LNCS 13320

Vincent G. Duffy (Ed.)

Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management

Health, Operations Management, and Design

13th International Conference, DHM 2022
Held as Part of the 24th HCI International Conference, HCII 2022
Virtual Event, June 26 – July 1, 2022
Proceedings, Part II

Part II

HCI 2022 INTERNATIONAL

Springer

Lecture Notes in Computer Science 13320

More information about this series at https://link.springer.com/bookseries/558

Vincent G. Duffy (Ed.)

Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management

Health, Operations Management, and Design

13th International Conference, DHM 2022
Held as Part of the 24th HCI International Conference, HCII 2022
Virtual Event, June 26 – July 1, 2022
Proceedings, Part II

Springer

Editor
Vincent G. Duffy
Purdue University
West Lafayette, IN, USA

ISSN 0302-9743 ISSN 1611-3349 (electronic)
Lecture Notes in Computer Science
ISBN 978-3-031-06017-5 ISBN 978-3-031-06018-2 (eBook)
https://doi.org/10.1007/978-3-031-06018-2

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Foreword

Human-computer interaction (HCI) is acquiring an ever-increasing scientific and industrial importance, as well as having more impact on people's everyday life, as an ever-growing number of human activities are progressively moving from the physical to the digital world. This process, which has been ongoing for some time now, has been dramatically accelerated by the COVID-19 pandemic. The HCI International (HCII) conference series, held yearly, aims to respond to the compelling need to advance the exchange of knowledge and research and development efforts on the human aspects of design and use of computing systems.

The 24th International Conference on Human-Computer Interaction, HCI International 2022 (HCII 2022), was planned to be held at the Gothia Towers Hotel and Swedish Exhibition & Congress Centre, Göteborg, Sweden, during June 26 to July 1, 2022. Due to the COVID-19 pandemic and with everyone's health and safety in mind, HCII 2022 was organized and run as a virtual conference. It incorporated the 21 thematic areas and affiliated conferences listed on the following page.

A total of 5583 individuals from academia, research institutes, industry, and governmental agencies from 88 countries submitted contributions, and 1276 papers and 275 posters were included in the proceedings to appear just before the start of the conference. The contributions thoroughly cover the entire field of human-computer interaction, addressing major advances in knowledge and effective use of computers in a variety of application areas. These papers provide academics, researchers, engineers, scientists, practitioners, and students with state-of-the-art information on the most recent advances in HCI. The volumes constituting the set of proceedings to appear before the start of the conference are listed in the following pages.

The HCI International (HCII) conference also offers the option of 'Late Breaking Work' which applies both for papers and posters, and the corresponding volume(s) of the proceedings will appear after the conference. Full papers will be included in the 'HCII 2022 - Late Breaking Papers' volumes of the proceedings to be published in the Springer LNCS series, while 'Poster Extended Abstracts' will be included as short research papers in the 'HCII 2022 - Late Breaking Posters' volumes to be published in the Springer CCIS series.

I would like to thank the Program Board Chairs and the members of the Program Boards of all thematic areas and affiliated conferences for their contribution and support towards the highest scientific quality and overall success of the HCI International 2022 conference; they have helped in so many ways, including session organization, paper reviewing (single-blind review process, with a minimum of two reviews per submission) and, more generally, acting as goodwill ambassadors for the HCII conference.

This conference would not have been possible without the continuous and unwavering support and advice of Gavriel Salvendy, founder, General Chair Emeritus, and Scientific Advisor. For his outstanding efforts, I would like to express my appreciation to Abbas Moallem, Communications Chair and Editor of HCI International News.

June 2022 Constantine Stephanidis

HCI International 2022 Thematic Areas and Affiliated Conferences

Thematic Areas

- HCI: Human-Computer Interaction
- HIMI: Human Interface and the Management of Information

Affiliated Conferences

- EPCE: 19th International Conference on Engineering Psychology and Cognitive Ergonomics
- AC: 16th International Conference on Augmented Cognition
- UAHCI: 16th International Conference on Universal Access in Human-Computer Interaction
- CCD: 14th International Conference on Cross-Cultural Design
- SCSM: 14th International Conference on Social Computing and Social Media
- VAMR: 14th International Conference on Virtual, Augmented and Mixed Reality
- DHM: 13th International Conference on Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management
- DUXU: 11th International Conference on Design, User Experience and Usability
- C&C: 10th International Conference on Culture and Computing
- DAPI: 10th International Conference on Distributed, Ambient and Pervasive Interactions
- HCIBGO: 9th International Conference on HCI in Business, Government and Organizations
- LCT: 9th International Conference on Learning and Collaboration Technologies
- ITAP: 8th International Conference on Human Aspects of IT for the Aged Population
- AIS: 4th International Conference on Adaptive Instructional Systems
- HCI-CPT: 4th International Conference on HCI for Cybersecurity, Privacy and Trust
- HCI-Games: 4th International Conference on HCI in Games
- MobiTAS: 4th International Conference on HCI in Mobility, Transport and Automotive Systems
- AI-HCI: 3rd International Conference on Artificial Intelligence in HCI
- MOBILE: 3rd International Conference on Design, Operation and Evaluation of Mobile Communications

List of Conference Proceedings Volumes Appearing Before the Conference

1. LNCS 13302, Human-Computer Interaction: Theoretical Approaches and Design Methods (Part I), edited by Masaaki Kurosu
2. LNCS 13303, Human-Computer Interaction: Technological Innovation (Part II), edited by Masaaki Kurosu
3. LNCS 13304, Human-Computer Interaction: User Experience and Behavior (Part III), edited by Masaaki Kurosu
4. LNCS 13305, Human Interface and the Management of Information: Visual and Information Design (Part I), edited by Sakae Yamamoto and Hirohiko Mori
5. LNCS 13306, Human Interface and the Management of Information: Applications in Complex Technological Environments (Part II), edited by Sakae Yamamoto and Hirohiko Mori
6. LNAI 13307, Engineering Psychology and Cognitive Ergonomics, edited by Don Harris and Wen-Chin Li
7. LNCS 13308, Universal Access in Human-Computer Interaction: Novel Design Approaches and Technologies (Part I), edited by Margherita Antona and Constantine Stephanidis
8. LNCS 13309, Universal Access in Human-Computer Interaction: User and Context Diversity (Part II), edited by Margherita Antona and Constantine Stephanidis
9. LNAI 13310, Augmented Cognition, edited by Dylan D. Schmorrow and Cali M. Fidopiastis
10. LNCS 13311, Cross-Cultural Design: Interaction Design Across Cultures (Part I), edited by Pei-Luen Patrick Rau
11. LNCS 13312, Cross-Cultural Design: Applications in Learning, Arts, Cultural Heritage, Creative Industries, and Virtual Reality (Part II), edited by Pei-Luen Patrick Rau
12. LNCS 13313, Cross-Cultural Design: Applications in Business, Communication, Health, Well-being, and Inclusiveness (Part III), edited by Pei-Luen Patrick Rau
13. LNCS 13314, Cross-Cultural Design: Product and Service Design, Mobility and Automotive Design, Cities, Urban Areas, and Intelligent Environments Design (Part IV), edited by Pei-Luen Patrick Rau
14. LNCS 13315, Social Computing and Social Media: Design, User Experience and Impact (Part I), edited by Gabriele Meiselwitz
15. LNCS 13316, Social Computing and Social Media: Applications in Education and Commerce (Part II), edited by Gabriele Meiselwitz
16. LNCS 13317, Virtual, Augmented and Mixed Reality: Design and Development (Part I), edited by Jessie Y. C. Chen and Gino Fragomeni
17. LNCS 13318, Virtual, Augmented and Mixed Reality: Applications in Education, Aviation and Industry (Part II), edited by Jessie Y. C. Chen and Gino Fragomeni

18. LNCS 13319, Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management: Anthropometry, Human Behavior, and Communication (Part I), edited by Vincent G. Duffy
19. LNCS 13320, Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management: Health, Operations Management, and Design (Part II), edited by Vincent G. Duffy
20. LNCS 13321, Design, User Experience, and Usability: UX Research, Design, and Assessment (Part I), edited by Marcelo M. Soares, Elizabeth Rosenzweig and Aaron Marcus
21. LNCS 13322, Design, User Experience, and Usability: Design for Emotion, Well-being and Health, Learning, and Culture (Part II), edited by Marcelo M. Soares, Elizabeth Rosenzweig and Aaron Marcus
22. LNCS 13323, Design, User Experience, and Usability: Design Thinking and Practice in Contemporary and Emerging Technologies (Part III), edited by Marcelo M. Soares, Elizabeth Rosenzweig and Aaron Marcus
23. LNCS 13324, Culture and Computing, edited by Matthias Rauterberg
24. LNCS 13325, Distributed, Ambient and Pervasive Interactions: Smart Environments, Ecosystems, and Cities (Part I), edited by Norbert A. Streitz and Shin'ichi Konomi
25. LNCS 13326, Distributed, Ambient and Pervasive Interactions: Smart Living, Learning, Well-being and Health, Art and Creativity (Part II), edited by Norbert A. Streitz and Shin'ichi Konomi
26. LNCS 13327, HCI in Business, Government and Organizations, edited by Fiona Fui-Hoon Nah and Keng Siau
27. LNCS 13328, Learning and Collaboration Technologies: Designing the Learner and Teacher Experience (Part I), edited by Panayiotis Zaphiris and Andri Ioannou
28. LNCS 13329, Learning and Collaboration Technologies: Novel Technological Environments (Part II), edited by Panayiotis Zaphiris and Andri Ioannou
29. LNCS 13330, Human Aspects of IT for the Aged Population: Design, Interaction and Technology Acceptance (Part I), edited by Qin Gao and Jia Zhou
30. LNCS 13331, Human Aspects of IT for the Aged Population: Technology in Everyday Living (Part II), edited by Qin Gao and Jia Zhou
31. LNCS 13332, Adaptive Instructional Systems, edited by Robert A. Sottilare and Jessica Schwarz
32. LNCS 13333, HCI for Cybersecurity, Privacy and Trust, edited by Abbas Moallem
33. LNCS 13334, HCI in Games, edited by Xiaowen Fang
34. LNCS 13335, HCI in Mobility, Transport and Automotive Systems, edited by Heidi Krömker
35. LNAI 13336, Artificial Intelligence in HCI, edited by Helmut Degen and Stavroula Ntoa
36. LNCS 13337, Design, Operation and Evaluation of Mobile Communications, edited by Gavriel Salvendy and June Wei
37. CCIS 1580, HCI International 2022 Posters - Part I, edited by Constantine Stephanidis, Margherita Antona and Stavroula Ntoa
38. CCIS 1581, HCI International 2022 Posters - Part II, edited by Constantine Stephanidis, Margherita Antona and Stavroula Ntoa

39. CCIS 1582, HCI International 2022 Posters - Part III, edited by Constantine Stephanidis, Margherita Antona and Stavroula Ntoa
40. CCIS 1583, HCI International 2022 Posters - Part IV, edited by Constantine Stephanidis, Margherita Antona and Stavroula Ntoa

http://2022.hci.international/proceedings

Preface

Software representations of humans, including aspects of anthropometry, biometrics, motion capture and prediction, as well as cognition modelling, are known as Digital Human Models (DHM), and are widely used in a variety of complex application domains where it is important to foresee and simulate human behavior, performance, safety, health and comfort. Automation depicting human emotion, social interaction and functional capabilities can also be modeled to support and assist in predicting human response in real world settings. Such domains include medical and nursing applications, education and learning, ergonomics and design, as well as safety and risk management.

The 13th Digital Human Modeling & Applications in Health, Safety, Ergonomics & Risk Management (DHM) Conference, an affiliated conference of the HCI International Conference 2022, encouraged papers from academics, researchers, industry and professionals, on a broad range of theoretical and applied issues related to Digital Human Modelling and its applications.

The research papers contributed to this year's volume spans across different fields that fall within the scope of the DHM Conference. In the context of anthropometry, human behavior, and communication, the physical aspects emphasized build on human modeling lessons of the past, whereas attentional aspects are providing evidence for new theories and applications. The study of DHM issues in various application domains has yielded works emphasizing task analysis, quality and safety in healthcare, as well occupational health and operations management. Digital human modeling in interactive product and service design is also discussed in this year's contributions. There are applications of interest shown across many industries, while multi-disciplinary and systems-related challenges remain for validation and generalizability in future work. Sensors-based modeling, information visualization, collaborative robots, and intelligent interactions are among the human-technology modeling and results reporting efforts this year.

Two volumes of the HCII 2022 proceedings are dedicated to this year's edition of the DHM Conference, entitled Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management: Anthropometry, Human Behavior, and Communication (Part I), and Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management: Health, Operations Management, and Design (Part II). The first volume focuses on topics related to ergonomic design, anthropometry, and human modeling, as well as collaboration, communication, and human behavior. The second volume focuses on topics related to task analysis, quality and safety in health-care, as well as occupational health and operations management, and Digital Human Modeling in interactive product and service design.

Papers of these volumes are included for publication after a minimum of two single–blind reviews from the members of the DHM Program Board or, in some cases, from members of the Program Boards of other affiliated conferences. I would like to thank all of them for their invaluable contribution, support and efforts.

June 2022 Vincent G. Duffy

13th International Conference on Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management (DHM 2022)

The full list with the Program Board Chairs and the members of the Program Boards of all thematic areas and affiliated conferences is available online at

http://www.hci.international/board-members-2022.php

HCI International 2023

The 25th International Conference on Human-Computer Interaction, HCI International 2023, will be held jointly with the affiliated conferences at the AC Bella Sky Hotel and Bella Center, Copenhagen, Denmark, 23–28 July 2023. It will cover a broad spectrum of themes related to human-computer interaction, including theoretical issues, methods, tools, processes, and case studies in HCI design, as well as novel interaction techniques, interfaces, and applications. The proceedings will be published by Springer. More information will be available on the conference website: http://2023.hci.international/.

General Chair
Constantine Stephanidis
University of Crete and ICS-FORTH
Heraklion, Crete, Greece
Email: general_chair@hcii2023.org

http://2023.hci.international/

Contents – Part II

Contents – Part I

Occupational Health and Operations Management

Automatic Classification of Working Activities for Risk Assessment in Large-Scale Retail Distribution by Using Wearable Sensors: A Preliminary Analysis

Giuseppe Andreoni[1], Giorgio Cassiolas[2], Carlo Emilio Standoli[1], Stefano Elio Lenzi[3], Paolo Perego[1], and Nicola Francesco Lopomo[2(✉)]

[1] Dipartimento di Design, Politecnico di Milano, Milan, Italy
[2] Dipartimento di Ingegneria dell´Informazione, Università degli Studi di Brescia, Brescia, Italy
nicola.lopomo@unibs.it
[3] Dipartimento di Neuroscienze, Biomedicina e Movimento, Università di Verona, Verona, Italy

Abstract. Providing reliable information on human activities and behaviors is an extremely important goal in various application areas such as healthcare, entertainment, and security. Within the working environment, a correct identification of the actual performed tasks can provide an effective support in the assessment of the risk associated to the execution of the task itself, and thus preventing the development of work-related musculoskeletal diseases. In this perspective, wearable-based Human Activity Recognition systems have been representing a prominent application. This study aimed to compare three different classification approaches appointed from supervised learning techniques, namely k-Nearest Neighbors, Support Vector Machine and Decision Tree. Motion data, related to several working activities realized in the large-scale retail distribution, were collected by using a full-body system based on 17 Inertial Measurement Units (MVN Analyze, XSens). Reliable features in both time- and frequency-domain were first extracted from raw 3D accelerations and angular rates data, and further processed by Principal Component Analysis, with 95% threshold. The classification models were validated via 10-fold cross-validation on a defined training dataset. k-Nearest Neighbors classifier, which provide the best results on the training session, was eventually tested for generalization on additional data acquired on few specific tasks. As a result, considering 5 main macro activities, k-Nearest Neighbors provided a classification accuracy of 80.1% and a computational time of 1865.5 s. To test the whole assessment process, the activities labelled by the classification model as handling of low loads at high frequency were automatically evaluated for risk exposure via OCRA Checklist method.

Keywords: Human activity classification · Wearable technology · Machine learning · Risk assessment · Work-related diseases · Large-scale retail distribution

V. G. Duffy (Ed.): HCII 2022, LNCS 13320, pp. 151–164, 2022.
https://doi.org/10.1007/978-3-031-06018-2_10

1 Introduction

During the last decade, the astounding development that microelectronics has been having in terms of computational power, performance, size, and costs, has been allowing more and more people to easily and seamlessly interact with "smart" devices and systems that can be even worn and used during their daily life activities [1, 2]. In parallel, the large amount of data deriving from the use of these technologies has led to the new rebirth of artificial intelligence through the implementation of machine learning and deep learning algorithms, applied - for example - to the recognition of the activities carried out during the day [3–5].

The Human Activity Recognition (HAR) mainly started with the analysis of video sequences, and complex image analysis algorithms have been the focus of extensive research for many years due to their great range of possible applications, even including the identification of hand gestures for the development of "natural" user interfaces [6]. Indeed, the shift towards wearable-based HAR solutions is considered a key requirement in many daily life applications, including health and wellness, and presents a fundamental impact in many scientific fields such as biomechanics, ergonomics, remote monitoring, safety, sports science, etc. [5, 7].Therefore, to ensure the expected outcomes for these fields of interest, it is necessary to design and implement accurate and reliable solutions able to correctly capture human motion, track the body movement and recognize each specific task.

The most paradigmatic examples of wearable sensors used in HAR applications are accelerometers, gyroscopes, and magnetometers, usually integrated in inertial measurement units (IMUs) or magneto-inertial measurement units (M-IMUs). Scientific literature reports different solutions which include the use of different kind of sensors usually in an integrated fashion and textiles; therefore, not only the movements are acquired but also physiological parameters (e.g., heart rate), global position and environmental conditions (e.g., temperature and relative humidity) result to be detected and analyzed, providing additional information that can be used even for ontological reasoning [8–10].). IMUs have been representing the gold standard solution embedded in several wearable technologies, including smartphones, and smartwatches or smartbands, and widely exploited for the recognition of several daily activities, such as standing, walking, sitting, running, cycling, lying, etc. [11, 12] IMUs have been adopted also for proper human motion analysis applications [13, 14], where several sensors are usually fixed on different landmarks of the human body and – thanks to specific calibration phases – joint angles are available for defined further assessments.

However, this approach (and the related tools) is apparently not generally applicable to unstructured daily life to observe long-term and multi-task activities, due to the limiting setup, which could somehow annoy the subject, or because wearing such devices can alter the comfort of the person and the naturalness of performing any gesture. On the other hand, this approach can be used in the recognition of human activities in well-defined contexts, such as the clinics, sports, and industry [10]. Focusing on industrial context, the use of wearable technologies and dedicated analytical algorithms have been demonstrated to be able to provide information for the risk assessment addressing the activities performed by the employees, in a perspective of risk mitigation and prevention of the development of work-related diseases [15, 16]. In this picture, wearable technologies can be used to quantitatively support the standard assessment of the risk, usually performed via technical standards [17–19]; a quantitative measurement of the performed task in terms of posture, duration, joint angles, velocities, and frequencies may provide even real-time indications on the exposure to a specific risk [16, 22] and preventing work-related diseases.

In addition to sensors, it is fundamental to focus on both the type and the quality of the data acquired and, above all, the algorithms and models that can be used for the recognition of the specific activities. From the data perspective, an activity recognition system can be broadly defined as a structured "organizer" that can be used to classify individual tasks with respect to similar characteristics. Also in wearable-based HAR, recognition can be performed by exploiting machine learning classification paradigms and many approaches are present in scientific literature covering several types of applications and input data [7, 10]; in general, two main methodologies based on machine learning techniques have been exploited for these applications: supervised and unsupervised approaches [23]. Supervised learning models included, for instance, k-Nearest Neighbors (kNN), Support Vector Machine (SVM) and Decision Tree; on the other hand, unsupervised learning models covered the use of Gaussian Mixture Models (GMM) and Hidden Markov Models (HMM). Focusing on these solutions, in general the features extracted from the raw data (i.e., transformations of accelerations and/or angular rates in time, frequency or time-frequency domains) are used as input for the classification algorithms; in case of HAR, the patterns of input data are associated with the activities under consideration (i.e., classes).

Due to the aforementioned reasons, we hypothesized that by exploiting the use of wearable IMUs is possible to recognize the activities realized by an employee during a specific working shift, and thus support the assessment of the risk exposure by means of quantitative information. The main aim of the current work was therefore to compare different classification models able to automatically identify the working activities specifically realized in the large-scale retail distribution, by exploiting motion data acquired by means of a full-body IMU-based system, and then provide useful information to automatically support the definition of the OCRA (Occupational Repetitive Action) Checklist method, used for specific risk assessment [20].

2 Materials and Methods

2.1 Subjects

Addressing the necessity to identify the working activities performed by the employees involved in large-scale retail distribution, we performed a preliminary ethnographic analysis keeping into account the anthropometric distribution (5°, 50° and 95° height percentile) and the sex (males and females) of the workers, and the active wards [21]. To cover all the possible working tasks, we specifically chose to have at least 6 people for each ward (3 height percentile for each sex) and to identify any possible shared activity among the different departments, to optimize the acquisition protocol. Several activities could not be inherently monitored due to the presence of stab-gloves or aprons reinforced in stainless steel, or water which could have led to critical issues for the sensors. Furthermore, for the aim of this preliminary analysis, we specifically selected the activities by considering the characteristics defined in the technical standard ISO 11228.

2.2 On-Field Acquisition Setup

The acquisition of the movements realized by the involved employees was performed by using a commercial full body motion capture system exploiting magneto-inertial measuring units (MVN Analyze, XSens). The system allowed to have both the raw data acquired by each single unit in terms of 3D accelerations, 3D angular rates and 3D inclinations, and – through proper modelling and calibration phase–all the 3D joint angles. Data were transmitted wirelessly between each motion tracker and the base station with a sampling frequency of 60 Hz.

The full-body protocol was based on the use of 17 wireless motion trackers fixed to the body by means of elastic Velcro band and customized clothes. Following the protocol defined by the manufacturer, the sensors were specifically placed on feet, lower legs (i.e., shanks), upper legs (i.e., thighs), pelvis (i.e., sacrum), shoulders (i.e., scapulae), sternum, head, upper arms, forearms, and hands.

Before acquiring the working task, an anatomical measurements of the users and a two-step calibration phase (static N-pose and dynamic level walking) were realized to determine sensor-to-body alignment and size of each body segment, according to the monitoring system's functioning. After the calibration, an accurate biomechanical model of the subject was available for motion tracking. An example of the on-field acquisition and provided real-time feedback is reported in Fig. 1.

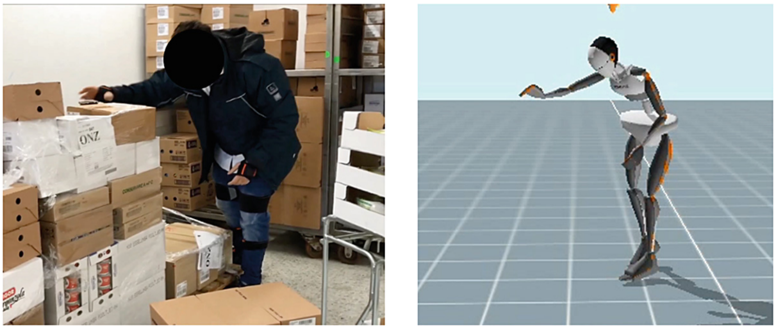

Fig. 1. Example of on-field acquisition and the corresponding biomechanical model, within the user interface (MVN studio, Xsens).

The used tracking system was able to estimate position, velocity, acceleration, orientation, angular velocity and angular acceleration of each body segment implemented in the biomechanical model. By means of custom-made functions developed in a high-level development environment (Matlab 2020, Mathworks Inc.), we were then able to import all the acquired information for the following processing and analysis steps. For the defined classification approach, we specifically used only the information related to the 3D acceleration and 3D angular rate expressed in the sensor frames, whereas for the risk assessment we used joint angles estimated through the calibrated biomechanical model.

2.3 Classification

Pre-processing and Windowing. To proceed with the working task classification, the data obtained from the acquisition system were manually segmented and labelled with the identifier of the corresponding task. Segmentation was manually realized by using the same acquisition software to mark each start and stop times through visual analysis, and then to export raw data, which therefore included a specific label associated to each defined task.

As previously reported, for the classification phase, we specifically considered only 3D accelerations and 3D angular rates acquired by each sensor for a total of 102 time series (17 sensors $\times$ 3 dimensions $\times$ 2 types of data). No conditioning approach was used to filter the time-domain information.

In order to support the correct extraction of the features to use in the classification phase, we implemented a 2s fixed-length sliding Hamming window with 25% of overlapping, so as to keep into account the overall dynamics of the tasks we acquired and the eventual transitions among the different activities [23, 24].

Features. To optimize classification performance and minimize computational time and complexity, several features were defined starting from what was reported in literature [25]. A total of 17 features were considered, as reported in Table 1.

Since the extracted features could have different offsets and scale factors, we normalized them by subtracting the mean value and scaling with respect to the variance, both calculated on the whole dataset [25].

After the features selection, to reduce the dimensionality of the problem, without losing discriminative capability, we applied the principal component analysis (PCA) approach, considering a threshold level corresponding to the 95% of the variance.

Classification Models. Starting from the analysis of literature [23], and considering the available type of data and the dimensionality of our problem, we implemented three main supervised classification models, namely a weighted k-Nearest Neighbors (kNN) with an Euclidean distance metric and k = 18, a Support Vector Machine (SVM) with an automatically scaled quadratic kernel function with a box constrain level of 1 and a Decision Tree (DT) with a maximum number of split of 20 based on Gini's diversity index. These models were preliminary tested considering several types of implementations (e.g., different SVM kernels) and hyperparameters (e.g., number of k neighbors), by exploiting a dedicated toolbox (ClassificationLearner, Mathworks Inc.).

Accuracy Assessment. The accuracy of the classification models was assessed by using a training dataset via 10-fold cross-validation approach. The possibility to generalize the models was then tested by using a test dataset based on working tasks performed by the same subjects but not included in the training dataset.

Table 1. List of the extracted features in both time- and frequency domain.

ID	Feature	Domain	Definition
1	Mean Value	Time	$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$
2	Maximum Value	Time	$max = max(x)$
3	Minimum Value	Time	$min = min(x)$
4	Range	Time	$\Delta(x) = max - min$
5	Number of zero crossing	Time	$nzc = \sum_{i=1}^{N}[sgn(x_i \cdot x_{i+1})]$ $sgn(x) = \begin{cases} 1 & x \geq 0 \\ 0 & otherwise \end{cases}$
6	Standard Deviation	Time	$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N-1}}$
7	Variance	Time	$\sigma^2 = \frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N-1}$
8	Mean Absolute Deviation	Time	$mad = median(\lvert x_i - median(x)\rvert)$
9	First Quartile	Time	Splitting off the lowest 25% of data from the highest 75%
10	Third Quartile	Time	Splitting off the highest 25% of data from the lowest 75%
11	Skewness	Time	$skew = E\left[\left(\frac{x-\mu}{\sigma}\right)^3\right]$
12	Kurtosis	Time	$kurt = E\left[\left(\frac{x-\mu}{\sigma}\right)^4\right]$
13	Spectral Energy	Frequency	$E = \sum_{i=1}^{M} Y_i^2$
14	Median Frequency	Frequency	$\sum_{i=1}^{mdf} Y_i = \frac{1}{2}\sum_{i=1}^{M} Y_i$
15	Mean Frequency	Frequency	$f_c = \frac{\sum_{i=1}^{M} f_i Y_i}{\sum_{i=1}^{M} Y_i}$
16	Peak Magnitude	Frequency	$P_m = max(Y_i)$
17	Peak Frequency	Frequency	$P_f = freq_{\lvert Pm}$

2.4 Automatic Risks Assessment

As highlighted in the Introduction, the analysis of postures and movement assumed by workers is critical to correctly define the level of risk to develop any kind of disorders, associated to their specific working activities. This study focused on the OCRA Checklist method, a simplify version of the more complex OCRA approach, as defined by the ISO 11228 technical standard [17–19]. To correctly understand this method, it is important to underline that the percentage of time is considered cumulatively for the movements realized by a specific joint; further, a time span is defined as "the time in which the worker maintain an incorrect posture (whenever the corresponding angle overcomes one of the thresholds, as reported in Table 2)". The percentage of time corresponding to the maintaining of an awkward posture is computed as $t_{\%} = t_{error}/t_{tot}$, where t_{error} is the effective time span and t_{tot} is the length of the assessment period [16].

As previously reported, thanks to the biomechanical model, we were able to extract the joint angles throughout all the temporal segments [22] here identified by using the optimal classification model.

Table 2. Angular displacement thresholds as defined by the OCRA checklist method.

Joint	Movement	Thresholds
Shoulder	Flexion/extension	$>80°$
	Pronation/supination (as dynamic movement)	$>60°$
Elbow	Flexion/extension (as dynamic movement)	$>60°$
Wrist	Palmar flexion/Dorsal extension	$>45°$
	Ulnar deviation	$>20°$
	Radial deviation	$>15°$

3 Results and Discussion

3.1 Population and Tasks

From the ethnographic analysis, six wards were identified for the realization of this study, specifically: fruits and vegetables, grocery, delicatessen, butchery, bakery, and dairy products' wards. The on-field acquisitions were performed by using the full-body protocol during 27 working days, involving almost 10 different stores [21] - characterized by different size and number of employees which affect work activities and performances. Fifty-two subjects participated voluntarily and were then enrolled in the general study. In this preliminary analysis, without losing generality, we focused our assessment on specific sessions realized by the only subjects employed in the grocery ward.

Concerning the common activities (and therefore the corresponding labelled classes) we initially identified 5 main tasks: 1) handling of high loads (label "HIGH"), 2) handling of low loads at high frequency (label "LOW"), 3) walking (label "WALK"), 4) using a cart (label "CART") and 5) standing (label "STAND"). To highlight the capability of the classification models the low loads activities were then split into more specific tasks. Further, during the analysis, we grouped tasks 3), 4) and 5) under a general macro activity label, as to balance the dataset, and to focus better on the manual handling problem.

3.2 Classification Models

The comparison between the three identified classification models (i.e., DT, SVM and kNN) highlighted that the best performance in terms of accuracy and computational time was provided by the kNN model. The results of this comparison are reported in Table 3.

Table 3. Comparison among Decision Tree (DT), Support Vector Machine (SVM) and kNN.

Classifier	Accuracy [%]	Computational time [s]
Decision Tree	76.1	254.1
Quadratic SVM	76.7	48612.0
Weighted kNN	80.1	1865.5

From the previous table is evident that SVM model required very long computational time for training (in some declination, even > 50′000 s); despite the overall classification performances – that were very similar to those achieved by the DT and however lower with respect to kNN -, we considered both these models not suitable for this specific application. kNN represents one of the most well-known and used nonparametric classification models in machine learning and data mining tasks. Despite its simplicity, kNN demonstrated to be one of the most effective algorithms in pattern recognition and it has been considered one of the top 10 methods in data mining [26]. As previously underlined, the type of kNN (i.e., weighted) and the value of k (= 18) were defined according to literature and preliminary assessment [27].

3.3 Overall Classification Accuracy

We started the analysis of classification performances by considering each individual task and the corresponding classes; in particular - besides high loads handling, low loads handling at high frequency, walking, using a cart and standing - we introduced further detailed labels about: unboxing, loading, packaging, labelling, replenishment, arrangement of products, displacement of boxes, arrangement of boxes and other activities. The confusion matrix related to the classification of all these tasks is reported in Fig. 2.

Considering all the 14 tasks, the overall performance of the identified classifier interm of accuracy was quite low (44.3%) with a computational time of 1530.4 s. This low performance was mainly due to the great unbalance of the dataset used in this first analysis, i.e., several activities contained many samples (e.g., replenishment) whereas others presented a reduced number of samples (e.g., displacement of the boxes); indeed, the number of samples for training and assessing different activity was not evenly distributed. This problem was mainly related to the distribution of the tasks along the daily shift and a general approach on the manual labelling process; to enhance the detailed classification of all the task a proper and well-defined labelling phase is required.

As next step in the analysis, we used to group to obtain the overall 5 main labels, namely "HIGH", "LOW", "WALK", "CART", "STAND", corresponding to handling of high loads, handling of low loads at high frequency, walking, using a cart, and staying

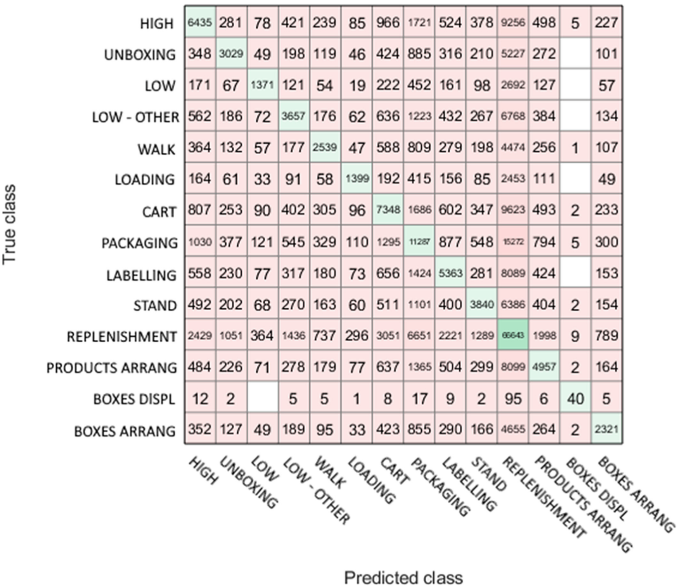

Fig. 2. Confusion matrix related to kNN classification by using 14 classes.

still, respectively. Clearly this choice allowed to correctly identify more activities, leading to an overall accuracy of 80.1% and a computational time of 1865.5s. The corresponding confusion matrix is reported in Fig. 3.

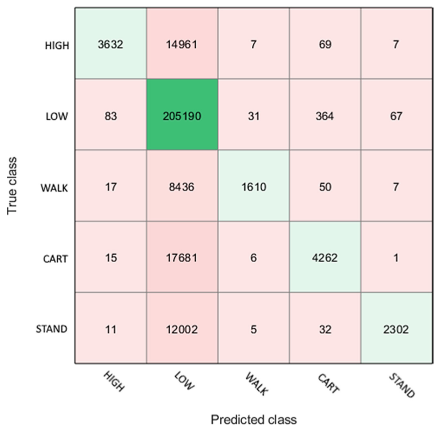

Fig. 3. Confusion matrix related to kNN classification by using three classes.

With this specific labelling, the mean Area under the Curve (AUC) value for the corresponding Receiver Operating Characteristic (ROC) was 0.73, that means that there was 73% chance that model will be able to distinguish between positive class and negative classes.

To focus on the only manual handling tasks, we tried to improve the classification performance groping the main tasks into 3 high level macro activities, namely “HIGH”, “LOW” and “OTHER”, which represented handling of high loads, handling of low loads at high frequency and any other activities, respectively. With only three classes the overall accuracy reached 81% with a computational time of 4068.7s. The corresponding confusion matrix is reported in Fig. 4.

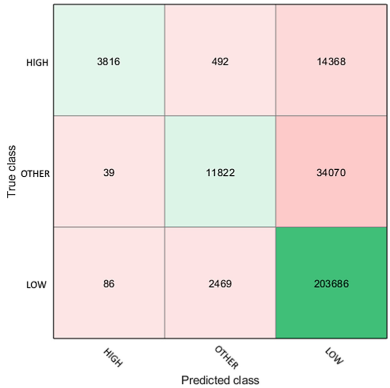

Fig. 4. Confusion matrix related to kNN classification by using three classes.

To generalize the performances obtained with the training dataset, the model was tested by using specific data extracted from four different sections recorded in different days. In particular, the identified working were: cash activity, hooks replenishment/supply, high shelves replenishment/supply and low shelves replenishment/supply. The accuracy obtained by using the kNN classification was 63.92% computed by averaging the results presented in Table 4.

Table 4. Performance obtained by using weighted kNN on the test dataset.

Task	Time duration [s]	Accuracy [%]
Cash activity	562 s	78.3
Hooks replenishment/supply	97	33.3
High shelves replenishment/supply	886	63
Low shelves replenishment/supply	671	57

Even in this real case, the performance of the classification model was limited by the presence of a reduced samples corresponding to the hooks’ replenishment/supply, whereas the best performance was achieved when considering the activities performed by the cashiers.

3.4 Risk Assessment

Once classified the tasks in the correct way, it was possible to implement an automatic assessment of the risk associated to each specific activity and for the different percentile. Without losing generality, we reported here the possibility to implement the OCRA Checklist method, as previously described. The considered sequences were extracted from the testing dataset and in the table Table 5 are reported the % of time, when the joint angle is beyond the thresholds as defined in Table 2.

Table 5. Percentage of time in which the worker is in an awkward posture, as defined by OCRA checklist method.

Subject	Joint	Time [%]
S001	Left elbow	22.72
	Right elbow	22.72
	Left ehoulder	6.36
	Right ehoulder	0.00
	Left wrist	8.03
	Right wrist	53.42
S006	Left elbow	6.28
	Right elbow	12.12
	Left shoulder	1.14
	Right shoulder	0.00
	Left wrist	39.38
	Right wrist	33.28
S007	Left elbow	4.20
	Right elbow	4.96
	Left shoulder	0.00
	Right shoulder	0.61
	Left wrist	5.30
	Right wrist	12.84

4 Conclusions

In this preliminary study, the obtained performances, in terms of accuracy, seem to be lower with respect to the results reported in several related studies [9, 24, 28] However, comparing algorithms performance across different studies present in scientific literature is a quite difficult task for several reasons, including the differences in the experimental protocols, the application behind the HAR problem, the type of sensors used and their location on the body, the metrics used for the performance assessment and model validation, and the overall number of the activities to classify.

The here obtained reduced performance was basically due to the unbalance of available information within the dataset. As evident in the previous paragraphs, the activities labelled as "LOW" were the 90% of all the available dataset and among these activities there was high variability. By using the chosen classification model, the available dataset was not well dimensioned and balanced, since the disparity in terms of dimensions of classes did not allow the classifier to learn in a good way how to recognize the classes with the "smallest" size, and this was also affected by possible overtraining issues, that reflected on the lower performances obtained when the testing dataset was used.

A possible future implementation could be obtained by following an iterative application of the proposed method [28]. After the separation into main classes, the same approach could be applied to each single class to reduce the unbalance that could limit the accuracy. Therefore, the class "LOW" could be split into several subclasses, where the distribution is maintained more or less the same. To correctly perform this approach, it is necessary to acquire and segment/label precisely each single activity, in a way to create classes with well-balanced dimensionality. A further potential solution could be realized by using unsupervised learning methods, which could lead to the use of "deep learning" approaches, where there is no need of manual labelling of the dataset, and the algorithms are able to learn the inherent structure of the dataset from the input data. However, as main drawback of these approaches is the need of a huge amount of quality data.

Acknowledgement. Prof. Lopomo and all the authors would like to thank Simone Bertè for the efforts he realized in the preliminary analysis of the data, which defined the basis for this work.

References

1. John Dian, F., Vahidnia, R., Rahmati, A.: Wearables and the Internet of Things (IoT), applications, opportunities, and challenges: a survey. IEEE Access **2020**(8), 69200–69211 (2020). https://doi.org/10.1109/ACCESS.2020.2986329
2. Kumari, P., Mathew, L., Syal, P.: Increasing trend of wearables and multimodal interface for human activity monitoring: a review. Biosens. Bioelectron. **90**, 298–307 (2017). https://doi.org/10.1016/j.bios.2016.12.001
3. Rast, F.M., Labruyère, R.: Systematic review on the application of wearable inertial sensors to quantify everyday life motor activity in people with mobility impairments. J. NeuroEng. Rehabil. **17**(1), 1–19 (2020). https://doi.org/10.1186/s12984-020-00779-y
4. Baig, M.M., Afifi, S., Gholam Hosseini, H., Mirza, F.: A systematic review of wearable sensors and IoT-based monitoring applications for older adults–a focus on ageing population and independent living. J. Med. Syst. **43**(8), 1–11 (2019). https://doi.org/10.1007/s10916-019-1365-7
5. Wang, Y., Cang, S., Yu, H.: A survey on wearable sensor modality centred human activity recognition in health care. Expert Syst. Appl. **137**, 167–190 (2019). https://doi.org/10.1016/j.eswa.2019.04.057
6. Raval, R.M., Prajapati, H.B., Dabhi, V.K.: Survey and analysis of human activity recognition in surveillance videos. Intell. Decision Technol. **13**(2), 271–294 (2019). https://doi.org/10.3233/IDT-170035

7. Meng, Z., Zhang, M., Guo, C., Fan, Q., Zhang, H., Gao, N., et al.: Recent progress in sensing and computing techniques for human activity recognition and motion analysis. Electronics **9**, 1357 (2020). https://doi.org/10.3390/electronics9091357
8. Hassan, M.M., Uddin, M.Z., Mohamed, A., Almogren, A.: A robust human activity recognition system using smartphone sensors and deep learning. Futur. Gener. Comput. Syst. **81**, 307–313 (2017). https://doi.org/10.1016/j.future.2017.11.029
9. Yurtman, A., Barshan, B.: Activity recognition invariant to sensor orientation with wearable motion sensors. Sensors **17**, 1838 (2017). https://doi.org/10.3390/s17081838
10. Lara, O.D., Labrador, M.A.: A survey on human activity recognition using wearable sensors. IEEE Sens. J. **15**, 1192–1209 (2013). https://doi.org/10.1109/SURV.2012.110112.00192
11. Demrozi, F., Pravadelli, G., Bihorac, A., Rashidi, P.: Human activity recognition using inertial, physiological and environmental sensors: a comprehensive survey. IEEE Sens. J. **8**, 210816–210836 (2020). https://doi.org/10.1109/ACCESS.2020.3037715
12. Yuan, G., Wang, Z., Meng, F., Yan, Q., Xia, S.: An overview of human activity recognition based on smartphone. IEEE Sens. J. **39**, 288–306 (2019). https://doi.org/10.1108/SR-11-2017-0245
13. Lopez-Nava, I.H., Munoz-Melendez, A.: Wearable inertial sensors for human motion analysis: a review. IEEE Sens. J. **16**, 7821–7834 (2016). https://doi.org/10.1109/JSEN.2016.2609392
14. Sztyle, T., Stuckenschmidt, H., Petrich, W.: Position-aware activity recognition with wearable devices. Pervasive Mob. Comput. **38**, 281–295 (2017). https://doi.org/10.1016/j.pmcj.2017.01.008
15. Ranavolo, A., Draicchio, F., Varrecchia, T., Silvetti, A., Iavicoli, S.: Wearable monitoring devices for biomechanical risk assessment at work: current status and future challenges—a systematic review. Int. J. Environ. Res. Public Health **15**, 2001 (2018). https://doi.org/10.3390/ijerph15092001
16. Lenzi, S.E., Standoli, C.E., Andreoni, G., Perego, P., Lopomo, N.F.: Comparison among standard method, dedicated toolbox and kinematic-based approach in assessing risk of developing upper limb musculoskeletal disorders. In: Ahram, T.Z. (ed.) Advances in Human Factors in Wearable Technologies and Game Design. Advances in Intelligent Systems and Computing, vol. 795, pp. 135–145. Springer, Cham (2019). https://doi.org/10.1007/978-3-319-94619-1_13
17. ISO. 11228–1:2021. Ergonomics—Manual handling—Part 1: Lifting, lowering and carrying. International Organization for Standardization. Geneva, Switzerland (2021)
18. ISO. 11228–2:2007. Ergonomics—Manual handling—Part 2: Pushing and pulling. International Organization for Standardization. Geneva, Switzerland (2007)
19. ISO. 11228–3:2007. Ergonomics—Manual handling—Part 3: Handling of low loads at high frequency. International Organization for Standardization. Geneva, Switzerland (2007)
20. Colombini, D., Occhipinti, E.: The OCRA method (OCRA index and checklist). updates with special focus on multitask analysis. In: Karkwoski, W., Salvendy, G. (eds.) Conference Proceedings. AHFE 2008 Las Vegas, July 2008. ISBN 978–1- 60643–712–4 (2008)
21. Standoli, C.E., Lenzi, S.E., Lopomo, N.F., Perego, P., Andreoni, G.: The evaluation of existing large-scale retailers' furniture using DHM. In: Proceedings of the Congress of the International Ergonomics Association, Florence, Italy, August 2018. Springer, Cham (2018). eBook ISBN 978-3-319-96080-7, https://doi.org/10.1007/978-3-319-96080-7
22. Lenzi, S.E., Standoli, C.E., Andreoni, G., Perego, P., Lopomo, N.F.: A software toolbox to improve time-efficiency and reliability of an observational risk assessment method. In: Bagnara, S., Tartaglia, R., Albolino, S., Alexander, T., Fujita, Y. (eds.) Proceedings of the 20th Congress of the International Ergonomics Association (IEA 2018). Advances in Intelligent Systems and Computing, vol. 820, pp. 689–708. Springer, Cham (2019). https://doi.org/10.1007/978-3-319-96083-8_86

23. Attal, F., Mohammed, S., Dedabrishvili, M., Chamroukhi, F., Oukhellou, L., Amirat, Y.: Physical human activity recognition using wearable sensors. IEEE Sens. J. **15**, 31314–31338 (2015). https://doi.org/10.3390/s151229858https://doi.org/10.3390/s151229858
24. Zhang, M., Sawchuk, A.: A feature selection-based framework for human activity recognition using wearable multimodal sensors. In: Proceedings of the 6th International ICST Conference Body Area Networks (2011). https://doi.org/10.4108/icst.bodynets.2011.247018
25. Sarcevic, P., Pletl, S., Kincses, Z.: Comparison of time-and frequency-domain features for movement classification using data from wrist-worn sensors. In: 2 EEE 15th International Symposium on Intelligent Systems and Informatics (SISY) (2017). https://doi.org/10.1109/SISY.2017.8080564
26. Wu, X., Kumar, V., Ross Quinlan, J., Ghosh, J., Yang, Q., Motoda, H., et al.: Top 10 algorithms in data mining. Knowl. Inf. Syst. **14**, 1–37 (2008). https://doi.org/10.1007/s10115-007-0114-2
27. Garcia, S., Derrac, J., Cano, J.R., Herrera, F.: Prototype selection for nearest neighbor classification: taxonomy and empirical study. IEEE Trans. Pattern Anal. Mach. Intell. **34**(3), 417–435 (2012). https://doi.org/10.1109/TPAMI.2011.142
28. Garcia-Ceja, E., Brena, R.F.: An improved three-stage classifier for activity recognition. Int. J. Pattern Recognit. Artif. Intell. **32**(01), 1860003 (2018). https://doi.org/10.1142/S0218001418600030

Author Index