them, and later enhance the workplace by assuring that tasks are within workers' capabilities and limitations.

An approach for accomplishing so is by making ergonomics a continuous process of risk identification through the implementation of ergonomic assessment tools, such as the following worksheets: Ovako Working Posture. Analysis System (OWAS), Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA), Ergonomic Assessment Work-Sheet (EAWS), The Strain Index (SI), etc. Besides those assessment methods, there is also a European standard, the EN 1005-4:2005, that is applied for evaluating working postures and movements in relation to machinery [43]. In Table 2.1 the evaluated body regions according to different techniques are represented.

Method	Wrist	Elbow	Shoulder	Cervical	Lumbar
RULA[44]	•	•	•	•	•
OWAS[45]			•		•
REBA[46]	•	•	•	•	•
EAWS[47]	•	•	•	•	•
SI[48]	•				

Table 2.1: Relevant body regions considered by each ergonomic assessment tool.

#### 2.1.2.1 Rapid Upper Limb Assessment

The RULA method is based on a five-step approach: in steps 1-3 the range of postures are analysed and then their scores are calculated; in step 4, other physical factors, e.g. muscle use and force, are brought into the assessment; finally, in step 5, all body part scores are included forming a Global Risk Index. Lastly, the action level can be classified as "green", "yellow"or "red", representing an increased risk of WMSDs respectively [49].

The traditional RULA assessment is the representation of a moment in the work cycle. Thus, before any evaluation, the specialist must observe the whole work cycle, to select the postures which will be assessed. The analysis will be performed, depending on the task, on either the longest held posture or what appears to be the worst significant posture. Since tasks may not be executed symmetrically with both arms, separate RULA scores sheets, for right and left sides of the body, may be applied [49].

The complete worksheet of RULA method can be found in Annex I. The diagram in Figure 2.1 represents the step 5 in RULA method, where all the assessed scores from different body regions, named local scores, are joined together to generate a final score. This grand score will reveal if there's any need for intervention and modifications on the work or workplace.



Figure 2.1: Diagram to obtain the final RULA score. Reproduced from [49].

## 2.1.3 Risk Factors

Most WMSDs develop over time and generally, there is no single cause for these lesions. They often result from a combination of several risk factors. According to the Occupational Safety and Health Administration, eight risk factors may lead to a strong probability of triggering WMSDs: force, repetition, awkward postures, static postures, quick motion, compression or contact stress, vibration, and extreme temperatures [13, 16]. The authors from [17] present a comparison between observational methods which is laid out in Table 2.2.

Table 2.2: Comparison between coverage across different ergonomic risk assessment tool.Adapted from [17].

Method	Posture	Load/Force	Movement frequency	Duration	Vibration	Recovery
RULA[44]	•	•	•			
OWAS[45]	•	•				
REBA[46]	•	•	•			
EAWS[47]	•	•	•	•	•	•
SI[48]	•	•	•	•		

The risk factors can be divided into two categories: work-related risk factors and individual-related risk factors, which will be described in the following sections. Machinery risk factors are also addressed.

### 2.1.3.1 Work-related Risk Factors

A work cycle is defined as a sequence of activities and movements repeated with little or no variation each time the job is performed. Whenever a worker has to perform a task outside of his/her body's capabilities, he/she is putting the musculoskeletal system at risk [50].

Typically, there can be considered three primary work-related ergonomic risk factors: task repetition, forceful exertions and awkward postures. Workers that are exposed to these workplace risk factors often are at a higher level of WMSDs risk.

- Task repetition Work processes that are repetitive in nature, often imply that the worker is controlled hourly or daily in production targets. Combining high task repetition with other risk factors can trigger WMSDs. A given task is considered repetitive if the work cycle time is 30 seconds or less or when the fundamental work cycle is more than 50% of the total work in its extension [13, 50].
- Forceful exertions Some tasks may require high force loads on the worker's body. High force requirements which lead to an increasing fatigue state can lead to WMSDs [13, 50].

• Awkward postures - Human joints are more effective when they operate close to the mid-range motion of the joint. When joints work outside of this mid-range, repetitively or sustained for some periods, the risk for WMSDs is increased. Awkward postures not only affect joints but also overload muscle and tendons that are around the affected joint [13, 50].

#### 2.1.3.2 Individual risk factors

There is an interaction between individual and work-related risk factors. The principal factors that will lead to individual risk are age, anthropometric characteristics and physical activity.

Nevertheless, other individual considerations may also influence the WMSDs risk. Workers who use poor work practices, create unnecessary stress on their bodies. Furthermore, workers with overall poor health habits, e.g., workers who smoke or drink excessively or are obese, put themselves at risk not only for WMSDs but also for chronic diseases. Poor rest and recovery lead to fatigue and, when fatigue outruns the worker's recovery system disorders are easily developed. At last, poor nutrition and hydration can also be play an import role in the development of WMSDs. Therefore, having a poor health profile places workers at a higher risk of developing musculoskeletal imbalance [49, 50].

#### 2.1.3.3 Machinery Risk Factors

The machinery design must have into account specific ergonomic aspects. Designers must collect information on existing tasks and evaluate the work-load that those impose on the operator. Then, the target population, to work with the machine, and the task should be defined. A good ergonomic design should meet the needs of 90% of the operators from the 5th to the 95th percentile [49, 51].

The list bellow indicates the potential WMSDs hazards of the machine's operation.

- Static postures and body movements;
- Manual handling of loads (above 3 kg);
- Force exertion;
- Repetitive movements;
- Hand-arm vibration;
- Whole-body vibration;
- Energetic load;
- Local mechanical stress.

Additionally, an approach to evaluate the health risks for static postures and movements is based on the U-shaped model represented in Figure 2.2. According to this model, the risk increases when a static posture is held or when there is a highly frequent movement [49, 51].



Figure 2.2: U-shaped model - health risks associated with postures and movements. Reproduced from [49].

## 2.2 Modelling Human Movement

A description of body position in directional and functional terms is fundamental for motion studies. Therefore, the movements of the body, or body segments, in the three anatomical planes should be accurately described [52]. This research centres on ergonomically supporting operators through motion tracking. Thus, it is necessary to summarise the concepts of human movement modelling/description.

## 2.2.1 Human Joints and Movements

Anatomical descriptions are based fundamentally on three major imaginary planes (see Figure 2.3): the frontal plane being the body observed from the front, i.e., face to face; the sagittal plane being the body observed from the side; and the transverse plane being the body observed from directly above the head. These planes intersect the human body in a standard anatomical position [53].



Figure 2.3: Human anatomical planes: frontal, sagittal and transverse plane (left to right). Adapted from [54].

The torso, or trunk, is an anatomical term which includes the thoracic and abdominal segments of the trunk and the perineum. Specifically, the thorax region, which has a cage-like shape, has an important role in protecting the viscera, breathing and movement. It's continuous with the neck superiorly and bounded by the diaphragm inferiorly [55].

The upper limbs are anchored to the thoracic cage through the bones of the shoulder region, which form the pectoral girdle, at the glenohumeral joint. The upper limb skeletal system is divided into four regions: the shoulder, arm, forearm and hand and its main function is to enable the mechanical manipulation of objects [55].

In the developed tracking method the referred regions are taken into account. Furthermore, it is important to perceive the relevant movements and the involved joints.

#### 2.2.1.1 Joints

A joint is defined as the interaction point between two or more bones. Frequently, the joints are named according to bones that are joined together [22, 56]. Since in this study an upper limb and torso tracking method is developed, a list of the most relevant joints, to evaluate human upper limb movement and posture, is presented.

- Shoulder complex the shoulder complex is composed by the clavicle, scapula and humerus, which are united through the glenuhumeral and acromioclavicular joints. The complex is connected to the axial skeleton through the sternoclavicular joint (a plane synovial joint). Moreover, the scapulothoracic and the sub-acromial joints are often incorporated in anatomical descriptions of the shoulder complex [57].
- Elbow complex the elbow complex is a compound synovial joint containing four articulations within a common fibrous capsule. The humeroulnar joint, between the humerus and ulna, and the humeroradial joint, between the humerus and

radius, are hinge type joints. The **superior radioulnar** and the **inferior radioulnar** articulations, between the radio and ulna, are a pivot type joints [58].

• Wrist complex - the wrist complex joint unites the hand to the forearm. The wrist's movements are carried out by two compound joints: the **radiocarpal** condyloid joint, formed by scaphoid, lumate, and triquetrum distally and by the radius and radioulnar disc proximally; and the **midcarpal** joints, formed by the two rows of carpal [59].

## 2.2.1.2 Movements

Different combinations in body joints allow for different basic movements. The Range of Motion (ROM), which describes the amount of mobility that can be demonstrated in a certain joint, is important when studying movements. However, there is some disparity in literature when addressing ROM, which may be explained by different conditions in determining the values.

Regarding the torso and the upper limb, different movements can be considered, along side with their range of motions.

### Torso

Torso's movements includes **flexion/extension**, bending forward/ backward the torso, in the sagittal plane. In the frontal plane, **lateral flexion/medial flexion**, the direction is set further away/closer from the midline of the body. In the transverse plane, **axial rotation** is the result of rotating the trunk along the vertical long axis of the body [53]. Torso's forward bending may reach 80° while backward bending is set to 25°. Additionally, the torso can endure 35° for lateral and medial flexion, and also 45° for axial rotation [60].

#### Shoulder joint

Arm's movements are represented in Figure 2.4. In the sagittal plane, the glenohumeral joint's movements comprises **flexion**/ **extension**, raising/lowering the arm. **Abduction**/**adduction** are movements of the frontal plane, consisting of raising/lowering the arm to the side. In the transverse plane, **lateral rotation/medial rotation** is considered, meaning that the arm is rotated along its long axis outward/inward [53].

Literature indicates that the arm is able to withstand flexion up to 180° and that extension may reach 60°. Additionally, it is also able to reach 180° abduction and 20° adduction and also, 90° and 20° for medial and lateral rotation respectively [56, 61].



Figure 2.4: Simplified arm's movements. Shoulder abduction, adduction, flexion, extension, medial and lateral rotation (left to right). Adapted from [61].

#### **Elbow complex**

Forearm's movements are illustrated in Figure 2.5. Movements of the elbow include **flexion/extension** of the forearm, decreasing/increasing the internal angle, in the sagittal plane. Forearm's movements can also be considered as a joint action, since the rotation of the two forearm bones, the radius and ulna, can be observed. Thus, comes **supina-tion/pronation**, which is represented by the rotation of the forearm to the palm up/down position [53].

Due to bony interference of the olecranon process of the ulna, in the olecranon fossa of the humerus, the elbow extension is limited. The normal full extension is established as zero degrees nonetheless, individual variations can be a few degrees positive or negative (hyperextension).The forearm is also able to withstand flexions up to 140°. The average normal ranges of forearm pronation and supination are approximately 90° and 80° respectively [56, 61].



(a) Flexion and Extension.

(b) Pronation and Supination.

Figure 2.5: Simplified forearm's movements. Elbow flexion, extension, pronation and supination (left to right). Adapted from [61].

#### Wrist complex

In the sagittal plane, **flexion/extension** movements can be described as bending the palm upward to the forearm/ bending the palm back from the forearm. Additionally, in the frontal plane, there can be **radial deviation/ulnar deviation**, meaning that hand is

moving closer to the radius bone/ulna bone [53].

Figure 2.6 represents hand's movements. The average range of wrist flexion/extension and radio/ulnar deviation are expressed in [56] as 66° of flexion, 55° of extension and, 20-25° of radial deviation and 30-35° ulnar deviation.



Figure 2.6: Wrist complex movements and respective range of motion. Wrist flexion, extension, radial deviation and ulnar deviation (left to right). Adapted from [62].

## 2.3 Motion Capture

Motion Capture (Mocap) is the process in which the movements of objects are recorded. Mocap technology was originally developed for gait analysis, yet, nowadays, it is most frequently used in gaming, movie and animation industry, but also by sports therapists, neuroscientists, and for validation and control of robotics and computer vision [63, 64].

The motion capture techniques can be divided into different categories. The following categories were considered in the development of this project:

- **Inertial motion capture** uses a set of inertial sensors which are worn by the subject. The recorded data is often transmitted wirelessly to a computer.
- Marker-based motion capture uses retroreflective markers, worn by the subject, which are tracked by infrared cameras.
- Markerless motion capture which has been involving due to increased research in computer vision, where algorithms are designed to identify human forms. This method has the advantage of having a non-intrusive nature. Regardless, data error ranges tend to be larger than marker-based solutions.

### 2.3.1 Inertial Motion Capture

The position and orientation of a given object are estimated by attaching sensors to the object in study. Furthermore, if the object happens to be a rigid body, and has sensors tightly attached to it, the sensor's data allows the extraction of direct information about position and orientation of the object [65].

An Inertial Measurement Unit (IMU) is a small and portable device that combines information obtained from multiple electromechanical sensors to estimate the spatial orientation of an object. Inertial sensors are constituted by accelerometers and gyroscopes and, some of them, also include magnetometers. IMUs have advantages over individual electromechanical sensors once the strengths of each individual electromechanical sensor component may help balance the limitations of another [66]. They are usually applied to determine orientation through sensor fusion methods, which will be introduced in Section 2.5.

#### 2.3.1.1 Accelerometer

Triaxial accelerometers are sensors capable of measuring simultaneously changes in acceleration in three orthogonal directions, however, the are also influenced by the gravitational acceleration of the Earth, i.e.,  $g = 9.8 \text{ m/s}^2$ . The accelerometer sensor is a inertialframe sensor, which means that when the device is in free fall, the acceleration is  $0 \text{ m/s}^2$ , in the falling direction, and when the device is laying flat on a table the acceleration, in upwards direction, will be equal to Earth's gravity. Thus, the measured signal has two components: a static and a dynamic one. The former is caused by the Earth's gravitational acceleration and the latter is due to device's movement. The measured acceleration is frequently represented in meters per second squared (m/s<sup>2</sup>), but some devices measure in g-force units (g) [67].

Through filtering methods it is possible to isolate accelerometer's components, e.g. the linear acceleration of a device. Therefore, a high-pass filter can help to isolate the linear acceleration and a low-pass filter can help to isolate the gravity [67].

The most relevant source of error of this sensor is the bias, which consists of an offset of accelerometer's output signal from the true value. However, it is possible to estimate the bias through the measurement of the long term average of the sensor's output, when it is not undergoing any acceleration [67, 68].

### 2.3.1.2 Gyroscope

A gyroscope is a sensor that measures the angular velocity of a device, represented in radians per second (rad/s). This sensor is usually three dimensional and can also be used to compute the device's relative orientation to a previous instant.

The gyroscope oscillate at a relative high frequency, being easily affected by other vibrations, e.g., the speaker on the same device, making it a sensor with higher power consumption [67].

Gyroscopes suffer from bias and numerical errors. The bias consists of an average output from the sensor when it is not undergoing any rotation and it shows itself after integration as an angular drift, increasing linearly over time. Another common problem is the calibration error, that is related with scale factors, alignments, and linearities of the gyroscopes. These types of errors are perceived only when the device is turning. They lead to the accumulation of additional drift in the integrated signal, the magnitude of which is proportional to the rate and duration of the motions [67, 68].

#### 2.3.1.3 Magnetometer

Magnetometers sensors are able to measure the magnetic field, meaning that, if there's no strong magnetic interference, the Earth's magnetic field will be sensed.

The triaxial magnetometer sensor provides a 3D vector pointing to the strongest magnetic field, representing it in microtesla ( $\mu$ T) units. Consequently, it enables to obtain the absolute orientation of the device relative to the North Pole.

Magnetometers are often influenced by buildings' ferromagnetic construction materials and electrical equipment. This magnetic interference is the main cause of measurement errors [67, 68].

To estimate the device's orientation is, at least, necessary the gravity vector, which means that the accelerometer sensor is required. If a gyroscope is provided, more precise readings are obtained.

### 2.3.2 Marker-based motion capture

The optical-passive marker method is the most commonly for motion capture, since it is flexible and has high accuracy. The Vicon motion capture system fits in this Mocap category.

Vicon, established in the early 1980s, is a developer of motion capture products and services which can be used for life science, entertainment and engineering industries [64].

With Vicon motion capture system, experiments ranging from balance studies to limb movement and gait studies can be performed. The system allows a passive motion capture through the use of reflective markers on the subject and, depending on the field of the study, there are available multiple options to configure and build the system by varying the number and model of the cameras, the room size the software and other. An example setup of Vicon motion capture system can be seen in Figure 2.7 [64, 69].

The authors from [70] state that Vicon's error from low to high speed experiments is lower than 2 mm.

The Vicon system is used in this study to perform a laboratory assessment comparing its results with the developed inertial motion capturing technique, described in the Chapter 4.

### 2.3.3 Markerless motion capture

The markerless technology does not demand the subjects to wear any special equipment for motion capture. The OpenPose system belongs to this category.

OpenPose is an open-source system for multi-person 2D pose detection, which includes body, foot, hand, and facial keypoints, making in total 135 keypoints, on single



Figure 2.7: Representation of Vicon setup - 10 Vicon cameras, capture volume, synchronisation box and computer. Reproduced from [64].

images. In Figure 2.8a can be found an example of a skeleton representation obtained with 18 keypoints [71].

The system uses an entire image as the input for a Convolutional Neural Network (CNN) to predict both confidence maps and Part Affinity Fields (PAFs). The former is associated with body part detection and the latter with part association. After, comes the parsing step which performs a bipartite matchings to associate body part candidates. In the last stage, it is all assembled into full body poses. Figure 2.8b shows an example of an output of OpenPose system [71].

In this study, the OpenPose python library is tested, in Chapter 4, and compared with a regular Mocap method, i.e., Vicon, and also with the developed inertial based algorithm.

## 2.4 Attitude Representation

Establishing the orientation of an object, with respect to a reference frame, is the ultimate goal of an attitude determination [22, 73].

Therefore, two coordinate frames are considered:

• Earth Reference Frame - The reference frame considered in the study is the East-North-Up (ENU) coordinate system, which is attached to the earth and represented by the orthogonal vector basis *E*, *N*, *U*. At a given point, P, in Earth's surface: *E* is tangent to the circle of constant latitude, also known as parallel circle, passing through P; *N* is tangent to the meridian circle passing through P; *U* points in the direction of P. Therefore, *E* points East, *N* points North and *U* points upwards, as



(a) OpenPose skeleton representation obtained with 18 keypoints. Reproduced from [72].



(b) OpenPose output example. Retrieved from [71].



shown in Figure 2.9a. Earth Reference Frame is always static independently of the orientation of the body.

• **Sensor Frame** - The sensor frame is tightly attached to the object, Figure 2.9b, whose attitude we would like to describe. The Sensor Frame is fixed to the sensor, however it changes relative to the Earth reference frame due to the sensor movement.



(a) Earth Reference Frame - East, North, Up coordinates.

(b) Sensor Frame.

Figure 2.9: Coordinate systems [74].

## 2.4.1 Quaternion Algebra

Introduced by William Rowan Hamilton, quaternion algebra is frequently used in orientation estimation algorithms. The quaternion, a four-dimensional complex number, can represent the orientation of a rigid body or coordinate frame in three-dimensional space [75, 76]. Comparing with Euler angle sequence rotation, which is another common method, quaternions present a major advantage, for they do not experience gimbal lock, i.e. the loss of a DoF that occurs when two axes of the three gimbals are turned into a parallel arrangement [75].

#### 2.4.1.1 Basic Definition and Representation

A full quaternion q is expressed, in equation (2.1), as the sum of a scalar  $q_0$  and a vector  $q = (q_1, q_2, q_3)$ .

$$q = q_0 + q = q_0 + q_1 i + q_2 j + q_3 k$$
(2.1)

The fundamental formula of quaternion algebra describes how the components behave and interact with each other:

$$i^2 = j^2 = k^2 = ijk = -1$$
 (2.2)

Furthermore,

$$\boldsymbol{k} = \boldsymbol{i}\boldsymbol{j} = -\boldsymbol{j}\boldsymbol{i} \tag{2.3}$$

$$\mathbf{i} = \mathbf{j}\mathbf{k} = -\mathbf{k}\mathbf{j} \tag{2.4}$$

$$\boldsymbol{j} = \boldsymbol{k}\boldsymbol{i} = -\boldsymbol{i}\boldsymbol{k} \tag{2.5}$$

Equations (2.2) to (2.5) are relevant to understand quaternion multiplication. These relations are often called as Hamilton's Rules.

#### 2.4.1.2 Quaternion Properties

The multiplication of two quaternions q and p, here given by  $\otimes$ , do not commutate, i.e.,  $q \otimes p \neq p \otimes q$ . The quaternion product, equation (2.6), can be determined using Hamilton's Rules, presented in section 2.4.1.1.

$$p \otimes q = p_0 q_0 - (p_1 q_1 + p_2 q_2 + p_3 q_3) + p_0 (q_1 \mathbf{i} + q_2 \mathbf{j} + q_3 \mathbf{k}) + q_0 (p_1 \mathbf{i} + p_2 \mathbf{j} + p_3 \mathbf{k}) + \mathbf{i} (p_2 q_3 - p_3 q_2) + \mathbf{j} (p_3 q_1 - p_1 q_3) + \mathbf{k} (p_1 q_2 - p_2 q_1)$$
(2.6)

As result of simplification and combining terms, results equation (2.7).

$$p \otimes q = p_0 q_0 - (pq) = p_0 q_0 - (pq) + p_0 q + q_0 p + (p \times q)$$
(2.7)

The quaternion conjugate, denoted here by  $q^*$ , is represented in equation (2.8).

$$q^* = q_0 - q = q_0 - iq_1 - jq_2 - kq_3$$
(2.8)

The norm of a quaternion, denoted as ||q||, is defined in equation (2.9). Quaternion norm is multiplicative.

$$||q|| = \sqrt{q_0^2 + q_1^2 + q_2^2 + q_3^2} = \sqrt{q \otimes q^*} = \sqrt{q^* \otimes q}$$
(2.9)

The inverse quaternion is given by equation (2.10).

$$q^{-1} = \frac{q^*}{\|q\|^2} \tag{2.10}$$

In the special case where the norm of a quaternion is unitary, the inverse is also the conjugate, as expressed in equation (2.11).

$$||q|| = 1 \Rightarrow q^{-1} = q^*$$
 (2.11)

## 2.4.1.3 Quaternions and Rotations

An arbitrary orientation of frame B relative to frame A can be discovered by rotating the angle  $\theta$  around an axis  ${}^{A}\hat{r}$ , defined in frame A [75, 77, 78], as shown in Figure 2.10.



Figure 2.10: Frame B orientation is obtained through a rotation of angle  $\theta$  around the axis  ${}^{A}\mathbf{\hat{r}}$ . Reproduced from [78].

Conventionally, to describe an orientation, a quaternion is first normalised thus, having a unit length, i.e, ||q|| = 1. A quaternion which has a unity norm is called a unit quaternion,  $\hat{q}$  [75, 77].

The unit quaternion  ${}^{A}_{B}\hat{q}$ , which describes the orientation of frame B relative to frame A is expressed in equation (2.12).

$${}^{A}_{B}\hat{q} = \left[q_{0}, q_{1}, q_{2}, q_{3}\right] = \left[\cos\frac{\theta}{2}, -r_{x}\sin\frac{\theta}{2}, -r_{y}\sin\frac{\theta}{2}, -r_{z}\sin\frac{\theta}{2}\right]$$
(2.12)

The quaternion conjugate can be used to switch the relative frames in a given orientation, i.e., to describe the orientation of frame A relative to frame B. Thus,  ${}^B_A \hat{q}$  is the conjugate of  ${}^A_B \hat{q}$ . Equation (2.13) represents the quaternion conjugate.

$${}^{A}_{B}\hat{q}^{*} = {}^{B}_{A}\hat{q} = \left[q_{0}, -q_{1}, -q_{2}, -q_{3}\right]$$
(2.13)

With the quaternion product compound orientations can be defined. This is, the compounded orientation  ${}^{A}_{C}\hat{q}$  can be described through the multiplication of the orientations  ${}^{B}_{A}\hat{q}$  and  ${}^{A}_{B}\hat{q}$ , represented in equation (2.14).

$${}^{A}_{C}\hat{q} = {}^{B}_{A}\hat{q} \otimes {}^{A}_{B}\hat{q}$$
(2.14)

A pure quaternion is a quaternion whose scalar part is zero. We can get a pure quaternion in frame  $B_{,}^{B}v$ , from equation (2.15).

$${}^{B}\boldsymbol{v} = {}^{A}_{B}\hat{q} \otimes {}^{A}\boldsymbol{v} \otimes {}^{A}_{B}\hat{q}^{*}$$

$$(2.15)$$

In turn,  ${}^{B}v$  also represents the rotation of a three dimensional vector.  ${}^{A}v$  and  ${}^{B}v$  are the same vector described in frame A and frame B respectively.

The orientation described by  ${}^{A}_{B}\hat{q}$  can be represented as the rotation matrix  ${}^{A}_{B}\mathbf{R}$  defined by equation (2.16) [77].

$${}^{A}_{B}\boldsymbol{R} = \begin{bmatrix} 1 - 2q_{3}^{2} - 2q_{4}^{2} & 2(q_{2}q_{3} - q_{1}q_{4}) & 2(q_{2}q_{4} + q_{1}q_{3}) \\ 2(q_{2}q_{3} + q_{1}q_{4}) & 1 - 2q_{2}^{2} - 2q_{4}^{2} & 2(q_{3}q_{4} + q_{1}q_{2}) \\ 2(q_{2}q_{4} - q_{1}q_{3}) & 2(q_{3}q_{4} + q_{1}q_{2}) & 1 - 2q_{2}^{2} - 2q_{3}^{2} \end{bmatrix}$$
(2.16)

For a pure rotation, the rotation matrix can be converted to a quaternion using the equation (2.17),

$$q_{0} = \sqrt{\frac{1 + m_{00} + m_{11} + m_{22}}{2}}$$

$$q_{1} = \frac{m_{21} - m_{12}}{4q_{0}}$$

$$q_{2} = \frac{m_{02} - m_{20}}{4q_{0}}$$

$$q_{3} = \frac{m_{10} - m_{01}}{4q_{0}}$$
(2.17)

where  $m_{ij}$  represent matrix entries.

### 2.4.1.4 Quaternion Intuition

For an easier quaternion interpertation it can be relevant to group them into classes [65]:

- **Pure quaternions** correspond to quaternions with null scalar component. These correspond to  $\mathbb{R}^3$ , the space of three-dimensional vectors.
- Quaternions with null vector component correspond to the scalar space,  $\mathbb{R}$ .

- Rotation quaternions are unitary quaternions, i.e, ||q|| = 1, which belong to the  $SO_3$  group of orthogonal matrices with determinant 1. These quaternions are useful to describe rotations in space.
- General quaternions have non null scalar and vector components and norm unequal to 1. They describe a combination of a rotation and scaling of vectors. Furthermore, if the quaternion norm is > 1, objects are stretched; consequently, if the quaternion norm is < 1, objects are compressed.



Figure 2.11: Representation of quaternions classes. Example of a pure and a rotation quaternions (left to right). Figures were generated through a quaternion simulator available in [79].

# 2.5 Sensor Fusion for Orientation Estimation

A single sensor system usually suffers from the following problems:

- Sensor deprivation Loss of perception on the desired object caused by the sensor's element failure;
- Limited spatial coverage Individual sensor, usually, covers only a limited region.
- Limited temporal coverage Occasionally a particular set-up time is required to perform and to transmit a measurement, thus limiting the maximum frequency of measurements.
- Imprecision Measurements are restricted to the precision of the employed sensing element.
- Uncertainty It appears when the sensor cannot measure all significant attributes or when the observation is ambiguous. An individual sensor is unable to reduce uncertainty in its perception because of its limited view of the object.

To overcome the listed problems, one can make use of a sensor fusion technique, which consists in combining sensory data such that outcome information is somewhat better than what it would be when individual sources were used [80]. Thus, the combination of measurements from the different sensors, allows to best estimate the IMU attitude through a sensor fusion algorithm, as shown in Figure 2.12.



Figure 2.12: Sensor fusion is applied to get the best attitude estimation. Adapted from [22].

There are several approaches for fusing IMU sensors and among them, algorithms like the Kalman filter, complementary filter, and particle filter are frequently employed.

### 2.5.1 Complementary Filter

In this study, a complementary filter based sensory fusion method was applied. In general, this type of filter performs an analysis in the signal's frequency domain for obtaining a better estimation of a particular quantity.

For attitude estimation, based in IMU readings, a complementary filter implements a high-pass filter on gyroscope's estimated orientation, whose data has been affected by low-frequency noise. Additionally, a low-pass filter on accelerometer's and magnetometer's data, which are affected by high-frequency noise, is applied. With the two filtered estimations, it is expected to obtain an all-pass and noise-free attitude estimation. The cut-off frequency value, which is the same for both filters, is found as a trade-off between the preserved bandwidth of each single signal [68, 81].

The combination of this low pass and high pass filter are expressed in equation (2.18).

$$\theta = \alpha \theta_g + (1 - \alpha) \theta_{am} \tag{2.18}$$

where  $\theta$  represents the filtered orientation,  $\theta_g$  the gyroscope orientation and  $\theta_{am}$  the orientation provided by accelerometer and magnetometer. The  $\alpha$  parameter is the filter coefficient, which can be calculated through equation (2.19) if the sample time period,  $T_s$ , and time constant,  $\tau$ , are known.

$$\alpha = \frac{\tau}{\tau + T_s} \tag{2.19}$$

Arm movements can be decoded from low-frequency time-domain signals [82, 83]. Thus, for the time constant,  $\tau$ , the value of 4 Hz was defined.

The **Madgwick filter** is a common implementation of a complementary filter. The algorithm uses a quaternion for representing a body's attitude and, its performance is controlled by an adjustable parameter which compensates gyroscope drift. Additionally, the filter combines an analytically derived gradient descent algorithm which enables: performance at low sampling rates; a magnetic distortion compensation algorithm; and, gyroscope bias drift compensation [78].

Another complementary filter approach is the **Mahony filter** which also employs quaternion representation for orientation estimation. The Mahony considers the disparity between the orientation from the gyroscope and the estimation from the magnetometer and accelerometer and weighs them according to its gains. Thus, two parameters control the algorithm's performance: the filter proportional gain and weighting process directly on the quaternions [84].

# **MOTION TRACKER FRAMEWORK**

This Chapter presents the proposed upper limb and torso motion tracking system. The methodology along with the relevant processes for the implementation will be described. Four anatomical segments are studied and, consequently, four Inertial Measurement Unit (IMU) devices are considered. To fuse the collected sensor's information a Quaternion-based Complementary Filter (QCF) approach is introduced. At last, the angular motion reconstruction is addressed.

## 3.1 System Overview

Through framework development, some system requirements had to be fulfilled. The following list presents them. Herewith, the system:

- 1. Must focus on the upper limbs and torso motion;
- 2. Must be robust to complex scenarios;
- 3. Should have minimum number of hyperparameters.

The developed upper limb and torso motion tracker system is a sequential algorithm designed to obtain the time-dependent angular information of several anatomical segments. Since the upper limbs and spine are regions with a higher prevalence and incidence to work-related musculoskeletal disorders, the upper body is at the main focus of this research. Therefore, four anatomical segments, shown in Figure 3.1, are defined: arm segment, as the segment between shoulder and elbow joint; forearm segment, as the segment between wrist joint; hand segment, as the segment between wrist and distal region of the third metacarpal; torso segment, as the segment between the jugular notch and the xiphoid process of the sternum.



Figure 3.1: The anatomical segments of the proposed framework: thorax, upper arm, forearm and hand. Adapted from [85].

The motion tracker implementation pipeline is depicted in Figure 3.2. Data acquisition is the first stage of the process, which is related to sensor signal acquisition. The system was thought to have the minimum invasiveness to the operator, yet maintaining a fair cost/effectiveness result. Thus, four devices are employed. Each of them is attached to one of the four considered segments, providing information on acceleration, angular velocity and magnetic field.

Signal processing methodology comprises pre-processing and orientation estimation. The first is explained in Section 3.3 and it is divided into two main processes: temporal synchronisation and noise reduction. Orientation estimation, detailed in Section 3.4, describes the applied sensor fusion method, the Quaternion-based Complementary Filter (QCF), and the necessary considerations to obtain the angular information of one segment relative to another or relative to an anatomical plane, the relative and absolute orientation respectively.



Figure 3.2: Motion tracker system pipeline.

## 3.2 Kinematic Model

The considered model admits flexion/extension, abduction/adduction (2 DoF), for shoulder joint, flexion/extension and pronation/supination (2 DoF) for the forearm, wrist's flexion/extension and ulnar/radial deviation (2 DoF). For the torso, the model allows flexion/extension and lateral flexion/extension (2 DoF). Consequently, the whole model admits 8 DoF and considers human movements of the upper limb and torso.

## 3.3 Signal Pre-Processing

The acquired inertial data, which comprises the information of accelerometers, gyroscope and magnetometers, must be pre-processed. Signal pre-processing consists of signal synchronisation, filtering and normalisation.

#### 3.3.1 Temporal Synchronisation

There are two major considerations when addressing the pre-processing of multiple sensor's and device's data: (1) ensuring equal sampling frequency; (2) ensuring temporal alignment.

Unsuccessful temporal synchronisation of different sensors can lead to shifted or stretched signals which would blur events [86]. Consequently, it would compromise the results of sensor fusion and distort the subsequent signal analysis. Often, this problem arises not only from fabrication discrepancy, wear-out results and temperature variations but also from devices' clocks, which can drift and affect the sample timing and, variations in communication latencies [86, 87]. Therefore, for allowing a high quality of multiple sensor fusion, synchronisation must be ensured.

To address this issue, a synchronisation pipeline was implemented and divided into two stages: (1) synchronisation at the sensor level and (2) synchronisation at the device level. The pipeline is summarised in Figure 3.3.

An IMU device is composed of three built-in sensors, which may have different sample rates, thereupon may sample datapoints with different timestamps, i.e.,  $t_{Raw}^{S1}$ ,  $t_{Raw}^{S2}$ ,  $t_{Raw}^{S3}$ . Adjusting the sampling frequency, at the sensor level, all sensors, within a device, will share the same time vector, e.g.  $t^{D1}$  for the IMU device 1.

Although sampling at the same rate, the signal information of different devices can present some delay relative to one another, i.e. clock drift. Thus, at the device level, the regular time vector, that resulted from a sensor synchronisation, will be used, along with synchronisation events, to determine the signal delay.

Synchronisation events are moments in time that were acquired at the same temporal instant but may be shifted between devices due to temporal misalignment.

The main goal is to calculate a common synchronised time,  $t_{Global}$ , which is shared among all the synchronised devices.



Figure 3.3: Temporal synchronisation stages. Acc - accelerometer, Gyro - gyroscope, Mag - magnetometer. Events refer to synchronisation events.

Consider three standalone devices, D1, D2 and D3 represented in Figure 3.4. Signals of different devices are presented and, marked on top of each is the considered synchronised event. The delay between signals is then calculated through the difference between events of different devices.



(a) Before device synchronisation. The synchronisation events (depicted by red vertical lines) are misaligned.



(b) After device synchronisation. The synchronisation events (depicted by red vertical lines) are aligned.

Figure 3.4: Synchronisation at the device level. The synchronisation events are represented by red vertical lines.

Equation (3.1) refers to the delay between device 1 and device 2 and the time delay between device 1 and 3, respectively,

$$\delta_{12} = e^{D2} - e^{D1}$$
  

$$\delta_{13} = e^{D3} - e^{D1}$$
(3.1)

with  $\delta_{12}, \delta_{13} \in \mathbb{R}$  and  $e^{D1}, e^{D2}, e^{D3} \in \mathbb{R}_0^+$ .

After settling the delays, time corrections proceeds in equation (3.2),

$$\tilde{t}_{1} = t_{1}$$
  
 $\tilde{t}_{2} = t_{1} - \delta_{12}$  (3.2)  
 $\tilde{t}_{3} = t_{1} - \delta_{13}$ 

where  $\tilde{t}_1$ ,  $\tilde{t}_2$  and  $\tilde{t}_3$  represent the synchronise time for the corresponding device. Lastly, in equation (3.3), a single synchronised time,  $t_{Global}$ , is defined (referred in Figure 3.3).

$$\widetilde{t}_1 = \widetilde{t}_2 = \widetilde{t}_3 = t_{Global} \tag{3.3}$$

## 3.3.2 Noise Reduction

Raw data from accelerometers and magnetometers surpassed a low-pass filter. The filter has the configuration of a first-order low-pass Butterworth prepared for a cutoff frequency of 1 Hz [88, 89]. With this filter, high-frequency variations in data are rejected, e.g, linear acceleration is discarded and the remaining acceleration, the gravitational, is kept which is the one that affects orientation.

In industry, the operator's movements frequency range is generally low, which also supports the decision for the cutoff frequency value.

### 3.3.3 Data Normalisation

Most frequently, sensor measurements are reported as non-normalised vectors. Thus, a normalisation was applied to the filtered IMU data. Let us consider  $v = [v_x, v_y, v_z]$ , that is normalised to  $v_n = [v_{xn}, v_{yn}, v_{zn}]$ . Equation (3.4) presents vector normalisation and equations (3.5) to (3.7) present the normalised components.

$$\|\boldsymbol{v}\| = \sqrt{v_x^2 + v_y^2 + v_z^2} \tag{3.4}$$

$$v_{xn} = \frac{v_x}{\|v\|} \tag{3.5}$$

$$v_{yn} = \frac{v_y}{\|v\|} \tag{3.6}$$

$$v_{zn} = \frac{v_z}{||v||} \tag{3.7}$$

## 3.4 Orientation Estimation

For acquire valuable information of limb's attitude, the signals gathered from accelerometers, gyroscopes and magnetometers should be combined through a sensor fusion method. This process aims to tackle the challenges associated with single sensor information.

The angular motion of a human segment can be represented through a recursively estimated quaternion and its properties. The block diagram, represented in Figure 3.5, addresses the QCF approach.

The implemented filter is derived from [81, 90]. Firstly, data from accelerometer and magnetometer sensors are combined in an algebraic algorithm. With this algorithm, a representation of Earth Reference Frame will be achieved, resulting in a reference quaternion. Thus, sensors' information, depicted in Sensor Frame, can be set to Earth Reference Frame.

Afterwards, an update quaternion, achieved from gyroscope's data, will be fused with the reference quaternion in QCF. Subsequently, a final estimated quaternion is obtained.



Figure 3.5: Block diagram of QCF approach.

Making use of rotational vectors, retrieved from the estimated quaternions, angular considerations relative to different segments can be established.

## 3.4.1 Algebraic Method

The algebraic method [91] is an approach to represent attitude through a  $3\times3$  rotation matrix. It combines the information of two different vectors to define an orthogonal coordinate system with the basis vectors.

Firstly, the normalised accelerometers, *g*, and magnetometers, *m*, vectors are characterised in equations 3.8 and 3.9, respectively.

$$\boldsymbol{g} = \begin{bmatrix} g_{x}, g_{y}, g_{z} \end{bmatrix}$$
(3.8)

$$\boldsymbol{m} = \begin{bmatrix} m_x, m_y, m_z \end{bmatrix} \tag{3.9}$$

According to East-North-Up (ENU) configuration, the cross product between m and g gives *East* (*E*) and, the cross product between g and *East* gives *North* (*N*):

$$\boldsymbol{E} = \boldsymbol{m} \times \boldsymbol{g} = \left[ m_y g_z - m_z g_y, m_z g_x - m_x g_z, m_x g_y - m_y g_x \right] = \left[ E_x, E_y, E_z \right]$$
(3.10)

$$\boldsymbol{N} = \boldsymbol{g} \times \boldsymbol{E} = \left[ g_y E_z - g_z E_y, g_z E_x - g_x E_z, g_x E_y - g_y E_x \right] = \left[ N_x, N_y, N_z \right]$$
(3.11)

Since g and m vectors are not perpendicular with each other, the cross product result is non-unitary. Consequently, E should be normalised, as in Section 3.3.3, before determining N.

The obtained orientation is given by the rotation matrix represented in equation 3.12.

$$\boldsymbol{R} = \begin{bmatrix} E_x & N_x & g_x \\ E_y & N_y & g_y \\ E_z & N_z & g_z \end{bmatrix}$$
(3.12)

Then, the obtained rotation matrix can be converted into a reference quaternion by equation (2.17). This quaternion express the orientation of a segment relative to Earth Reference Frame. However, it does not represent the final orientation, once it only relies on accelerometers and magnetometers readings. Nonetheless, this quaternion is presented as measurements to QCF in order to obtain the final estimate quaternion.

### 3.4.2 Quaternion Based Complementary Filter

The quaternion-based attitude method updates the estimated quaternion through gyroscope's measurement and rectifies it based on a reference quaternion from the accelerometer and magnetometer measurements. The filter architecture is schematised in Figure 3.6.



Figure 3.6: Quaternion based complementary filter architecture.

The gyroscope's data can be represented through a quaternion,  $q_w$ , as suggested in equation (2.12) from Section 2.4.1.3. The previous instant attitude which is updated with the gyroscope's quaternion, results in an update quaternion,  $q_{U_t}$ , which represents the device rotation.

For initialising the filter, the update quaternion is set equal to the reference quaternion. This way, both of them represent the same device orientation. Nevertheless, for every sensor reading interval, a rectification and calculation of the estimated quaternion take place.

Applying an interpolation between these two quaternions, the reference and the update, have advantages for both measures can be emphasised. A Spherical Linear Interpolation (SLERP) allows to weight between the two quaternions. The filter weight-value is determined through equation (2.19), introduced in Section 2.5.1. Once the gyroscope is very accurate in short intervals it is more weighted. Nevertheless, to stabilise the unwanted sensor drift, a minor amount of the interpolation is directed towards accelerometer and magnetometer, which are sensors more trustworthy in the long term. Therefore, after each time interval, an interpolation is performed to correct the orientation.

The estimated orientation exhibits the QCF characteristics which combines highfrequency measures from gyroscope and low-frequency from accelerometers and magnetometers to deliver reliable motion information.

## 3.5 Angular Trajectory Reconstruction

After determining the orientation of human segments through the QCF, it is possible to make assumptions on angular motion.

Figure 3.7 represents the angular reconstruction of abduction and adduction movements, while using a single IMU on the upper arm.

Assuming that consecutive IMU devices, placed on the upper limb segments, are aligned, i.e., have one local axis that has the same direction as another. Using the estimated quaternion,  $q_E$ , the aligned direction, e.g, [0, 0, 1, 0], can be represented in sensor frame through a pure quaternion, v as in equation 3.13.

$$\boldsymbol{v} = \boldsymbol{q}_E \otimes \left[0, 0, 1, 0\right] \otimes \boldsymbol{q}_E^* \tag{3.13}$$

Excluding the scalar part of v results in a  $\mathbb{R}^3$  vector, hereafter expressed as direction vector. Making use of the dot product between two vectors, the angle between segments can be determined, as represented in equation (3.14),

$$\theta = \arccos\left(\frac{\boldsymbol{v} \cdot \boldsymbol{u}}{\|\boldsymbol{v}\| \cdot \|\boldsymbol{u}\|}\right) \tag{3.14}$$

where v and u are two vectors representing two different segments, and  $\theta$  is the angle formed between v and u.

Angular information between two consecutive segments are defined as relative orientation. On the other hand, the angle between a segment and an anatomical plane is defined as absolute orientation.



Abduction and adduction

Figure 3.7: Example of angular reconstruction of abduction and adduction movement. Movement description: five seconds in a neutral pose; abduction reaching shoulder line; pose sustained for five seconds; full abduction; pose sustained for five seconds; adduction until shoulder line; pose sustained for five seconds; full adduction until neutral pose; pose sustained for five seconds.

Figure 3.8 represents two different angular considerations. In Figure 3.8a, an abducted arm is observed along with a representation of an inertial device attached to the upper arm. Taking the sagittal plane into consideration, the abduction angle can be calculated. For that matter, the complementary angle between a normal vector of the sagittal plane, the vector PR, with the direction vector of the sensor, vector PQ, provides the abduction angular information. In Figure 3.8b, an abducted arm is also represented. Two devices are illustrated, one on the upper arm and another on the lower arm. Now, the focus is on the flexion angle between arm and forearm segments. Thus, using only the direction vectors of each device the relative orientation is determined.

It is relevant to explain that the anatomical planes were defined using the local axes of an inertial device placed on a subject's torso. Additionally, the IMU device placed on torso segment is relevant to determine torso flexion and lateral flexion. The angle of these last movements are accomplished by comparing torso's current state with torso's rest position.

### 3.5.1 Pronation and Supination

Pronation and supination, Figure 3.9, consist of a set of movements which happen when the wrist rotates, allowing to flip the palm either face up or face down. Considering the right hand, supination is defined as the clockwise motion while the counterclockwise motion is named as pronation.





(a) Angle between the arm segment and the normal vector of sagittal plane.

(b) Angle between the arm and forearm segments.

Figure 3.8: Vector considerations for angular reconstruction. Left - absolute orientation. Right - relative orientation.



Figure 3.9: Supination and pronation movements (left to right). Adapted from [92].

Ergonomically, it is relevant to understand how often these movements occur. When subjects force their hands to pronate or supinate, a static load (i.e. muscle use for maintaining a static position or posture) and strain are placed on joints, muscles, ligaments and membranes in the arm, leading to fatigue, pain and injury. Therefore, excessive supination and pronation can be a risk factor [93]. The adopted method to identify pronation and supination is described in the following paragraphs.

The accelerometer sensor was selected to report these specific motion changes. The method is based on the acceleration information of a device placed either on the hand or on the forearm and the behaviour of accelerometer's z-axis, in Sensor Frame coordinates.

Firstly, a normalisation of the accelerometer sensor is performed. Then, a convolutionbased filter is applied to the z-axis accelerometer signal, using a window length of 50. Afterwards, a median filter is applied using a kernel size of 201 followed after by a signal derivative. The window length and kernel size are empiric values. Local maximums of the z-axis derivative acceleration correspond to pronation while local minimums correspond to supination. Figure 3.10 represents the applied method.



Figure 3.10: Method to identify pronation and supination movements. The acceleration is represented by acc. Top to bottom: normalised acceleration, z-axis, with movements identification; normalised acceleration, z-axis, after applying the convolution-based and the median filters; signal derivative where minimums represent supination and maximums represent pronation.



## Results

In this Chapter, the proposed method is compared against other state-of-the-art inertial methods, a computer vision approach based on OpenPose and a ground truth provided by an optical-passive tracking system. The tracking system was assessed under two distinct scenarios: (1) laboratory validation and (2) field assessment. While the laboratory study provides an estimated response of the algorithm from a controlled context, the field assessment allows to evaluate the potential of an ergonomic risk assessment tool and evaluate the impact of explaining risk factors.

# 4.1 Inertial Signal Acquisition

Inertial motion data was recorded using a set of inertial sensor devices designed by Fraunhofer AICOS. The sensing framework is called the Internet of Things in Packages (IoTiP), represented in Figure 4.1, and consists of a miniaturised hardware architecture of embedded electronics for wireless devices.

An IoTiP is a standalone wireless device composed by a customised set of built-in sensors to measure several physical realities. IoTiPs have a modular architecture, allowing a seamless and quick integration among different sensing requirements.

In the context of this work, the base module was used, composed of a 9-DoF IMU (triaxial accelerometer, gyroscope and magnetometer). The IoTiP has a wireless charging unit (QI compliant) and also complies with the Bluetooth Smart protocol. The base IoTiP module specifically measures variations in acceleration, angular velocity and magnetic field.





The IoTiP communicates to an Android application called Recorder, developed by Fraunhofer AICOS, which provides control functionality, battery monitoring and firmware updates to the devices. The Recorder application allows to record sensor data from multiple devices (including smartphone and IoTiPs) and also to store annotations in real-time during the acquisition protocol. Figure 4.2 presents the temporal events for starting an acquisition through the Recorder application.



Figure 4.2: Screenshots of Recorder application. From left to right: Recorder's home interface; sensors and devices selection; subject and sensors position; selection of desired workstation; acquisition interface with annotations panel.

The correct placement and positioning of the sensing devices is essential for the estimation process of angular movement. Since this research focused on monitoring four human segments, a total of four IMUs were attached to each segment. It is important to refer that the smartphone is considered as an IMU device, once it can also sense acceleration, angular velocity and the magnetic field.

The IMU devices were placed at the following regions: IMU 1, IMU 2 and IMU 3 were positioned at the posterior side of the hand, forearm and arm, respectively. Particularly,

IMU 2 was placed in the wrist area and IMU 3 was located in the elbow region. These three IMU devices were attached firmly with elastic bands. IMU 4 was positioned in the thorax area. To assure a common axis alignment, the local axes direction of each device must be known before attaching the device to the subject. It was considered that the Y-axis of all devices points up. Figure 4.3 illustrates the inertial devices placement.



Figure 4.3: Placement of the IMU devices: three units on the upper limb and one unit on the torso. The devices were commonly aligned with Y-axis pointing up.

## 4.2 Laboratory Validation

A protocol was designed (Appendix C) to serve as a validation study of the proposed upper limb and torso tracking method. To measure the tracking error, the Vicon motion capture system was used as ground truth. Vicon is a state-of-the-art Motion Capture (Mocap) with a reported error lower than 2 mm [70].

Since the proposed framework is intended to be used through long-term acquisitions during the operator's work shifts, it is expected that albeit a Quaternion-based Complementary Filter (QCF) based upon on a sensor fusion approach is implemented, sensor drift will still be residually accumulated over time. To tackle this issue, one strategy might consist of using another layer of information to introduce redundancy in the system and correct sensor drift periodically. A possible layer of information is using video, which has the advantage of not suffering drift related issues. Despite the video processing is more computationally expensive than inertial processing, it can be used during short iterations to reset the drift from sensors. Therefore, a video collection on the validation protocol is introduced to test and characterise the OpenPose library, as a potential redundant system to compute angular information between anatomical joints.

The study was conducted at Fraunhofer AICOS Human Motion Lab, located in Porto, and was composed of 14 subjects which were asked to follow a prescribed acquisition protocol to measure the angular error across all considered joints in a wide range of different movements. Table 4.1 summarises the subjects' characteristics.

Table 4.1: Subjects' characteristic. m: male; f: female; yr: average years; r: ratio.

Subjects' characteristics				
Number	14			
Gender (m:f)	9:5			
Age $(\overline{yr} \pm \sigma)$	$26 \pm 3$			
<b>Dominant hand</b> (r)	Right hand (14:14)			

The validation protocol is composed of two main parts: one describes a static movement evaluation and the other details a dynamic evaluation. The concepts static and dynamic denote if the subject is standing or walking while doing the designated movements, respectively.

Within each part, there are multiple Sets focused on different segments' movements. Table 4.2 summarises the studied segments in each Set.

Table 4.2: Validation protocol. Considered sets, for static and dynamic evaluations, with respective anatomical segments.

Static Evaluation	<b>Dynamic Evaluation</b>
Set 1 - Arm and forearm Set 2 - Forearm and hand Set 3 - Torso Set 4 - Arm and torso	Set 5 - Arm and torso Set 6 - Arm and torso

### 4.2.1 Equipment and Placement

Subjects wore a motion capture setup composed of four IMUs sampling at 100 Hz and optical markers tracked by Vicon cameras at 100 Hz. The Vicon setup was composed of ten cameras, measuring an acquisition area of 8x4 m, and two standard cameras filming the whole exercise, which were also used as input for OpenPose algorithm.

The IMUs were located as described in Section 4.1. Markers' positions followed Vicon's Upper Limb Model Guide descriptions. Figure 4.4 exhibits markers' placement. The precision of marker placement is crucial for achieving accurate results.


Figure 4.4: Vicon Upper Limb Model marker placement. Front and rear view. The adopted model did not consider the RBAK marker. Retrieved from [94].

In Vicon's upper limb model, left and right side markers are placed symmetrically. For the purpose of this study it was defined to monitor one limb. Thus, according to participants dominant hand, the IMUs were placed on the corresponding limb. Since all participants were right-handed, the right upper limb model was considered, as shown in Figure 4.5. Fourteen markers were used although thirteen were tracked in trials - one marker was specifically used for calibration procedures. Ten markers were placed on the upper limb, two on the back and the other two on the thorax. Figure 4.6 displays a subject with all sensors and markers attached.



Figure 4.5: Screeshot from Vicon Nexus right upper limb model. Frame example. Markers are represented as spheres and anatomical segments are depicted connecting the markers.

It is worth to mention that all Vicon cameras had to be calibrated before acquisitions. The calibration method required the use of a calibration object composed of five fixed markers. The calibration object was also used to establish a coordinate frame. An incorrect calibration process would contribute to noisy tracking or loss of information on

### CHAPTER 4. RESULTS

marker position. Additionally, whenever the experience room encountered light variations, which affect cameras perceiving of markers, a calibration was required.



Figure 4.6: Side-view subject with inertial devices and optical markers attached.

# 4.2.2 Dataset Overview

Raw data is composed of 2 recording hours. Tables 4.3 and 4.4 summarise the considered actions for static and dynamic evaluation, respectively. Several movements can be recognised and analysed, by the segmentation of inertial data and videos, which was accomplished trough manual annotations. The anatomical position is present in all sets since the subject was required to perform this position in the beginning and at the end of each test.

Segment	Torso	Arm	Forearm	Hand
Flexion/Extension	٠	•	•	٠
Lateral Flexion	•			
Abduction/Adduction		•		
Radial/Ulnar deviation				•
Anatomical Position	•	•	•	•

Table 4.4: Studied actions for dynamic evaluation.

Action	Torso	Arm	Forearm	Hand
Flexion	•			
Flexion/Extension	_	•		
Anatomical Position	•	•	•	•

Once different equipment was employed to acquire data, i.e., video cameras and sensing devices, temporal synchronisation issues arise. Nonetheless, if video cameras are considered as another IMU device, the synchronisation issue is solved through the method presented in Section 3.3.1. A visual examination confirmed that all recordings were synchronised by the temporal alignment procedure.

## 4.2.3 Motion tracking performance

For applying the QCF the  $\alpha$  parameter must be established. Using equation (2.19),  $\alpha$  was set to 0.975. To evaluate the reliability of the angular motion reconstruction, the results with the proposed method, namely QCF, were compared with three other available sensor fusion methods. Madgwick and Mahony algorithms were used based on the implementation provided by *scikit-kinematics* Python package [65]. Another quaternion based complementary filter approach was implemented - the AGCF - using only accelerometer and gyroscope data.

In a first evaluation, a comparison between different inertial sensor fusion algorithms (i.e. QCF, Madgwick, Mahony, and AGCF) with Vicon was performed. The second evaluation compared the results from QCF with OpenPose algorithm and Vicon.

It is relevant to explain that the procedure adopted to adjust the light conditions of the tests is complex. On one hand, the best conditions for using Vicon require low ambient light, while on the other hand, the conditions for using OpenPose require regular ambient light so that the subject's skeletal image contours can be identified by the model.

It was decided to minimise Vicon's error, since it was considered the ground truth of this study and, low ambient light conditions were applied. However, this fact degraded the performance of OpenPose algorithm.

Due to inadequate light conditions on Sets 2, 3 and 4, the OpenPose valid data was composed only of Sets 1, 5 and 6. Therefore, a comparison between the IMU and Vicon can be presented for the exercises in all sets. Though, the comparison between the IMU and OpenPose is performed only with data from Sets 1, 5 and 6.

#### 4.2.3.1 Sensor fusion methods comparison

Different sensor fusion methods were applied to the dataset and afterwards, angular reconstruction was addressed. The results from the different methods were then compared. Figure 4.7 displays an example of exercises from Set 1.

In this particular example, the Madgwick and Mahony approaches have a higher signal-to-noise ratio, behaving almost identically. The AGCF has the most unstable re-construction, and in its turn, the QCF curve is closer to Vicon's.



Figure 4.7: Angular reconstruction of Set 1 arm's exercises. Comparison of different sensor fusion methods.

To perform a quantitative performance assessment of the proposed method three evaluation metrics were used: the Cumulative Distribution Function (CDF), Mean Absolute Error (MAE) and the Root-Mean-Square Error (RMSE). Firstly, the CDFs were calculated to assess each segment performance under different sensor fusion methods, as represented in Figures 4.8 and 4.9, for static and dynamic evaluation, respectively. The CDFs took into account the error for all sets across different anatomical segments and considered the actions described in Tables 4.3 and 4.4.

The CDF represents the probability that a variable is less than or equal to a value. The probability is represented in the vertical axis and the horizontal axis is the allowable domain for the given probability function.

By examining the static evaluation graphs, it is possible to conclude that for torso Madgwick, Mahony and QCF have similar behaviour. The AGCF method has the worst performance for that segment: during 80% of the total acquisition time, it has an error lower than 50°, while others present an error lower than 15°. The AGCF presents, globally, higher errors when comparing it with other methods yet, for the hand segment, the AGCF exhibits a better outcome. Nevertheless, QCF presents overall better results.

It can be observed that the results from the dynamic assessment are slightly better than the static evaluation. The algorithm performance was expected to be lower in the dynamic trials. However, that is not observed. A fair comparison between static and dynamic evaluations can not be established since the number of samples for static evaluation is higher than in dynamic evaluation and, consequently, the dataset is unbalanced.

Apart from the AGCF, the methods similarly perform the reconstruction thus, the CDF graphs have the same shape. It should be noticed that: the arm's segment presents the lowest error - during 80% of the total acquisition time, the techniques have an error lower than 10°; the hand is the segment with the highest error consideration - during



Figure 4.8: Cumulative distribution function for the absolute error for each considered algorithm across different segments - static evaluation.

80% of the total acquisition time, the methods have an error less than  $20^\circ$ .

The overall performance of QCF reports better outcomes than the other methods. Nevertheless, the default parameters of Madgwick and Mahony were used across different sets and which can explain the performance variation of these techniques.

Unlike the other admitted methods, the AGCF employs only two sensors, the accelerometer and the gyroscope, which may affect the required time to ensure the filter stabilises in the predicted value, reducing its efficacy, i.e. the filter converge to the predicted value.

Once the QCF achieved better results, detailed error tables for this filter are presented. Tables for the remaining methods are presented in Appendix D. Table 4.5 summarises the MAE of QCF for static evaluation. MAE is given by equation (4.1),

$$MAE = \frac{\sum_{i=0}^{N} |y_i - \hat{y}_i|}{N}$$
(4.1)

where  $y_i$  denotes the ground truth value at time *i* observed N times provided by Vicon



Figure 4.9: Cumulative distribution function for the absolute error for each considered algorithm across different segments - dynamic evaluation.

and  $\hat{y}_i$  denotes the predicted value at time *i* estimated *N* times by the upper limb and torso tracking method.

<b>QCF MAE</b> $(\mu \pm \sigma)^{\circ}$						
Action/Segment	Torso	Årm	Forearm	Hand		
AnatomicalPos	$7 \pm 4$	$11 \pm 12$	$14 \pm 12$	$10 \pm 6$		
Flexion	$15 \pm 4$	$13 \pm 9$	$27 \pm 20$	$37 \pm 12$		
Extension	$5\pm5$	$14 \pm 14$	$6 \pm 15$	$37 \pm 11$		
Lateral Flexion	$4\pm5$	-	-	-		
Abduction	-	$15 \pm 17$	-	-		
Adduction	-	$11 \pm 9$	-	-		
Radial Deviation	-	-	-	$12 \pm 6$		
Ulnar Deviation	-	-	-	$15 \pm 11$		

Table 4.5: Mean absolute error regarding QCF method for each anatomical segment including all static sets.

The results suggest that QCF presents lower performance for the hand segment, particularly in flexion and extension. Additionally, during flexion exercise, forearm and arm's error is high. Nevertheless, the performance of the arm and the torso are, in general, satisfying. Algorithms can be analysed using their RMSE as a measure of how well they describe a given set of observations. Equation (4.2) gives the RMSE.

RMSE = 
$$\sqrt{\frac{\sum_{i=0}^{N} (\hat{y}_i - y_i)^2}{N}}$$
 (4.2)

While MAE measures an average of the absolute differences between prediction and the actual observations, where all errors influence MAE proportionally, RMSE performs the square root of the average of squared differences between predictions and actual observations. Although both can represent an average model prediction error, RMSE gives a relatively high weight to large errors.

In this study, RMSE is used as an evaluation criterion of the different methods. Table 4.6 presents the RMSE results of QCF for segments performance, in static evaluation.

Action/Segment	QCF RN Torso	ASE (°) Arm	Forearm	Hand
AnatomicalPos	8	16	18	12
Flexion	21	16	34	39
Extension	8	19	23	38
Lateral Flexion	6	-	-	-
Abduction	-	23	-	-
Adduction	-	14	-	-
Radial Deviation	-	-	-	14
Ulnar Deviation	-	-	-	18

Table 4.6: Root mean square error regarding QCF method for each anatomical segment including all static sets.

Similarly to Table 4.5, the RMSE table shows evidence that the hand segment has the lowest performance for flexion and extension movements. In order to further understand why the hand segment had higher overall RMSE than others, data was carefully explored using time series and the recorded video.

This particular inspection made clear that there were evident problems with markers' recognition on the hand segment. Figure 4.10 illustrates an example where a subject performs wrist flexion an extension. The angular variation, through visual inspection, is greater than 90° however, Vicon reconstruction only detects a smaller difference, which is less than 10°. Only one marker characterised the hand portion. Thus, that marker is essential to perform a validation of hand movements and, when a tracking failure occurs, it may comprise the accuracy of the Vicon system. Consequently, the error of inertial data is higher.

The dynamic evaluation protocol aimed to simulate actions involving the simultaneous movement of the torso and the upper arms segments. This situation occurs in



Figure 4.10: Sequence of hand movements and respective angular reconstruction using Vicon software. A - rest position; B - Wrist extension; C - Wrist flexion.

manufacturing scenarios, as quite often operators are required to walk, stand and bend to interact with tools and machinery. Tables 4.7 and 4.8 are related to dynamic assessment.

For the dynamic evaluation, flexion and flexion/extension were distinguish. Arm's flexion and extension were performed continuously, without any pause. Hence, these two movements were combined in the analysis.

<b>QCF MAE</b> $(\mu \pm \sigma)^{\circ}$						
Action/Segment	Torso	Arm	Forearm	Hand		
AnatomicalPos	$6 \pm 5$	8 ± 6	$15 \pm 13$	8 ± 6		
Flexion Flexion/Extension	23 ± 29 -	$-25 \pm 23$	-	-		

Table 4.7:	Mean	absolute	error	regarding	QCF	method	for	each	anatomical	segment
including a	all dyna	amic sets.								

Table 4.8: Root mean square error regarding QCF method for each anatomical segment including all dynamic sets.

QCF RMSE (°)						
Action/Segment	Torso	Arm	Forearm	Hand		
AnatomicalPos	7	10	20	10		
Flexion	36	-	-	-		
Flexion/Extension	-	34	-	-		

The algorithm performance was expected to reduce during dynamic trials. However,

that is not observed. An explanation can be the reduced amount of data when comparing with the static tests - only two sets had dynamic considerations.

The detection of pronation and supination involves the identification of the action itself and not an angle error quantification. Hence, the sensitivity was used to report the performance of an identification method for these movements. Sensitivity is defined as the proportion of true positives which are correctly identified.

The applied method, to identify pronation and supination, described in Section 3.5.1 from Chapter 3, only relies on accelerometer data and thus, requires no sensor fusion technique. Table 4.9 exhibits the sensitivity results, where it can be observed that pronation and supination were successfully identified. Therefore, in a controlled scenario, the accelerometer's Z-axis is found to be an efficient identification method.

Nevertheless, in the industrial context, movement's variability is larger and might change the sensor behaviour. Consequently, in real scenarios, the identification performance might be lower than the laboratory results.

Sensitivity (%)				
Method/Movement	Pronation	Supination		
Accelerometer Z-axis	100	100		

Table 4.9: Pronation and supination identification.

#### 4.2.3.2 Inertial method and OpenPose comparison

A comparison between the IMUs and OpenPose was completed particularly with data from Sets 1, 5 and 6. Hand segment had to be neglected due to inadequate low light conditions. Figure 4.11 represents an example of an angular reconstruction from Set 1, exhibiting an example of QCF and OpenPose performance.



Figure 4.11: Angular reconstruction of Set 1 arm's exercises. QCF, Vicon and OpenPose results.

In this example, both methods, the QCF and OpenPose, mimic the behaviour of Vicon's yet, the video-based algorithm presents a higher error.

Figures 4.12 and 4.13 represent the CDF graphs of QCF and OpenPose for the considered Sets.



Figure 4.12: Cumulative distribution function for the absolute error of OpenPose and QCF across different segments - Set 1.



Figure 4.13: Cumulative distribution function for the absolute error of OpenPose and QCF across different segments - dynamic evaluation.

From Set 1 CDF analysis, it is possible to conclude that arm and forearm's movements present a lower error when assessed with OpenPose algorithm, this is, 80% of the total acquisition time it presents an error inferior to 10° and 30°, respectively. However, the torso's reconstruction shows better results with QCF.

Contrarily to Set 1, in dynamic trials OpenPose presents better results for torso movements and QCF has a higher performance for arm and forearm exercises.

The results from the static assessment, Set 1, are detailed in Tables 4.10 and 4.12 for QCF and in Tables 4.11 and 4.13 for OpenPose measurements. Additionally, results from dynamic approach are revealed in Tables 4.14 and 4.15 uniquely for OpenPose - information regarding QCF is presented in Tables 4.5 and 4.6 from Section 4.2.3.1.

### CHAPTER 4. RESULTS

<b>QCF MAE</b> $(\mu \pm \sigma)^{\circ}$				
Movement/Segment	Torso	Árm	Forearm	
AnatomicalPos	6 ± 5	$10 \pm 13$	$16 \pm 17$	
Flexion	$23 \pm 29$	$15 \pm 12$	$33 \pm 24$	
Extension	-	-	$21 \pm 17$	
Abduction	-	$15 \pm 17$	-	
Adduction	-	$11 \pm 9$	-	

Table 4.10: Mean absolute error regarding QCF method for each anatomical segment include static Set 1.

Table 4.11: Mean absolute error regarding OpenPose method for each anatomical segment include static Set 1.

<b>OpenPose MAE</b> $(\mu \pm \sigma)^{\circ}$					
Movement/Segment	Torso	Arm	Arm, Forearm		
AnatomicalPos	$4\pm 8$	$9\pm7$	$23 \pm 12$		
Flexion	$30 \pm 26$	$16 \pm 3$	$9 \pm 10$		
Extension	-	-	$19 \pm 8$		
Abduction	-	$9\pm5$	-		
Adduction	-	$9\pm10$	-		

Table 4.12: Root mean square error regarding QCF method for each anatomical segment include static Set 1.

QCF RMSE (°)					
Movement/Segment	Torso	Arm	Arm, Forearm		
AnatomicalPos	8	16	24		
Flexion	36	19	41		
Extension	-	-	27		
Abduction	-	23	-		
Adduction	-	14	-		

Table 4.13: Root mean square error regarding OpenPose method for each anatomical segment include static Set 1.

<b>OpenPose RMSE (°)</b>			
Movement/Segment	Torso	Arm	Arm, Forearm
AnatomicalPos	9	12	26
Flexion	40	16	13
Extension	-	-	21
Abduction	-	11	-
Adduction	-	14	-

The static error tables allow to infer that: the anatomical position error is very similar in both methods, for the considered segments; arm and forearms's flexion exercises are better estimated with OpenPose; Torso's error is substantially high in both techniques.

<b>OpenPose MAE</b> $(\mu \pm \sigma)^{\circ}$			
Movement/Segment	Torso	Arm	Arm, Forearm
AnatomicalPos	$1 \pm 7$	$11 \pm 7$	$24 \pm 12$
Flexion	$30 \pm 26$	-	-
Flexion/Extension	-	$34 \pm 29$	-

Table 4.14: Mean absolute error regarding OpenPose method for each anatomical segment including all dynamic sets.

Table 4.15: Root mean square error regarding OpenPose method for each anatomical segment including all dynamic sets.

<b>OpenPose RMSE (°)</b>			
Movement/Segment	Torso	Arm	Arm, Forearm
AnatomicalPos	7	13	27
Flexion	40	-	-
Flexion/Extension	-	45	-

The dynamic approach reveals that the QCF method presents an overall better reconstruction than OpenPose. The static and dynamic assessments allow to infer that torso flexion error is unusually high in both methods. Furthermore, errors from dynamic trials are higher, particularly in flexion/extension of the right arm.

#### 4.2.4 Summary

The laboratory assessment provided a validation tool for IMU devices and also allowed to establish a comparison with an alternative motion capture technique - the OpenPose.

Vicon software is a very accurate motion capture technique, with a positioning error lower than 2 mm. Thus, its results are widely used as ground truth. However, Vicon technology is complex. Specifically, calibration procedures and adjusting cameras aperture to existing light are intricate processes, which can compromise the system's capacity to identify markers. This fact might compromise the quality of the ground truth and ultimately the reported errors.

It has been shown that the QCF results are better when compared with other sensor fusion techniques. However, the alternative methods have parameters that ramained with constant value.

The hand segment needs additional validation. This segment's angular estimation trough the IMUs may be closer to the reality than the used reference once, the reconstruction of the hand's motion using Vicon's software arose issues. This fact might have compromised the results.

Regarding the computational complexity, the OpenPose method was significantly more expensive than inertial sensors. Even using the GPU for faster calculation, it took approximately one hour to analyse individual sets (which have approximated lengths less than two minutes).

# 4.3 Industrial Assessment

The second study was performed in a automotive manufacturing environment. It aimed to assess the ergonomic risk of workstations, in which repetitive movements are employed. The ergonomic evaluation was performed using the developed upper limb and torso motion tracker and explanations on the risk results were also reported.

For participating in the study, subjects signed and obtained an informed consent, available at Appendix A. Beforehand, participants had detailed written information on the study objectives and recording data. Additionally, they could solicit any verbal clarification to the researcher. At any moment, subjects could ask to cease the collaboration without consequences, having total freedom to decide their participation in the research.

When researches require the collection of personal and sensitive data, confidentiality must be addressed. Data confidentiality is of the utmost importance and was ensured during the development of this study. Each participant information was anonymously collected, by associating with each subject a unique number. Personal data such as age and gender, and written questionnaires were also referred by the corresponding identification number. The acquired data was only used for this project research purposes.

In this pilot project, 12 manufacturing workers were asked to perform their working tasks while using the sensing devices attached to their upper bodies. Under this study, subjects were also filmed. The video system allowed visual support for the inertial data. Table 4.16 summarises participants' characteristics.

Table 4.16: Industrial assessment subjects'	characteristics. m	n: male; f: female;	<del>yr</del> : average
years; $\overline{h}$ : average height in cm; r: ratio.			

Subjects' characteristics		
Number	12	
Gender (m:f)	9:3	
Age $(\overline{yr} \pm \sigma)$	36 ± 9	
<b>Height</b> $(\overline{h} \pm \sigma)$	$172 \pm 7$	
<b>Dominant hand</b> (r)	Right hand (11:12)	

An assembly line is composed of several timed processes which are regularly updated. It is also a space where subjects with distinct skills and responsibilities work. In the considered automotive factory there are distinct assembly lines. Three workstations from Bodyshop assembly line were analysed. In Bodyshop, cars' doors are assembled. Particularly at: Liftgate workstation the back doors are mounted; Fender workstation involves front doors tasks; Doors workstation demands tasks on front doors and cars' hood.

Workstations activities usually require two operators at the same time performing manual processes in each side of a car.

#### 4.3.1 Equipment and Placement

Operators wore four IMUs located as described in Section 4.1. The developed protocol for the field trial, instructed that the subjects had to perform two calibration positions - the N and T pose - in the beginning, and at the end of the test, which permits to verify if signals were not disturbed through the work cycles, i.e. while performing the same poses the signal should be similar. Additionally, inertial devices can be zeroed with the N-pose. Figure 4.14 illustrates calibration poses and a completely equipped subject.



(a) Calibration poses representation. Adapted from [95].

Source: Volkswagen Autoeuropa.

Figure 4.14: Left - calibration positions: N-pose and T-pose. Right- A worker performing T-pose. The subject is equipped with four IMUs: three on the right upper limb and one on the thorax.

#### 4.3.2 Dataset Overview

It must be noticed that each operator is essential in a workstation. The production line could not be compromised by the necessity to equip participants, thus requiring an extra effort from another team member.

Some challenges may occur when recording data for long periods. The smartphone, which integrates all device's information, heats up and application failure may happen. Additionally, Bluetooth connection can also fail, during long runs, causing the loss of a

device's data. Some of these issues occurred in the field tests.

The curated dataset is composed of 4.23 recording hours. While the Liftgate workstation is analysed through the labour chores of four operators, making a total of 41 cycles, the Fender workstation considers three subjects' tasks, taking into account 34 cycles. The Doors workstation only contemplates two workers and a total of 24 cycles.

To manage data analysis, the inertial information was resampled to 50 Hz. Afterwards, the QCF approach was employed, setting the  $\alpha$  parameter to 0.95 for reconstructing the angular motion. The cycle duration of each subject's activity was manually annotated.

#### 4.3.3 Ergonomic Evaluation and Explanation

The ergonomic evaluation and explanation of the acquired data are organised as represented in Figure 4.15. Research questions that each stage addresses are also depicted.



Figure 4.15: Ergonomic risk evaluation and explanation.

The general workstation risk presents the application of an ergonomic assessment through an index score. Consequently, studied workstations are evaluated. Moreover, the general workstation explanation provides an average of the executed movements. In team explanation, a comparison between workers of the same workstation is given. Finally, approaching the individual level, a subject's report is presented.

#### 4.3.3.1 General Workstation Risk

Before adopting strategies to improve working conditions, situations that can contribute to operators' risk must be identified. Ergonomic indexes grant information on the main risk factors, allowing to prioritise interventions. The RULA worksheet can be used to screen and identify harmful postures. In this research, an adapted version of RULA's was developed. Figure 4.16 exhibits a comparison between the RULA method and an adapted version developed on the context of this work named as Adjusted Rapid Upper Limb Assessment (AdRULA).

	RULA	AdRULA
Parameters	Upper arm; Lower arm; Wrist; Trunk; Legs; Neck; Muscle use; Force/Load.	Upper arm; Lower arm; Wrist; Trunk.
Postures Selection	Frequently postures or Prolonged postures or Postures that involve large forces or muscular activity, cause discomfort or are considered extreme.	A posture every 0.02s.
Assessment Method	Observational	Direct

Figure 4.16: Comparison of RULA and AdRULA methods. Studied body regions, posture selection and posture capture.

The selection of postures for the RULA method analysis is generally based on: (1) the posture sustained for the longest period, or (2) the most difficult posture and work task (based on initial observation), or (3) the posture where the highest force loads occur. Most frequently RULA captures postures through observational methods, i.e., through field observations, photographs or video systems.

The AdRULA focus on the subject's upper limbs and torso, selects postures every 0.02s and apprehends poses via direct measurements, e.g., wearable technology.

Although having different considerations, the local and final scores are determined similarly in both methods. Therefore, the workstations risk score is defined as:

- 1-2 negligible risk; no action required.
- 3-4 low risk; change may be needed.
- 5-6 medium risk; further investigation, change the posture soon.
- 6+ very high risk, implement change now.

The average score of workstations was determined using AdRULA index and it is represented in Figure 4.17. The charts demonstrate that, in general, when operators perform tasks in the considered workstations they stand for a longer period in a level 3-4 risk zone which represents a low risk. Despite being a small percentage, the Liftgate and Fender workstations present a level 5 risk. Accordingly, those workstations represent a higher risk to operators in terms of postures.





#### 4.3.3.2 General Workstation Explanation

From an ergonomic perspective, it is relevant to identify which movements contribute to a higher risk of injuries. Figure 4.18 represents the full distribution of a workstation's movements, in the form of a probability density of these data.

It can be interpreted that the torso's movements have similar angular distribution for the considered workstations. Moreover, for Liftgate and Fender, the hand movements have a higher probability of performing flexion exercises around 50° while in the Doors workstation the highest probability stands in the 25° range. Flexions and extensions between arm and forearm segments present the most differences. While in the Liftgate, the arm presents a highest density probability around 50°-100°, Fender and Doors present two prominent probability peaks - 50° and 25° for Fender and, 90° and 25° for Doors.

Overall, by demanding more labour in arms and hands, the Liftgate is classified with higher scores. Doors workstation, with a larger probability of poses around the segment's neutral zone, is evaluated with lower levels.



Figure 4.18: Representation of operator's average flexion and extension movements from Liftgate, Fender and Doors workstations with AdRULA score thresholds.

#### 4.3.3.3 Team Explanation

While working in the same workstation, operators might not share the same characteristics, e.g., height, weight, limbs length, and others. Additionally, the way a given subject performs a task may also be related to the career experience. Therefore, workers complete the same tasks, required by the workstation, presenting differences in movements amplitude.

The Liftgate workstation is reported with a considerable percentage of level 4 score and also reaches level 5. Thus, the subsequent analysis will be related to it. Figure 4.19 represents the probability density of four different subjects performing the exercises that Liftgate workstation expects. Subjects' characteristics are also depicted.

It can be observed that the flexion/extension highest probability for arm and forearm segments ranges from 50° to 100°, being the subject 1 with the highest probability of movements at 100° level. The probability density for the torso's movements is very similar to the whole participants, except for subject 1 - which has a considerable percentage



Figure 4.19: Comparison of average flexion and extension movements distribution from four different subjects while performing Liftgate's tasks, with AdRULA score thresholds. Right side - subjects' characteristics.

of time in flexion ranging from 20°-60°, resulting in a score of 3. Hands flexion/extension movements present the highest diversity. Operators 1, 2 and 4 have a higher probability of angular movements below 50°, while subject 3 has a more uniformly distributed probability.

It must be noted that the hand's flexion range of motion does not exceed 66°. The charts representation suggest differently. Thus, one must not neglect that the employed devices have errors.

In Figures 4.19 and 4.18, the following movements are not illustrated: shoulder abduction/adduction, forearm's pronation/supination, torso lateral flexion and hand's radial/ulnar deviation. The AdRULA classification does not considerer the angular variation of the mentioned actions but rather relies on their binary state, i.e. if a movement occurs or not. For instance, if the studied arm is abducted the local classification for the segment receives an extra point. Similar adjustments are applied in other segments.

Throughout the analysis, it can be reasoned that among operators from the same workstation, which have different characteristics, angular movements distribution is not identical. Consequently, the individual's ergonomic risk will be different from an average worker.

#### 4.3.3.4 Individual Explanation

In a workstation, not only an operator's performance change over time, e.g. due to fatigue, but also within a work cycle, risk variations can be identified. A cycle temporal analysis and individuals reports may help to recognise the subjects-related risk.

Frequently, the risk exposure reference is the effect of averaging subjects' performance in a given workstation. However, the average reality might hide an individual's potential hazards. Figure 4.20 shows an example of an operator's evaluation, during a work cycle, and the workstation average result. The punctuation is similar, yet it must be noted that the considered subject spends a higher percentage of the work cycle time in a level 5. This type of occurrences should be carefully analysed to prevent short and long term injuries.



Figure 4.20: A participants cycle score comparison with the average score of the workstation.

In Figure 4.21, the subject's cycle classification is provided. This specific Liftgate's cycle has the duration of 96 s.



Figure 4.21: Time dependent AdRULA scoring. Representation of one work cycle performed by subject 1 from Liftgate workstation. Green: score 1-2; Yellow: score 3-4; Orange: score 4-5; Red: score 6+.

As observed in Figure 4.20 and in Figure 4.21, the subject sustains, in general, a 3-4 score level. However, in some periods the score 5 is reached, namely from seconds 42 to 45 and 91 to 94.

Figure 4.22 provides a temporal analysis specifically from seconds 42 to 45. Segments' angular motion can be translated into AdRULA score, generating four local scores. Although segments' local scores are not particularly high considering flexion and extension, it was verified that, during this interval, the arm was abducted, the hand had deviation and that the torso presented side bending. Accordingly, these segments received an extra point, and the local AdRULA punctuation was: arm with a 4 index; forearm with a 2 index; hand with a 4 index; and torso with a 4 index. The combination of the local indexes traduced a global score of level 5, which can explained by a higher angular demand on the segments.

The score punctuation might not be simple to interpret and consequently, hinder work-physicians and team leaders to perceive operators' need. The individual analysis helps to understand if operators perform tasks within the workstation risk range or if their characteristics intensify/mitigate the risk. Thus, having personal reports, with detailed movements information at cycle-level, can be an advantage for improving injuries-preventive recommendations and for adjusting work conditions. The global movement performance, in a work cycle, is illustrated in Figure 4.23.

In this particular work-cycle the subject most frequently had: the torso in the flexion interval of  $0^{\circ}-20^{\circ}$ ; the upper arm in the  $-20^{\circ}-20^{\circ}$  flexion/extension range; the lower arm in the flexion interval of  $60^{\circ}-100^{\circ}$ ; finally, the hand segment in  $15^{\circ}$ < extension zone.



Figure 4.22: Temporal analysis of seconds 42 to 45 from a subject performing Liftgate's tasks. Arm, forearm, hand and trunk flexion/extension movements along with the correspondent AdRULA score.

### 4.3.4 Workers relation with sensors

After acquiring data through the IMU system, subjects answered a questionnaire reporting their impressions on the usability of the devices in an industrial field. The average response of the participants is represented in Figure 4.24.

Subjects commonly answered that while they participated in the study, performing their workstation tasks, the devices did not influence their movements, cause fatigue or pain or made their work-activities more difficult. Furthermore, the IMUs did not require any readjustment being suitable for working in that type of scenario. Nevertheless, some mentioned that the hand device is the least comfortable, once the working gloves tighten it throughout the acquisition.



Figure 4.24: Radar chart with the average opinion of 12 subjects' on using IMU devices in an industrial context. Agreement scale: 1 (totally disagree) - 5 (fully agree).

## 4.3.5 Summary

The field section provided an intrinsic view of an ergonomic assessment in a real manufacturing context. Three workstations were studied and, participants wore the multiple IMU system while they performed the required tasks.

The results showed that the system allows a posture-focused evaluation. Moreover, to apprehend the outcome, it is necessary an explanation which is provided through the angular motion information. Subjects own characteristics influence how an exercise is completed. Therefore, explanations at workstation, team and individual level are essential, providing detailed information on the risk assessment.

The industrial assessment not only allowed a feasibility test focused on the ergonomic risk assessment but also provided an interaction of workers with wearable technology.



Figure 4.23: Detailed information on a subject's movement over a work cycle. Percentage of time spent in each pose. Adapted from [33].

# **CONCLUSION AND FUTURE WORK**

This chapter summarises the developed work and the obtained results throughout this dissertation. Guidelines for future research are also proposed.

# 5.1 Main Conclusions

Work-related Musculoskeletal Disorders (WMSDs) represent a significant portion of occupational injuries, affecting operators from all sectors. The frequency of these injuries increases due to repetitive tasks, leading to absenteeism, early retirement and loss of productivity. An ergonomic assessment should be emphasised to identify risk factors, allowing to prioritise work-related interventions.

Throughout this dissertation, three major contributions were presented. Firstly, an upper limb and torso human motion tracking algorithm, which relies on inertial sensor information, was used to estimate the absolute and relative orientation of anatomical joints. Secondly, it was developed an adjusted ergonomic risk score based on direct measurements. Finally, an ergonomic risk explanation approach, based on the comprehensive analysis of the angular risk factors, was provided.

The experimental nature of this project supported the development of two different assessments - validation and field assessment. While the validation tests provided, in a controlled environment, the error characterisation of the motion tracker, the field assessment allowed a feasibility study of the proposed framework on a manufacturing context. Both evaluation studies provided two distinct datasets composed by inertial sensor data.

Several conclusions were established using the validation dataset. The Quaternionbased Complementary Filter (QCF) approach has the competitive advantage to other sensor fusion methods and requires no parameters tuning. The averaged Root-Mean-Square Error (RMSE) for static trials is 11°, 22°, 25° and 24° for the torso, hand, forehand and hand segments, respectively. Concerning the dynamic set, it was obtained an averaged RMSE of 22°, 18°, 20° and 10°, respectively for the aforementioned segments.

The OpenPose approach was used as an alternative Motion Capture (Mocap) method, with similar performance to QCF, yet it has some challenges. Despite being computational complex, this markerless technology may present occlusions, i.e. when the algorithm fails to track a limb, and, additionally, it does not provide a true 3D tracking, while its utilisation is limited to defined camera angles.

With the field dataset, the analysis was towards an ergonomic risk assessment. The designed tracking system has an average level of scalability, explainability and invasiveness. It relies on four inertial sensors which allowed to obtain information at an intermediate level, calculating low-level metrics of ergonomic risk efficiently.

Employing the estimated orientation of anatomical joints, provided by the system, it is possible to conduct a postural ergonomic risk assessment. The workstations that presented a higher level of risk, behold tasks that, effectively, require extreme positions, e.g. overhead work.

Nowadays, the global risk score is often agnostic to operators' age, anthropometric characteristics and work experience variability and the predefined workstation's scores are based on an average worker. While completing the risk analysis, it is possible to point out evident motion variability among operators who perform the same workstation's tasks. Hence, an individual ergonomic approach is better suited for preventing injuries, once it can unmask risk poses. The evaluation should be individual-related and not the collective.

At last, providing explainability to risk assessments is an added value to occupational physicians once it allows characterising motions and provides a more comprehensive analysis of the risk factors which contributed to the resulting score.

The current solution was performed in a manufacturing scenario, although the framework can be also applied in a different type of contexts. In offices, where a chair and desk make the workday of a large number of employees, an ergonomic analysis could be fundamental for awareness and prevention of disorders. Additionally, this framework could also be applied to monitor physiotherapy and rehabilitation-related motion activities.

With the present work, we provide a strong basis to support the potential of using inertial sensors as an effective method for detailed ergonomic assessment in industrial environments.

# 5.2 Future Work

This dissertation leaves some unsolved problems and opens new research questions to which devote additional research effort will be applied in the future. The description of some of the ideas to explore are detailed in the following paragraphs.

An **alternative protocol to evaluate the hand segment** must be designed. During the experimental validation, the optical Mocap method used as a reference did not reconstruct the motion of the hand segment as expected. Therefore, investigating another technique or tool, e.g. goniometers, which could be used to monitor hand's movements, would be valuable.

**Reducing long term system bias**. A possible way for achieving it is by reducing the system's angle error using multimodal sensor fusion approaches, e.g. using video recordings as an aid to reset the sensor's long-term drift.

**Measuring and calculating additional parameters** is an approach to complement the postural analysis. The adopted inertial devices, IoTiPs, are modular, which suggests that other type of information can be easily integrated. Examples of parameters that could be explored in manufacturing environments are noise and tools' vibration.

Adopting other ergonomic assessment tools, e.g. Ergonomic Assessment Work-Sheet (EAWS), can be approached as a way of extending the postural analysis. The applied ergonomic method was derived from RULA, an ergonomic worksheet that is focused mainly on the upper limbs and torso's posture of operators, representing the results in a discrete score. With the contribution of a specialist, a continuous score worksheet can also be designed.

Placing the devices correctly on operators is a requirement for reducing the error impact on further stages of an ergonomic analysis. However, it is a constraint for participants to leave the assembly line during work-shifts once it can compromise the line production. Hence, the research required that other operators, which were not directly involved in the research, employed an extra effort for maintaining the colleague's tasks while the equipping procedure was running. Thus, shortening sensor placing while assuring its correct position could be addressed through special clothes with sensors embedded or by designing a tool to recognise accurate placing.

# BIBLIOGRAPHY

- E. Schneider, X. Irastorza, and S. Copsey. OSH in Figures: Work-related Musculoskeletal Disorders in the EU — Facts and Figures. European Agency for Safety and Health at Work, Jan. 2010. ISBN: 978-92-9191-261-2. DOI: 10.2802/10952.
- [2] A. Luttmann, M. Jäger, B. Griefahn, G. Caffier, and F. Liebers. *Preventing Musculoskeletal Disorders in the Workplace*. 5. World Health Organization, 2003. ISBN: 92 4 159053 X. URL: https://www.who.int/occupational\_health/publications/en/oehmsd3.pdf.
- [3] L. Peppoloni, A. Filippeschi, E. Ruffaldi, and C. Avizzano. "A novel wearable system for the online assessment of risk for biomechanical load in repetitive efforts." In: *International Journal of Industrial Ergonomics* 52 (2016), pp. 1–11. DOI: 10.1016/J.ERGON.2015.07.002. URL: https://www.sciencedirect.com/science/article/abs/pii/S0169814115300081{\#}!.
- [4] Eurostat Statistics Explained. Self-reported work-related health problems and risk factors - key statistics. 2017. URL: https://ec.europa.eu/eurostat/statisticsexplained/index.php?title=Self-reported\_work-related\_health\_problems\_ and\_risk\_factors\_-\_key\_statistics\#Consequences\_of\_work-related\_ health\_problems (visited on 08/17/2019).
- [5] D. H. Seidel, D. Ditchen, U Hoehne-Hückstädt, M. Rieger, and B. Steinhilber. "Quantitative Measures of Physical Risk Factors Associated with Work-Related Musculoskeletal Disorders of the Elbow: A Systematic Review." In: *International Journal of Environmental Research and Public Health* 16 (Jan. 2019), p. 130. DOI: 10.3390/ijerph16010130.
- [6] Health and Safety Executive. Work-related ill health and occupational disease in Great Britain. URL: http://www.hse.gov.uk/statistics/causdis/ (visited on 08/17/2019).
- [7] N. Vignais, M. Miezal, G. Bleser, K. Mura, D. Gorecky, and F. Marin. "Innovative system for real-time ergonomic feedback in industrial manufacturing." In: *Applied Ergonomics* 44.4 (2013), pp. 566–574. ISSN: 18729126. DOI: 10.1016/j.apergo. 2012.11.008. URL: http://dx.doi.org/10.1016/j.apergo.2012.11.008.

- [8] J. S. Thorsten Wuest David Romero. Introducing 'Operator 4.0,' a tech-augmented human worker. 2017. URL: http://theconversation.com/introducing-operator-4-0-a-tech-augmented-human-worker-74117 (visited on 09/07/2019).
- [9] T. C. d'Escury. New Study Industrie 4.0. 2016. URL: https://www.rolandberger. com/en/Publications/The-Industrie-4.0-transition-quantified.html (visited on 08/28/2019).
- [10] M. Goenaga, P. Radtke, K. Speicher, and R. Westinner. Ops 4.0: Fueling the next 20 percent productivity rise with digital analytics. 2017. URL: https://www.mckinsey. com/business-functions/operations/our-insights/ops-4-0-fueling-thenext-20-percent-productivity-rise-with-digital-analytics (visited on 09/07/2019).
- [11] A. B. Correia, P. Deus, J. R. Baptista, and P. Palha. Indústria 4.0 Construir a empresa digital. 2019. URL: https://www.pwc.pt/pt/temas-actuais/industria-40.html (visited on 09/03/2019).
- F. Caputo, A. Greco, E. D'Amato, I. Notaro, and S. Spada. "IMU-Based Motion Capture Wearable System for Ergonomic Assessment in Industrial Environment." In: Springer Nature (2019), pp. 215–225. DOI: 10.1007/978-3-319-94619-1\_21.
- [13] A. S. Uva, F. Carnide, F. Serranheira, L. C. Miranda, and M. F. Lopes. Lesões Musculoesqueléticas Relacionadas com o Trabalho. Guia de Orientação para a Prevenção. Lisboa: Direcção-Geral da Saúde, 2008. ISBN: 978-972-675-169-4.
- [14] S. Bevan. "Economic impact of musculoskeletal disorders (MSDs) on work in Europe." In: Best Practice & Research Clinical Rheumatology 29.3 (2015). Occupation and Musculoskeletal Disorders, pp. 356 –373. ISSN: 1521-6942. DOI: https://doi.org/10.1016/j.berh.2015.08.002. URL: http://www.sciencedirect.com/science/article/pii/S1521694215000947.
- [15] P. McGee. Germany invests to prolong employees' working lives. 2019. URL: https: //www.ft.com/content/f1b294b8-9cbe-11e8-88de-49c908b1f264 (visited on 01/24/2019).
- [16] Occupational Safety and Health Administration. Ergonomics : The Study of Work. 2000. URL: http://www.dlt.ri.gov/arrigan/pdfs/Studyofwork.pdf (visited on 03/14/2019).
- [17] G. C. David. "Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders." In: *Occupational Medicine* 55.3 (2005), pp. 190–199. DOI: 10.1093/occmed/kqi082.
- [18] N. Vignais, F. Bernard, G. Touvenot, and J. C. Sagot. "Physical risk factors identification based on body sensor network combined to videotaping." In: *Applied Ergonomics* 65 (2017). DOI: 10.1016/j.apergo.2017.05.003.

- [19] D. Battini, A. Persona, and F. Sgarbossa. "Innovative real-time system to integrate ergonomic evaluations into warehouse design and management." In: *Computers and Industrial Engineering* 77 (2014). ISSN: 03608352. DOI: 10.1016/j.cie.2014. 08.018. URL: http://dx.doi.org/10.1016/j.cie.2014.08.018.
- [20] L. Peppoloni, A. Filippeschi, E. Ruffaldi, and C. A. Avizzano. "(WMSDs issue) A novel wearable system for the online assessment of risk for biomechanical load in repetitive efforts." In: *International Journal of Industrial Ergonomics* 52 (2014), pp. 1–11. ISSN: 18728219. DOI: 10.1016/j.ergon.2015.07.002. URL: http://dx.doi.org/10.1016/j.ergon.2015.07.002.
- [21] E.-P. Takala, I. Pehkonen, M. Forsman, G.-Å. Hansson, S. E. Mathiassen, W. P. Neumann, G. Sjøgaard, K. B. Veiersted, R. H. Westgaard, and J. Winkel. "Systematic evaluation of observational methods assessing biomechanical exposures at work." In: *Scand J Work Environ Health* 36.1 (2010).
- [22] A. C. C. Pereira. "Inertial sensor-based 3D upper limb motion tracking and trajectories reconstruction." Master's thesis. Faculdade de Engenharia Universidade do Porto, 2016.
- [23] Å. Kilbom. "Repetitive work of the upper extremity: Part I-Guidelines for the practitioner." In: *Elsevier Ergonomics Book Series* 1.C (1994), pp. 145–150. DOI: 10.1016/S1572-347X(00)80010-5.
- [24] S. J. Ray and J. Teizer. "Real-time construction worker posture analysis for ergonomics training." In: Advanced Engineering Informatics 26.2 (2012), pp. 439–455.
  DOI: 10.1016/j.aei.2012.02.011. URL: http://dx.doi.org/10.1016/j.aei. 2012.02.011.
- [25] D. M. Godfrey R. Conway and G. ÓLaighin. "Direct measurement of human movement by accelerometry." In: *Medical engineering & physics* (2008), pp. 1364–1386.
  DOI: https://doi.org/10.1016/j.medengphy.2008.09.005.
- [26] H. Zhou and H. Hu. "Inertial motion tracking of human arm movements in stroke rehabilitation." In: *International Conference on Mechatronics & Automation*. July. 2005, pp. 1306–1311.
- [27] H. Zhou, H. Hu, and Y. Tao. "Inertial measurements of upper limb motion." In: Medical and Biological Engineering and Computing 44.6 (2006). DOI: 10.1007/ s11517-006-0063-z.
- [28] J. M. Cabeças. "The risk of distal upper limb disorder in cleaners: A modified application of the Strain Index method." In: *International Journal of Industrial Ergonomics* 37.6 (2007), pp. 563–571. DOI: 10.1016/j.ergon.2007.03.002.

- [29] G. Bleser, G. Hendeby, and M. Miezal. "Using egocentric vision to achieve robust inertial body tracking under magnetic disturbances." In: *Proceedings of International Symposium on Mixed and Augmented Reality (ISMAR)* (Oct. 2011), pp. 103–109. DOI: 10.1109/ISMAR.2011.6092528.
- [30] X. Yan, H. Li, A. R. Li, and H. Zhang. "Wearable IMU-based real-time motion warning system for construction workers' musculoskeletal disorders prevention." In: Automation in Construction 74 (2017), pp. 2–11. ISSN: 0926-5805. DOI: https://doi.org/10.1016/j.autcon.2016.11.007. URL: http://www.sciencedirect.com/science/article/pii/S0926580516303314.
- [31] K. Bauters, J. Cottyn, D. Claeys, M. Slembrouck, P. Veelaert, and H. van Landeghem.
  "Automated work cycle classification and performance measurement for manual work stations." In: *Robotics and Computer-Integrated Manufacturing* 51 (2018). DOI: 10.1016/j.rcim.2017.12.001.
- [32] P. D. Weill. "The Relationship Between Investment in Information Technology and Firm Performance: A Study of the Valve Manufacturing Sector." In: *Massachusetts Institute of Technology (MIT), Sloan School of Management, Working papers* 3 (Jan. 2003). DOI: 10.1287/isre.3.4.307.
- [33] ViveLab Ergo Ltd. 2017. URL: https://www.vivelab.cloud/software (visited on 08/17/2019).
- [34] IBM Corporation. 2018. URL: https://www.ibm.com/pt-en/marketplace/iotsafer-workplace (visited on 08/17/2019).
- [35] Soter Analytics. URL: http://www.soteranalytics.com/soterspine.html (visited on 08/17/2019).
- [36] IEA. Definition and Domains of Ergonomics. 2019. URL: www.iea.cc (visited on 01/14/2019).
- [37] W. Karwowski. International Encyclopedia of Ergonomics and Human Factors. 2nd ed. Vol. 3. Taylor & Francis, Mar. 2006. ISBN: 9780415304306.
- [38] M. S. Sanders and E. J. McCormick. *Human Factors In Engineering and Design*. 7. McGraw-Hill Education, 1993. ISBN: 007054901X.
- [39] M. G. Helander and L. Zhang. "Field studies of comfort and discomfort in sitting." In: *Ergonomics* (1997). DOI: 10.1080/001401397187739.
- [40] W. Karwowski. "Handbook of Human Factors and Ergonomics, Fourth Edition." In: ed. by G. Salvendy. 4th ed. John Wiley & Sons, 2012. Chap. Chapter 1 - The Discipline of Human Factors and Ergonomics (Pages: 1-37). ISBN: 9780470528389.
   DOI: 10.1002/9781118131350.
- [41] World Health Organization. Musculoskeletal conditions. 2019. URL: https:// www.who.int/news-room/fact-sheets/detail/musculoskeletal-conditions (visited on 09/16/2019).

- [42] Occupational Safety and Health Administration. *Ergonomics*. URL: https://www.osha.gov/SLTC/ergonomics/ (visited on 08/10/2019).
- [43] J. Moar, D. Ramos, and P. Arezes. "Defining the Angles' Range in Ergonomics Assessment Using 3D Cameras and Surface EMG." In: Advances in Safety Management and Human Factors. Vol. 491. Jan. 2016, pp. 463–472. ISBN: 978-3-319-41928-2.
  DOI: 10.1007/978-3-319-41929-9 42.
- [44] L. McAtamney and E. N. Corlett. "RULA: a survey method for the investigation of work-related upper limb disorders." In: Applied Ergonomics 24.2 (1993), pp. 91 –99. ISSN: 0003-6870. DOI: https://doi.org/10.1016/0003-6870(93)90080-S. URL: http://www.sciencedirect.com/science/article/pii/000368709390080S.
- [45] O. Karhu, P. Kansi, and I. Kuorinka. "Correcting working postures in industry: A practical method for analysis." In: *Applied Ergonomics* 8.4 (1977), pp. 199 –201. ISSN: 0003-6870. DOI: https://doi.org/10.1016/0003-6870(77)90164-8. URL: http://www.sciencedirect.com/science/article/pii/0003687077901648.
- [46] S. Hignett and L. McAtamney. "Rapid Entire Body Assessment (REBA)." In: Applied Ergonomics 31.2 (2000), pp. 201 –205. ISSN: 0003-6870. DOI: https://doi.org/ 10.1016/S0003-6870(99)00039-3. URL: http://www.sciencedirect.com/ science/article/pii/S0003687099000393.
- [47] K. Schaub, G. Caragnano, B Britzke, and R. Bruder. "The European Assembly Worksheet." In: *Theoretical Issues in Ergonomics Science* 14 (Jan. 2012), pp. 1–23.
   DOI: 10.1080/1463922X.2012.678283.
- [48] J. Moore and A. Garg. "The Strain Index: A Proposed Method to Analyze Jobs For Risk of Distal Upper Extremity Disorders." In: American Industrial Hygiene Association Journal 56.5 (1995), pp. 443–458. DOI: 10.1080/15428119591016863.
- [49] J. A. Ringelberg and T. Koukoulaki. *Risk Estimation for Musculoskeletal Disorders in Machinery Design Integrating a User Perspective*. 2002.
- [50] M. Middlesworth. The Definition and Causes of Musculoskeletal Disorders. 2019. URL: https://ergo-plus.com/musculoskeletal-disorders-msd/ (visited on 08/10/2019).
- [51] N. Delleman, M. Boocock, B. Kapitaniak, P. Schaefer, and K. Schaub. "prEN 1005-4: Evaluation of Working Postures in Relation to Machinery." In: *Proceedings of the IEA 2000/HFES 2000 Congress* (2000).
- [52] S. Kumar. Perspectives In Rehabilitation Ergonomics. CRC Press, 2003.
- [53] A. Freivalds. Biomechanics of the Upper Limbs. Mechanics, Modeling and Musculoskeletal Injuries. 2nd ed. CRC Press, 2011. ISBN: 978-1-4200-9120-5.
- [54] Scanning Planes. URL: http://www.impocus.ca/basics-of-scanning----scanning-planes- (visited on 03/17/2019).

- [55] C. F. Smith, A. Dilley, B. S. Mitchell, and R. L. Drake. *Gray'S Surface Anatomy and Ultrasound*. Elsevier, 2018. ISBN: 978-0-7020-7018-1.
- [56] N. Berme, A. E. Engin, and K. M. C. da Silva, eds. Biomechanics of Normal and Pathological Human Articulating Joints. Martinus Nijhoff Publishers, 1985. ISBN: 9789401087629. DOI: 10.1007/978-94-009-5117-4.
- [57] E. Culham and M. Peat. "Functional Anatomy of the Shoulder Complex." In: *Journal of Orthopaedic & Sports Physical Therapy* 18.1 (1993). PMID: 8348135, pp. 342–350.
  DOI: 10.2519/jospt.1993.18.1.342. eprint: https://doi.org/10.2519/jospt. 1993.18.1.342. URL: https://doi.org/10.2519/jospt.1993.18.1.342.
- [58] M. Stroyan and K. E. Wilk. "The Functional Anatomy of the Elbow Complex." In: *Journal of Orthopaedic & Sports Physical Therapy* 17.6 (1993). PMID: 8343787, pp. 279–288. DOI: 10.2519/jospt.1993.17.6.279. eprint: https://doi.org/10. 2519/jospt.1993.17.6.279. URL: https://doi.org/10.2519/jospt.1993.17. 6.279.
- [59] P. J. Mansfield and D. A. Neumann. "Chapter 6 Structure and Function of the Wrist." In: Essentials of Kinesiology for the Physical Therapist Assistant (Third Edition). Ed. by P. J. Mansfield and D. A. Neumann. Third Edition. St. Louis (MO): Mosby, 2019, pp. 120 –140. ISBN: 978-0-323-54498-6. DOI: https://doi.org/10.1016/B978-0-323-54498-6.00006-0. URL: http://www.sciencedirect.com/science/article/pii/B9780323544986000060.
- [60] D. Lura. "Modeling upper body kinematics while using a transradial prosthesis." Master's thesis. College of Engineering, University of South Florida, Dec. 2008.
- [61] C. L. Taylor. "The Biomechanics of Control in Upper-Extremity Prostheses." In: *National Academy of Sciences* 2.3 (1955), pp. 4–25.
- [62] P. Y. Loh and S. Muraki. "Effect of Wrist Deviation on Median Nerve Cross-Sectional Area at Proximal Carpal Tunnel Level." In: *Iranian Journal of Public Health* 43 (Nov. 2014), pp. 180–185.
- [63] P. Nogueira. Motion Capture Fundamentals. A Critical and Comparative Analysis on Real-World Applications. Tech. rep. Faculdade de Engenharia da Universidade do Porto, 2011. URL: https://paginas.fe.up.pt/~prodei/dsie12/papers/paper\_ 7.pdf.
- [64] Vicon Motion Systems. What is Motion Capture. URL: https://www.vicon.com/ what-is-motion-capture (visited on 07/27/2019).
- [65] T. Haslwanter. 3D Kinematics. 2018. ISBN: 9783319752761. DOI: 10.1007/978-3-319-75277-8.
- [66] M. C. J. Schall, N. B. Fethke, H. Chen, S. Oyama, and D. I. Douphrate. "Accuracy and repeatability of an inertial measurement unit system for field-based occupational studies." In: *Ergonomics* (2015). DOI: http://dx.doi.org/10.1080/ 00140139.2015.1079335.
- [67] K. R. Christiansen and A. Shalamov. Motion Sensors Explainer. 2017. URL: https: //www.w3.org/TR/motion-sensors (visited on 07/29/2019).
- [68] S. Ayub, A. Bahraminisaab, and B. Honary. "A Sensor Fusion Method for Smart phone Orientation Estimation." In: 13th Annual Post Graduate Symposium on the Convergence of Telecommunication, Networking and Broadcasting. Liverpol, 2012.
- [69] Vicon Motion Systems. Vicon Motion Capture Center. URL: https://www.brandeis. edu/graybiel/facilities/vicon.html (visited on 07/22/2019).
- [70] P. Merriaux, Y. Dupuis, R. Boutteau, P. Vasseur, and X. Savatier. "A Study of Vicon System Positioning Performance." In: *Sensors (Switzerland)* 17.7 (July 2017), pp. 1–18. ISSN: 14248220. DOI: 10.3390/s17071591.
- [71] Z. Cao, T. Simon, S.-E. Wei, and Y. Sheikh. "Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields." In: *CVPR*. 2017.
- [72] A. Solano. Human pose estimation using OpenPose with TensorFlow (Part 2). 2017. URL: https://arvrjourney.com/human-pose-estimation-using-openposewith-tensorflow-part-2-e78ab9104fc8 (visited on 08/14/2019).
- [73] J. Kriz. Earth Coordinates. 2019. URL: https://www.nosco.ch/mathematics/en/ earth-coordinates.php (visited on 07/30/2019).
- [74] Motion and position sensors. 2017. URL: https://google-developer-training. gitbooks.io/android-developer-advanced-course-concepts/content/unit-1-expand-the-user-experience/lesson-3-sensors/3-2-c-motion-andposition-sensors/3-2-c-motion-and-position-sensors.html (visited on 01/30/2019).
- [75] M. Gravelle. Quaternions and their Applications to Rotation in 3D Space. 2006.
- [76] Y.-B. Jia. Quaternions. 2018. URL: http://web.cs.iastate.edu/~cs577/ handouts/quaternion.pdf (visited on 04/17/2019).
- [77] J. Diebel. "Representing Attitude: Euler Angles, Unit Quaternions, and Rotation Vectors." In: *Matrix* 58 (Jan. 2006).
- [78] S. O. H. Madgwick. An efficient orientation filter for inertial and inertial / magnetic sensor arrays. Mar. 2010. URL: https://www.samba.org/tridge/UAV/madgwick\_ internal\_report.pdf (visited on 07/22/2019).
- [79] Quaternions. 2016. URL: https://quaternions.online (visited on 09/07/2019).
- [80] W. Elmenreich. An Introduction to Sensor Fusion. 2002.

- [81] R. Valenti, I. Dryanovski, and J. Xiao. "Keeping a Good Attitude: A Quaternion-Based Orientation Filter for IMUs and MARGs." In: Sensors 15 (Aug. 2015), pp. 19302– 19330. DOI: 10.3390/s150819302.
- [82] R. Wagenaar and R. van Emmerik. "Resonant frequencies of arms and legs identify different walking patterns." In: *Journal of Biomechanics* 33.7 (2000), pp. 853 –861. ISSN: 0021-9290. DOI: https://doi.org/10.1016/S0021-9290(00) 00020 8. URL: http://www.sciencedirect.com/science/article/pii/S0021929000000208.
- [83] J. Friedman. Introduction to human movement analysis. 2010. URL: https://www. curiousjason.com/talks/Introduction\_to\_human\_movement\_analysis\_part\_ 1.pdf (visited on 06/22/2019).
- [84] R. Mahony, T. Hamel, and J. Pflimlin. "Complementary filter design on the special orthogonal group SO(3)." In: *Proceedings of the 44th IEEE Conference on Decision* and Control. 2005, pp. 1477–1484. DOI: 10.1109/CDC.2005.1582367.
- [85] URL: http://www.pandis.me/wp-content/uploads/2014/01/BSP2.jpg (visited on 06/02/2019).
- [86] S. Stieber, R. Dorsch, and C. Haubelt. "Accurate Sample Time Reconstruction of Inertial FIFO Data." In: Sensors 17.12 (2017). ISSN: 1424-8220. DOI: 10.3390/ s17122894.
- [87] S. E. Schmidt, K. Emerek, A. S. Jensen, C. Graff, J. Melgaard, P. Sgaard, K. Srensen, and J. J. Struijk. "Temporal alignment of asynchronously sampled biomedical signals." In: 2016 Computing in Cardiology Conference (CinC). 2016, pp. 1–4. DOI: 10.22489/CinC.2016.014-311.
- [88] H. Zhou and H. Hu. "Upper limb motion estimation from inertial measurements." English. In: *International Journal of Information Technology* 13 (Jan. 2007), pp. 1–14.
- [89] H. Zhou and H. Hu. "Inertial sensors for motion detection of human upper limbs." In: Sensor Review 27 (Apr. 2007). DOI: 10.1108/02602280710731713.
- [90] S. Colton. The Balance Filter A Simple Solution for Integrating Accelerometer and Gyroscope Measurements for a Balancing Platform. 2007.
- [91] G. M. Lerner. "Three Axis Attitude Determination." In: Spacecraft Attitude Determination and Control. Ed. by J. Wertz. Vol. 73. Astrophysics and Space Science Library. Springer Netherlands, 2012. Chap. 12, pp. 420–435. ISBN: 9789400999077.
- [92] Radioulnar Joints. URL: http://www.anatomyqa.com/anatomy/upperlimb/ radioulnar-joints-supination-and-pronation/ (visited on 04/10/2019).
- [93] Supination as a Risk Factor. 2018. URL: http://www.ergopedia.ca/risk\_ factors/Supination\_as\_a\_Risk\_Factor.html (visited on 09/17/2019).
- [94] Vicon Motion Systems. Upper Limb Model. Product Guide. 2007. URL: http://www. vicon.com (visited on 06/13/2019).

[95] F. Chan. *T-Pose for CSP 3D Models v2 Male and Female*. 2019. URL: https://assets. clip-studio.com/en-us/detail?id=1741844 (visited on 06/12/2019).



# INFORMED CONSENT TO PARTICIPANTS, Portuguese Version

The following page includes a copy of the consent form adopted to inform participants of the research. In it, procedures' information, regarding data collection, is reported.



www.fraunhofer.pt Rua Alfredo Allen 455/461 4200-135 Porto, PORTUGAL

#### CONSENTIMENTO PARA PARTICIPAÇÃO EM INVESTIGAÇÃO

A Associação Fraunhofer Portugal Research faz trabalho de investigação destinado a encontrar soluções que promovam o bem-estar da população.

No âmbito de Dissertação de Mestrado em Eng.<sup>a</sup> Biomédica da Faculdade de Ciências e Tecnologias em colaboração com a Associação Fraunhofer Portugal Research, estamos a desenvolver um projeto piloto em linha de montagem para avaliação direta da exposição ao risco ergonómico dos movimentos de operários.

Neste estudo, iremos proceder à recolha de dados sociodemográficos e dados de sensores inerciais que serão utilizadas durante o período de recolha de dados. Serão adicionalmente gravados vídeo, som e imagem com vista à construção de um registo que permitirá ajudar o trabalho de processamento dos dados resultantes da aquisição. Se concordar, ser-lhe-á solicitada a colocação de sensores durante o seu dia de trabalho.

Gostaríamos de contar com a S/ participação. A participação não envolve qualquer prejuízo ou dano material e não haverá lugar a qualquer pagamento. Os dados recolhidos são confidenciais.

A S/ participação é voluntária, podendo em qualquer altura cessá-la sem qualquer tipo de consequência.

Agradecemos muito o S/ contributo, fundamental para a nossa investigação!

#### O participante:

Declaro ter lido e compreendido este documento, bem como as informações verbais fornecidas e aceito participar nesta investigação. Permito a utilização dos dados que forneço de forma voluntária, para os fins descritos. Declaro ainda que autorizo a publicação das imagens nos diversos meios de comunicação social e em publicações científicas e conferências ou outro tipo de evento científico ou de divulgação do projeto.

Nome do participante: \_

Assinatura do participante: \_\_\_\_

Data \_\_\_ / \_\_\_ / \_\_\_\_

Investigador responsável: Sara Santos Nome: Assinatura: \_\_\_\_\_\_ Telefone: 220 430 345

E-mail: sara.santos@fraunhofer.pt

ESTE DOCUMENTO É FEITO EM DUPLICADO: UM PARA O PARTICIPANTE E OUTRO PARA O INVESTIGADOR. 1/

1/1

\_\_Data \_\_\_ / \_\_\_ / \_\_\_



# Participant's questionnaire, Portuguese Version

The following page provides a copy of the questionnaire presented to participants after performing the trial. It aimed to inquire about the subject's impressions on the usability of the devices in an industrial field.

#### APPENDIX B. PARTICIPANT'S QUESTIONNAIRE, PORTUGUESE VERSION

#### Aquisição nº\_\_\_\_

Leia as seguintes afirmações e marque com um X um número segundo o seu grau de concordância.

1. O sistema de sensores é confortável.

Discordo	1	2	3	4	5	Concordo
totalmente	1	2	5	4	5	totalmente

2. Os meus movimentos são influenciados pelo sistema de sensores.

totalmente I 2 3 4 5 totalmente
---------------------------------

3. O sistema de sensores provoca dor.

Discordo	1	r	3	1	5	Concordo
totalmente	1	2	5	+	5	totalmente

4. Senti fatiga após realizar as atividades laborais devido ao sistema de sensores.

5. Senti dificuldades a executar as atividades laborais devido ao sistema de sensores.

totalmente	Discordo totalmente	1	2	3	4	5	Concordo totalmente
------------	------------------------	---	---	---	---	---	------------------------

6. Em algum momento, senti necessidade de ajustar/reposicionar os sensores.

Discordo totalmente 1	2 3	4	5	Concordo totalmente
--------------------------	-----	---	---	------------------------

7. Penso que este sistema pode ser usado no local de trabalho.

Discordo	1	2	3	4	5	Concordo
totalmente	1	2	5		5	totalmente

8. Comentários.



## VALIDATION PROTOCOL, PORTUGUESE VERSION

The following document provides a copy of the developed validation protocol in the scope of this dissertation. It guided the laboratory tests in which a comparison between the proposed inertial system and a reference, provided by the Vicon system, was performed.

#### PROTOCOLO VALIDAÇÃO

**Objetivo:** Realizar a validação de algoritmo de rastreamento angular para o membro superior e tronco em ambiente controlado.

#### Equipamento necessário:

- 3 x IMUs tri-axial;
- 1 x Smartphone com a aplicação Recorder v1.9.0 instalada;
- VICON Setup (marcadores, câmaras,...)
- 1 x Câmera de vídeo

#### Posição e fixação dos sensores:

As unidades inerciais, telemóvel e marcadores devem ser colocados no colaborador nas seguintes posições:

O IMU 1 é colocado na parte posterior da mão. O IMU 2 é colocado no antebraço, na parte posterior do mesmo, na zona do pulso, e apertado com uma mão elástica. O IMU 3 é posicionado na área do cotovelo, na parte posterior do braço e apertado com uma cotoveleira elástica.

Devem ser colocados marcadores seguindo o modelo disponível para o membro superior pela Vicon.

O Smartphone deve ser colocado no peito do utilizador, com o seu eixo local Y orientado para cima.

Considerando o utilizador em posição anatómica: os eixos locais dos IMUs deverão estar alinhados uns com os outros, sabendo que o eixo local Y de cada IMU deve estar orientado para cima.

#### **Orientação dos IMUs/ Smartphone:**







#### PROCEDIMENTO

Antes da aquisição

- 1. Efectuar a calibração dos IMUs
- 2. Colocação dos IMUS conforme descrito em Posição e fixação dos sensores
- 3. Explicar ao voluntário os movimentos a efectuar
- 4. Preparar a gravação de vídeo
- 5. Iniciar a aquisição dos sistemas

#### I- Avaliação Estática

Parte 1 - Avaliação angular entre os segmentos do braço e antebraço

- 1. Posição anatómica (durante 30s)
- 2. Realizar a abdução do ombro ( $\theta = 90^{\circ}$  durante 5s)

3. Realizar flexão/extensão do cotovelo com o braço em abdução (x3 com pausa de 5s entre cada um dos movimentos)

- 4. Posição anatómica (durante 5s)
- 5. Realizar a flexão e extensão do cotovelo (x3 com pausa de 5s entre cada um dos movimentos)
- 6. Posição anatómica (durante 10s)

Parte 2 – Avaliação angular entre os segmentos do antebraço e mão

- 1. Sentar o voluntário numa cadeira com o braço apoiado (durante 30s)
- 2. Realizar o desvio ulnar e o desvio radial (x3)
- 3. Apoiar novamente o braço (5s)
- 4. Realizar a flexão e extensão do punho (3x)
- 5. Apoiar novamente o braço (5s)
- 6. Realizar movimentos de pronação/supinação (x3 com pausa de 5s entre cada um dos movimentos)
- 7. Ficar em posição anatómica (10s)

Parte 3 – Avaliação da inclinação do tronco

- 1. Posição anatómica (durante 30s)
- 2. Realizar a flexão/extensão do tronco (de 5s entre cada um dos movimentos)
- 3. Posição anatómica (durante 5s)
- 4. Realizar a flexão lateral do tronco (esquerda e direita durante 5s)
- 5. Posição anatómica (durante 5s)
- 6. Realizar a rotação do tronco (esquerda e direita durante 5s)
- 7. Posição anatómica (durante 10s)

Parte 4 – Avaliação dos movimentos angulares do braço face ao plano frontal.

- 1. Posição anatómica (durante 30s)
- 2. Realizar a flexão do ombro ( $\theta = 90^{\circ}$  durante 5s)
- 3. Realizar a flexão completa do ombro (90°<  $\theta$  durante 5s)
- 4. Realizar a extensão do ombro ( $\theta = 90^{\circ}$  durante 5s)
- 5. Realizar a extensão completa do ombro ( $\theta = 0^{\circ}$  durante 5s)
- 6. Posição anatómica (durante 5s)
- 7. Inclinar o tronco aproximadamente 45°
- 8. Efetuar os pontos 1-5
- 9. Posição anatómica (durante 5s)
- 10. Rotação do voluntário no sentido dos ponteiros do relógio.
- 11. Efectuar os pontos 1-5
- 12. Posição anatómica (durante 10s)

#### II- Avaliação Dinâmica

Parte 1 – Movimentos em situação de marcha.

1. Posição anatómica (durante 30s)

2. Caminhar entre as marcas (2) assinaladas no chão, realizando flexões/extensão sucessivas do cotovelo. Terminar o exercício na marca inicial do chão.

Parte 2 - Movimentos em situação de marcha com alteração do plano frontal

- 1. Posição anatómica (durante 30s)
- 2. Caminhar entre as marcas assinaladas no chão (3) realizando:
  - 1-2: Marcha normal sem inclinação do tronco; Movimento de flexão/extensão do ombro (<= 90°)
  - 2-3 : Marcha normal com inclinação do tronco; Movimento de flexão/extensão do ombro (<= 90°)



## Sensor fusion algorithms Results

### D.1 Madgwick

Table D.1: Mean absolute error regarding Madgwick method for each anatomical segment including all static sets.

<b>Madgwick MAE</b> $(\mu \pm \sigma)^{\circ}$							
Action/Segment	Torso	Arm	Forearm	Hand			
AnatomicalPos	$7 \pm 5$	$17 \pm 14$	$26 \pm 20$	19 ± 22			
Flexion	$15 \pm 14$	$13 \pm 10$	$38 \pm 33$	$36 \pm 12$			
Extension	6 ± 5	$13 \pm 14$	$26 \pm 30$	$38 \pm 11$			
Lateral Flexion	$4 \pm 5$	-	-	-			
Abduction	-	$27 \pm 21$	-	-			
Adduction	-	$12 \pm 10$	-	-			
Radial Deviation	-	-	-	$12 \pm 6$			
Ulnar Deviation	-	-	-	$15 \pm 11$			

Table D.2: Root mean square error regarding Madgwick method for each anatomical segment including all static sets.

Ma	adgwick	RMSE	(°)	
Action/Segment	Torso	Arm	Forearm	Hand
AnatomicalPos	8	22	33	29
Flexion	21	16	50	38
Extension	8	19	40	39
Lateral Flexion	6	-	-	-
Abduction	-	35	-	-
Adduction	-	16	-	-
Radial Deviation	-	-	-	13
Ulnar Deviation	-	-	-	18

Table D.3: Mean absolute error	regarding Madgwick	method for each	anatomical segmen
including all dynamic sets.			

М	adgwick I	MAE ( $\mu \pm c$	σ)°	
Action/Segment	Torso	Arm	Forearm	Hand
AnatomicalPos	6 ± 5	8 ± 6	$15 \pm 13$	$10 \pm 11$
Flexion	$24 \pm 29$	$15 \pm 11$	-	-
Flexion/Extension	-	$25 \pm 24$	-	-

Table D.4: Root mean square error regarding Madgwick method for each anatomical segment including all dynamic sets.

Madgwick RMSE (°)						
Action/Segment	Torso	Arm	Forearm	Hand		
AnatomicalPos	7	10	20	15		
Flexion	37	19	-	-		
Flexion/Extension	-	34	-	-		

### D.2 Mahony

Table D.5: Mean absolute error regarding Mahony method for each anatomical segment including all static sets.

<b>Mahony MAE</b> $(\mu \pm \sigma)^{\circ}$					
Action/Segment	Torso	Arm	Forearm	Hand	
AnatomicalPos	$7 \pm 4$	$14 \pm 14$	$18 \pm 16$	$19 \pm 21$	
Flexion	$15 \pm 14$	$13 \pm 11$	$36 \pm 30$	$36 \pm 12$	
Extension	$6 \pm 5$	$14 \pm 14$	$25 \pm 32$	$38 \pm 11$	
Lateral Flexion	$4 \pm 5$	-	-	-	
Abduction	-	$20 \pm 17$	-	-	
Adduction	-	$16 \pm 12$	-	-	
Radial Deviation	-	-	-	$12 \pm 6$	
Ulnar Deviation	-	-	-	$15 \pm 11$	

Table D.6: Root mean square error regarding Mahony method for each anatomical segment including all static sets.

Mahony RMSE (°)					
Action/Segment	Torso	Arm	Forearm	Hand	
AnatomicalPos	8	20	25	28	
Flexion	21	18	47	38	
Extension	8	20	40	39	
Lateral Flexion	6	-	-	-	
Abduction	-	26	-	-	
Adduction	-	21	-	-	
Radial Deviation	-	-	-	13	
Ulnar Deviation	-	-	-	18	

<b>Mahony MAE</b> $(\mu \pm \sigma)^{\circ}$						
Action/Segment	Wrist					
AnatomicalPos	$12 \pm 15$	$10 \pm 12$	$17 \pm 19$	$10 \pm 12$		
Flexion	$15 \pm 12$	$15 \pm 11$	-	-		
Flexion/Extension	-	$21 \pm 19$	-	-		

Table D.7: Mean absolute error regarding Mahony method for each anatomical segment including all dynamic sets.

Table D.8: Root mean square error regarding Mahony method for each anatomical segment including all dynamic sets.

Mahony RMSE (°)					
Action/Segment	Torso	Arm	Forearm	Hand	
AnatomicalPos	19	16	25	16	
Flexion	19	19	-	-	
Flexion/Extension	-	28	-	-	

### D.3 AGCF

Table D.9: Mean absolute error regarding AGCF method for each anatomical segment including all static sets.

<b>AGCF MAE</b> $(\mu \pm \sigma)^{\circ}$					
Action/Segment	Torso	Arm	Forearm	Hand	
AnatomicalPos	$44 \pm 8$	$23 \pm 24$	$32 \pm 26$	$13 \pm 13$	
Flexion	$18 \pm 14$	$29 \pm 15$	$78 \pm 40$	$31 \pm 15$	
Extension	$45 \pm 6$	$17 \pm 15$	$36 \pm 34$	$38 \pm 25$	
Lateral Flexion	$25 \pm 11$	-	-	-	
Abduction	-	$21 \pm 16$	-	-	
Adduction	-	$25 \pm 17$	-	-	
Radial Deviation	-	-	-	$21 \pm 28$	
Ulnar Deviation	-	-	-	$20 \pm 30$	

Table D.10: Root mean square error regarding AGCF method for each anatomical segment including all static sets.

AGCF RMSE (°)						
Action/Segment	Torso	Arm	Forearm	Hand		
AnatomicalPos	45	34	42	18		
Flexion	23	33	88	34		
Extension	46	23	49	45		
Lateral Flexion	27	-	-	-		
Abduction	-	26	-	-		
Adduction	-	31	-	-		
Radial Deviation	-	-	-	35		
Ulnar Deviation	-	-	-	36		

<b>AGCF MAE</b> $(\mu \pm \sigma)^{\circ}$					
Action/Segment	Torso	Årm	Forearm	Hand	
AnatomicalPos	$47 \pm 5$	19 ± 22	$34 \pm 30$	$13 \pm 14$	
Flexion	$16 \pm 16$	$17 \pm 9$	-	-	
Flexion/Extension	-	$32 \pm 23$	-	-	

Table D.11: Mean absolute error regarding AGCF method for each anatomical segment including all dynamic sets.

Table D.12: Root mean square error regarding AGCF method for each anatomical segment including all dynamic sets.

AGCF RMSE (°)						
Action/Segment	Torso	Arm	Forearm	Hand		
AnatomicalPos	48	29	45	19		
Flexion	23	19	-	-		
Flexion/Extension	-	39	-	-		



### **RAPID UPPER LIMB ASSESSMENT**

This annex presents the Rapid Upper Limb Assessment worksheet. The RULA ergonomic assessment tool analyses biomechanical and postural demands of job tasks on the neck, trunk and upper limbs.

Designed for easy use, the tool requires no expert in ergonomics. Scores for each body region are entered in proper sections: section A, for the arm and wrist, and section B, for neck and trunk. Afterwards, tables are used to compile the risk factors variables, assembling a single global score which represents the risk level of work-related musculoskeletal disorders.







Task Name

Date: