

Ana I. Pereira · Florbela P. Fernandes ·
João P. Coelho · João P. Teixeira ·
Maria F. Pacheco · Paulo Alves ·
Rui P. Lopes (Eds.)

Communications in Computer and Information Science

1488

Optimization, Learning Algorithms and Applications

First International Conference, OL2A 2021
Bragança, Portugal, July 19–21, 2021
Revised Selected Papers

 Springer



Ana I. Pereira · Florbela P. Fernandes ·
João P. Coelho · João P. Teixeira ·
Maria F. Pacheco · Paulo Alves ·
Rui P. Lopes (Eds.)

Optimization, Learning Algorithms and Applications

First International Conference, OL2A 2021
Bragança, Portugal, July 19–21, 2021
Revised Selected Papers



Springer

Editors

Ana I. Pereira 
Instituto Politécnico de Bragança
Bragança, Portugal

João P. Coelho 
Instituto Politécnico de Bragança
Bragança, Portugal

Maria F. Pacheco 
Instituto Politécnico de Bragança
Bragança, Portugal

Rui P. Lopes 
Instituto Politécnico de Bragança
Bragança, Portugal

Florbela P. Fernandes 
Instituto Politécnico de Bragança
Bragança, Portugal

João P. Teixeira 
Instituto Politécnico de Bragança
Bragança, Portugal

Paulo Alves 
Instituto Politécnico de Bragança
Bragança, Portugal

ISSN 1865-0929 ISSN 1865-0937 (electronic)
Communications in Computer and Information Science
ISBN 978-3-030-91884-2 ISBN 978-3-030-91885-9 (eBook)
<https://doi.org/10.1007/978-3-030-91885-9>

© Springer Nature Switzerland AG 2021

This work is subject to copyright. All rights are reserved by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.

The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.

The publisher, the authors and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, expressed or implied, with respect to the material contained herein or for any errors or omissions that may have been made. The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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

Preface

The volume CCIS 1488 contains the refereed proceedings of the International Conference on Optimization, Learning Algorithms and Applications (OL2A 2021), an event that, due to the COVID-19 pandemic, was held online.

OL2A 2021 provided a space for the research community on optimization and learning to get together and share the latest developments, trends, and techniques as well as develop new paths and collaborations. OL2A 2021 had more than 400 participants in an online environment throughout the three days of the conference (July 19–21, 2021), discussing topics associated to areas such as optimization and learning and state-of-the-art applications related to multi-objective optimization, optimization for machine learning, robotics, health informatics, data analysis, optimization and learning under uncertainty, and the Fourth Industrial Revolution.

Four special sessions were organized under the following topics: Trends in Engineering Education, Optimization in Control Systems Design, Data Visualization and Virtual Reality, and Measurements with the Internet of Things. The event had 52 accepted papers, among which 39 were full papers. All papers were carefully reviewed and selected from 134 submissions. All the reviews were carefully carried out by a Scientific Committee of 61 PhD researchers from 18 countries.

July 2021

Ana I. Pereira

Organization

General Chair

Ana Isabel Pereira

Polytechnic Institute of Bragança, Portugal

Organizing Committee Chairs

Florbela P. Fernandes

Polytechnic Institute of Bragança, Portugal

João Paulo Coelho

Polytechnic Institute of Bragança, Portugal

João Paulo Teixeira

Polytechnic Institute of Bragança, Portugal

M. Fátima Pacheco

Polytechnic Institute of Bragança, Portugal

Paulo Alves

Polytechnic Institute of Bragança, Portugal

Rui Pedro Lopes

Polytechnic Institute of Bragança, Portugal

Scientific Committee

Ana Maria A. C. Rocha

University of Minho, Portugal

Ana Paula Teixeira

University of Trás-os-Montes and Alto Douro, Portugal

André Pinz Borges

Federal University of Technology – Paraná, Brazil

Andrej Košir

University of Ljubljana, Slovenia

Arnaldo Cândido Júnior

Federal University of Technology – Paraná, Brazil

Bruno Bispo

Federal University of Santa Catarina, Brazil

Carmen Galé

University of Zaragoza, Spain

B. Rajesh Kanna

Vellore Institute of Technology, India

C. Sweetlin Hemalatha

Vellore Institute of Technology, India

Damir Vrančić

Jozef Stefan Institute, Slovenia

Daiva Petkeviciute

Kaunas University of Technology, Lithuania

Diamantino Silva Freitas

University of Porto, Portugal

Esteban Clua

Federal Fluminense University, Brazil

Eric Rogers

University of Southampton, UK

Felipe Nascimento Martins

Hanze University of Applied Sciences,
The Netherlands

Gaukhar Muratova

Dulaty University, Kazakhstan

Gediminas Daukšys

Kauno Technikos Kolegija, Lithuania

Glaucia Maria Bressan

Federal University of Technology – Paraná, Brazil

Humberto Rocha

University of Coimbra, Portugal

José Boaventura-Cunha

University of Trás-os-Montes and Alto Douro, Portugal

José Lima

Polytechnic Institute of Bragança, Portugal

Joseane Pontes

Federal University of Technology – Ponta Grossa,
Brazil

Juani Lopéz Redondo

University of Almeria, Spain

Jorge Ribeiro	Polytechnic Institute of Viana do Castelo, Portugal
José Ramos	NOVA University Lisbon, Portugal
Kristina Sutiene	Kaunas University of Technology, Lithuania
Lidia Sánchez	University of León, Spain
Lino Costa	University of Minho, Portugal
Luís Coelho	Polytechnic Institute of Porto, Portugal
Luca Spalazzi	Marche Polytechnic University, Italy
Manuel Castejón Limas	University of León, Spain
Marc Jungers	Université de Lorraine, France
Maria do Rosário de Pinho	University of Porto, Portugal
Marco Aurélio Wehrmeister	Federal University of Technology – Paraná, Brazil
Mikulas Huba	Slovak University of Technology in Bratislava, Slovakia
Michał Podpora	Opole University of Technology, Poland
Miguel Ángel Prada	University of León, Spain
Nicolae Cleju	Technical University of Iasi, Romania
Paulo Lopes dos Santos	University of Porto, Portugal
Paulo Moura Oliveira	University of Trás-os-Montes and Alto Douro, Portugal
Pavel Pakshin	Nizhny Novgorod State Technical University, Russia
Pedro Luiz de Paula Filho	Federal University of Technology – Paraná, Brazil
Pedro Miguel Rodrigues	Catholic University of Portugal, Portugal
Pedro Moraes	Polytechnic Institute of Cávado e Ave, Portugal
Pedro Pinto	Polytechnic Institute of Viana do Castelo, Portugal
Rudolf Rabenstein	Friedrich-Alexander-University of Erlangen-Nürnberg, Germany
Sani Rutz da Silva	Federal University of Technology – Paraná, Brazil
Sara Paiva	Polytechnic Institute of Viana do Castelo, Portugal
Sofia Rodrigues	Polytechnic Institute of Viana do Castelo, Portugal
Sławomir Stępień	Poznan University of Technology, Poland
Teresa Paula Perdicoulis	University of Trás-os-Montes and Alto Douro, Portugal
Toma Roncevic	University of Split, Croatia
Vitor Duarte dos Santos	NOVA University Lisbon, Portugal
Wojciech Paszke	University of Zielona Gora, Poland
Wojciech Giernacki	Poznan University of Technology, Poland

Approaches to Classify Knee Osteoarthritis Using Biomechanical Data	417
<i>Tiago Franco, P. R. Henriques, P. Alves, and M. J. Varanda Pereira</i>	
Artificial Intelligence Architecture Based on Planar LiDAR Scan Data to Detect Energy Pylon Structures in a UAV Autonomous Detailed Inspection Process	430
<i>Matheus F. Ferraz, Luciano B. Júnior, Aroldo S. K. Komori, Lucas C. Rech, Guilherme H. T. Schneider, Guido S. Berger, Álvaro R. Cantieri, José Lima, and Marco A. Wehrmeister</i>	
Data Visualization and Virtual Reality	
Machine Vision to Empower an Intelligent Personal Assistant for Assembly Tasks	447
<i>Matheus Talacio, Gustavo Funchal, Victória Melo, Luis Piardi, Marcos Vallim, and Paulo Leitao</i>	
Smart River Platform - River Quality Monitoring and Environmental Awareness	463
<i>Kenedy P. Cabanga, Edmilson V. Soares, Lucas C. Viveiros, Estefânia Gonçalves, Ivone Fachada, José Lima, and Ana I. Pereira</i>	
Health Informatics	
Analysis of the Middle and Long Latency ERP Components in Schizophrenia	477
<i>Miguel Rocha e Costa, Felipe Teixeira, and João Paulo Teixeira</i>	
Feature Selection Optimization for Breast Cancer Diagnosis	492
<i>Ana Rita Antunes, Marina A. Matos, Lino A. Costa, Ana Maria A. C. Rocha, and Ana Cristina Braga</i>	
Cluster Analysis for Breast Cancer Patterns Identification	507
<i>Beatriz Flávia Azevedo, Filipe Alves, Ana Maria A. C. Rocha, and Ana I. Pereira</i>	
Overview of Robotic Based System for Rehabilitation and Healthcare	515
<i>Arezki A. Chellal, José Lima, Florbela P. Fernandes, José Gonçalves, Maria F. Pacheco, and Fernando C. Monteiro</i>	
Understanding Health Care Access in Higher Education Students	531
<i>Filipe J. A. Vaz, Clara B. Vaz, and Luís C. D. Cadinha</i>	



Machine Vision to Empower an Intelligent Personal Assistant for Assembly Tasks

Matheus Talacio^{1,2}, Gustavo Funchal^{1(✉)}, Victória Melo¹, Luis Piardi^{1,2},
Marcos Vallim², and Paulo Leitao¹

¹ Research Center in Digitalization and Intelligent Robotics (CeDRI),
Instituto Politécnico de Bragança, Campus de Santa Apolónia,
5300-253 Bragança, Portugal

{gustavofunchal,victoria,piardi,pleitao}@ipb.pt

² Universidade Tecnológica Federal do Paraná (UTFPR),
Avenida 7 de Setembro 3165, Curitiba 80230-901, Paraná, Brazil
matheustalacio@alunos.utfpr.edu.br, mvallim@utfpr.edu.br

Abstract. In the context of the fourth industrial revolution, the integration of human operators in emergent cyber-physical systems assumes a crucial relevance. In this context, humans and machines can not be considered in an isolated manner but instead regarded as a collaborative and symbiotic team. Methodologies based on the use of intelligent assistants that guide human operators during the execution of their operations, taking advantage of user friendly interfaces, artificial intelligence (AI) and virtual reality (VR) technologies, become an interesting approach to industrial systems. This is particularly helpful in the execution of customised and/or complex assembly and maintenance operations. This paper presents the development of an intelligent personal assistant that empowers operators to perform faster and more cost-effectively their assembly operations. The developed approach considers ICT technologies, and particularly machine vision and image processing, to guide operators during the execution of their tasks, and particularly to verify the correctness of performed operations, contributing to increase productivity and efficiency, mainly in the assembly of complex products.

1 Introduction

The 4th industrial revolution is pushing the adoption of emergent technologies, e.g., Internet of Things (IoT), Artificial Intelligence (AI), Big data, collaborative robots and Virtual Reality (VR), aiming to transform the way factories operate to increase their responsiveness and reconfigurability. In particular, Industry 4.0 enables the increasing level of automation and digitization in the factories of the future [5], with Cyber-Physical Systems (CPS) acting as a backbone to develop such emergent production systems and contributing to develop smart processes, machines and products. CPS aims to connect the various physical components, e.g., sensors and actuators, with cyber systems composed by controllers and communication networks to achieve a common goal [9].

In this emergent CPS environment, humans have a very important role since they are the most flexible elements in automated systems, being required their symbiotic integration. In particular, instead of performing repetitive and monotonous tasks that can be fully automated, humans will be requested to perform add-value tasks, e.g., assembly of complex and/or customized products or performing maintenance interventions.

In this context, intelligent assistants and virtual interfaces can be used to assist humans to realize their manual operations in a faster and more cost-effective manner, taking advantage of the huge amount of data available at the shop floor, as well as the emergent ICT technologies, e.g., AI and VR [3]. These intelligent assistants can support the online monitoring of the equipment condition during the execution of the assembly and maintenance operations, and combine this information with diagnostic reports and their previous experience in analogous situations, to determine the best action plans to be carried out. In such systems, besides the intelligence behind the guidance system, it is important to consider automatic systems that dynamically verifies the correctness of performed operations, warning the need to correct the operation and only allowing to proceed in case the operation is complete and successfully performed.

Such automatic verification usually involves the use of machine vision techniques, which in industry context presents several constraints, namely related to environmental illumination and shadowing, time response and the irregular geometries of the pieces to be checked. These systems can be empowered with the use of AI techniques and should be integrated with the other functionalities of the intelligent assistants.

Having this in mind, this paper describes the development of a machine vision solution, as part of an intelligent personal assistant (IPA), that supports human operators to perform faster and more cost-effectively their assembly operations. In particular, the IPA application uses ICT technologies and image processing techniques to guide operators to assembly correctly customized and complex products, checking the correctness of the performed operations. The activities carried out by the operator are supervised through an intelligent system that will verify the assertiveness of the assembly to ensure that the operation cycle will only end when the system detects that the assembly is correct, even for the scenarios considering 3D assemblies, in which the final product is assembled step by step, and each step is understood as a complete activity. Since the algorithm is executed in real-time, a check to verify if an operator is modifying the assembly is included. The developed solution allows to increase the productivity of operators through the direct integration with emerging technologies, and strongly contributes for the human integration with highly automated applications.

The rest of the paper is organized as follows. Section 2 contextualizes the related work on developing intelligent assistants, as well as the use of machine vision to verify the correctness of assembly operations. Section 3 presents the IPA system architecture for the case study and Sect. 4 describes the development of the machine vision system to verify the correctness of assembly operations for the two scenarios considered in the case study. Section 5 discusses the achieved

experimental results, and particularly the user experience. Finally, Sect. 6 rounds up the paper with the conclusions and points out the future work.

2 Related Work

Industry 4.0 relies on the use of CPS complemented with emergent digital technologies to achieve more intelligent, adaptive and reconfigurable production systems. Also important is the integration of the human operators into the production processes for enhanced product value, achieving manufacturing flexibility in complex human-machine systems, where humans and machines can not be considered in an isolated manner but instead regarded as a collaborative team [8]. This requires the presence of operators on the design of human-centred adaptive manufacturing systems, allowing a symbiotic integration.

However, the execution of some operations, e.g., assembly and maintenance, is normally complex and requires high-level expertise from the operators to execute them efficiently in short time, with the required quality and with the minimal impact on the normal production cycles. This requires to enable the human-machine collaboration, through the use of innovative technologies, e.g., machine vision, machine learning and VR, that will support the operators during the realization of their tasks.

In this context, IPA is a guidance software system that can support the execution of operations, facilitating the interaction between the operators and machines or computers, based on data mining from images, video, and voice commands captured from sensors distributed in the environment [6,14]. The use of IPA, as an intelligent assistant to inform the operator with real-time and historical data and guide through the best action plan to perform the operation [7], can improve the quality of executed operations, particularly in case of complex and/or customised ones. As an example, maintenance technicians can use an IPA system to obtain useful real-time information about the machine condition, recommendations and actions to be taken, as well as useful information, e.g., documents, websites or videos [4]. These systems can provide real-time information and instructions, replacing traditional methods that rely on printed manuals and real machines that can be damaged [13].

The more common commercial versions of IPA are, e.g., Amazon Alexa, Microsoft Cortana, Google Assistant or Apple Siri. In industrial environments, IPA are, e.g., being used to training as a means of learning through the first-person experience [1,10], to train operators in new machine maintenance procedures [16] and to support operators in performing complex and customised assembly tasks and maintenance operations [15].

The use of IPA can include mechanisms to automatically verify the correctness of the performed operations, namely assembly operations. In this context, artificial vision, also known as machine vision, plays an important role in the supervision of assembly operations since it allows the acquisition and analysis of image data, which would not be possible only by inference of context in software. In industrial environments, the verification of 3D product assemblies

is not possible by using simple 2D images, which requires to consider alternative cameras that allows to measure the distance of points in the field of view, providing a 3D image of the scene. Several technologies can be considered to accomplish this objective, e.g., TOF (Time of Flight), used by Microsoft Kinect 2.0 and Microsoft Azure Kinect, and stereo vision, used by Intel Realsense and Stereolabs ZED. The acquired images are analysed by using image processing techniques to recognize shapes and objects, e.g., contour matching, morphological operations and feature detection. In case of recognition of complex shapes, these techniques can be combined with machine learning algorithms.

The referred commercial intelligent assistants solutions usually provide speech recognition functionalities but miss the image recognition, which is crucial in industrial environments. Additionally, the use of such intelligent assistants in industrial environments is still rare, with the majority running as laboratory prototypes, mainly due to the industrial constraints and complexity, e.g., lighting, objects geometry and object overlay.

Several aspects can influence the use and confidence of the IPA technology, e.g., usability, security and privacy [2]. At the practical level, there are some challenges to be faced regarding the adoption of IPA supporting technologies in industrial environments. These solutions need to be matured to avoid creating entropy within the maintenance process and operators need to be adequately trained to operate the system in a proper manner. The IPA's human-interaction barrier models need to be improved, and AI systems need to prove reliability. Another aspect is related to the ergonomic evolution of the head mounted devices, which need to be more comfortable for operators to use during the entire shift or even complete the maintenance intervention [12].

3 System Architecture for the Intelligent Personal Assistant

This section presents the setup of the assembly workbench and the system architecture of the IPA that will be mentoring operators to the execute assembly operations based on LEGO pieces from different shapes and colours.

3.1 Description of the Case Study

In this work, an IPA is used to support operators to perform their customised and/or complex assembly operations in a more efficient manner. For this purpose, the IPA is combined with a workbench structure, illustrated in Fig. 1, providing an intuitive and guidance information to the user regarding the task to be performed, as well as the capability to verify the correctness of the operation execution. As example, the IPA informs the operator about the action plan to perform the operation, namely which step to be executed, how to execute the step, and which piece or tool should be used in this step.

The physical structure comprises several devices that support the human-machine interface. In terms of data collection, the workbench has an Intel



Fig. 1. IPA workbench layout to support the human-machine interface.

Realsense camera responsible for capturing the image over the working space, which will be processed by a machine vision algorithm to detect whether the instructions given are correctly performed. This system is also able to acquire the depth of the scene, thus enabling the verification of assemblies in a three-dimensional space. A microphone is available to support the human-machine interface by collecting the voice instructions provided by the operator during the execution of the assembly procedure, e.g., the feedback related to the conclusion of an operation step. Since the industrial environment can be noisy, the platform can in alternative provide the feedback by using the touch screen interface.

In terms of output devices, the workbench comprises a monitor and a projector that are responsible for providing information to the operator, e.g., instructions to operator and feedback from operator. The image of the projector is displayed over the working space. A LED tape is used to easily indicate to the operator which piece placed in the several dispensers should be used in a certain process step.

The IPA should consider the execution of two case study scenarios. In the first case study scenario, the operator must assemble gift boxes according to the orders received by clients, with each gift box product comprising four slots where individual components (with different colour and shape) should be correctly placed. In the second scenario, the system is used to support the assembly of more complex three-dimensional products, but unlike the first, the instructions are passed on incremental steps and the system checks if the current step has been completed to allow to proceed to the next assembly step.

3.2 System Architecture

The IPA system architecture, illustrated in Fig. 2, comprises several modules, interconnected via standard protocols, namely using REST services.

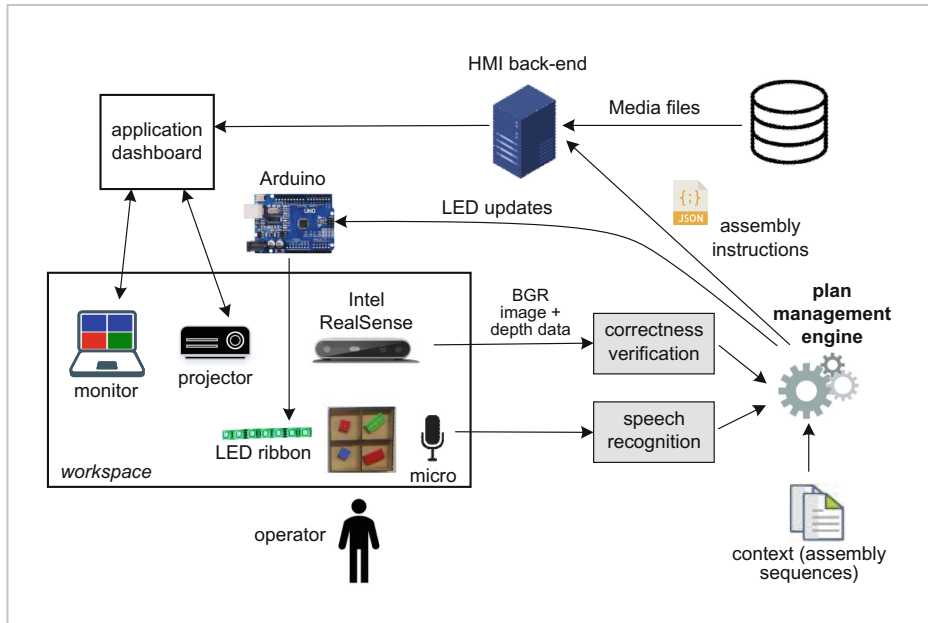


Fig. 2. System architecture for the IPA system.

The process plan management module is responsible to manage the execution of the process plan, expressed as a JSON file, related to the assembly operation. This process considers the assembly plan procedure, the feedback from the environment, i.e. from the camera that allows to check the correctness of the assembly step, and the feedback from the operator, e.g., using the voice commands to ask more information to execute the instruction.

The interaction with the operator is performed by the dashboard application, where the step by step guidance instructions to be executed by the operator are displayed through a monitor and a projector, complemented with supporting documents and videos. Following the order to assemble a customised product, the requested configuration is displayed to the operator through the human-interface at the beginning of the cycle. The intelligent assistant is continuously checking the assembly correctness and only finalizes the operation cycle when a perfect match is achieved. The intelligent assistant system also indicates to the operator which slots/pieces are correctly assembled and which are not.

An important functionality provided by the IPA is to verify the correctness of the operation performed by the operator through the use of machine vision techniques; in case of an assembly operation performed incorrectly, the intelligent system will indicate the error and the assembly procedure can only proceed after a correct assembly.

The correctness verification module is responsible to verify the correctness of the step execution by using machine vision algorithms. For this purpose, the module is continuously receiving the image acquired by the Intel Realsense camera and uses a machine vision algorithm to determine the important characteristics of the image, being able to conclude if the operation was performed correctly (see more details in the next section).

The results of the analysis of the correctness of the operation execution is provided to the plan management engine by using a REST service. In order to optimize the system performance and avoid the overload on the connection with the server, this module only sends the detection status when there is any change (comparing the last REST payload sent with the new generated one). Also, the depth map of the scene is always checked, so it is possible to detect if the operator is still busy performing the assembly and the recognition is paused until it is concluded.

Finally, the LED strips are controlled by an C/C++ application running in an Arduino Uno microcontroller that receives the information of which led area should be turned on through an UDP socket. Note that during the execution of assembly tasks, the LED strip will indicate the container where the operator should pick the pieces to execute the current step.

The proposed system aims to contribute to develop an intelligent context-awareness system, which helps human operators to perform faster and more cost-effectively their assembly operations. In addition, it is expected that this solution can contribute to increase the operator's productivity through the integration of emerging technologies, adding value to human operations that must compete with highly automated industries.

4 Image Processing to Verify Assembly Correctness

Image processing techniques are used to verify the correctness of the assembly operation performed by the operator in real time by comparing the image acquired by the Intel RealSense camera with the execution instruction previously provided by the IPA. For this purpose, an algorithm for image recognition was firstly implemented, which will later be used to verify the correctness of the assembly operation in two different scenarios, namely the gift-box and the complex assembly. The image processing algorithms were codified in Python, ensuring fast run-time, easy development and camera compatibility, and support the use of image manipulation libraries.

4.1 Image Recognition and Classification Algorithm

The first step in the correctness verification process is related to the image recognition, which uses the OpenCV library to implement image processing, e.g., filtering, morphology, contour detection and colour space conversion, on real-time applications. The developed image recognition algorithm, illustrated in Fig. 3, identifies the different objects in the image, in terms of shape, colour and position.

Briefly, the algorithm changes the colour space of images from Red-Green-Blue (RGB) to Hue-Saturation-Value (HSV), since the last presents better performance in machine vision algorithms and it is more adequate for the detection of the colour. In fact, this colour space allows to represent the colors easily for the filter since they are closer to the perception of colours in relation to the

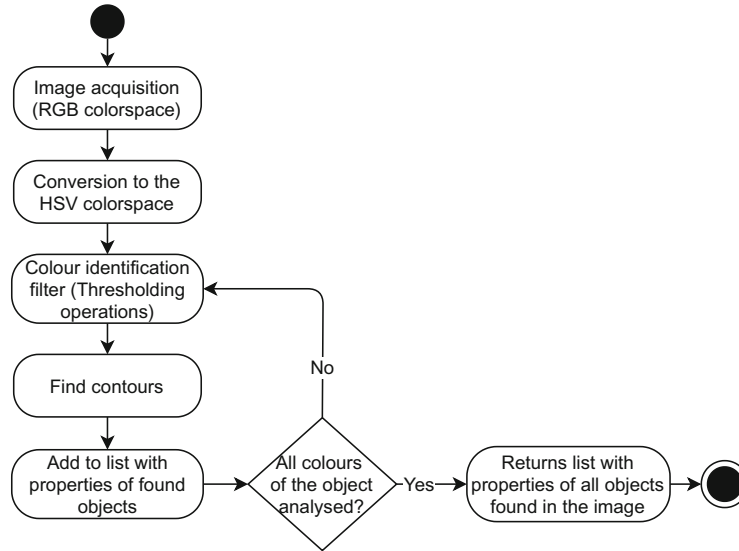


Fig. 3. Algorithm for the image recognition.

human eyes [11]. Considering the image after the colour space conversion, the use of the OpenCV library, and particularly the *inRange* function, allows applying a threshold filter to isolate the pixels from the image by defining a range in the colour space. As result, a binary image is obtained, with the pixels that are within the defined range for each colour assuming the white colour and the pixels that are not within the range assuming the black colour. This process is performed for all the available colours of objects to be identified and the range is defined for each colour. From the binary image it is possible to find the contour of the different objects by using the *findContours* method, which extracts information about the area, center of mass and vertex position of the object.

This image recognition algorithm is performed for both case study scenarios. However, the algorithm to verify the assembly correctness is dependent of the scenario and will be described in the following sections.

4.2 Verification Algorithm for the Gift-Box Assembly

In this scenario, the application generates a configuration for the gift-box according to the received orders, i.e. which pieces (defined in terms of shape and colour) should be placed in each one of the four box slots. The operator receives the information related to this configuration, through the projector and monitor, and performs the assembly operation by placing the pieces in the target slots of the gift-box. The requirements to confirm the correct assembly include the verification if only one piece is placed in each slot and if the piece has the colour as requested in the configuration instructions. The algorithm to verify the correctness for the gift-box assembly is illustrated in Fig. 4.

The image recognition algorithm described in the previous section is used to list the objects present at the scene. Then, for the gift-box assembly verification algorithm, the *pointPolygonTest* function from the OpenCV library, is used to

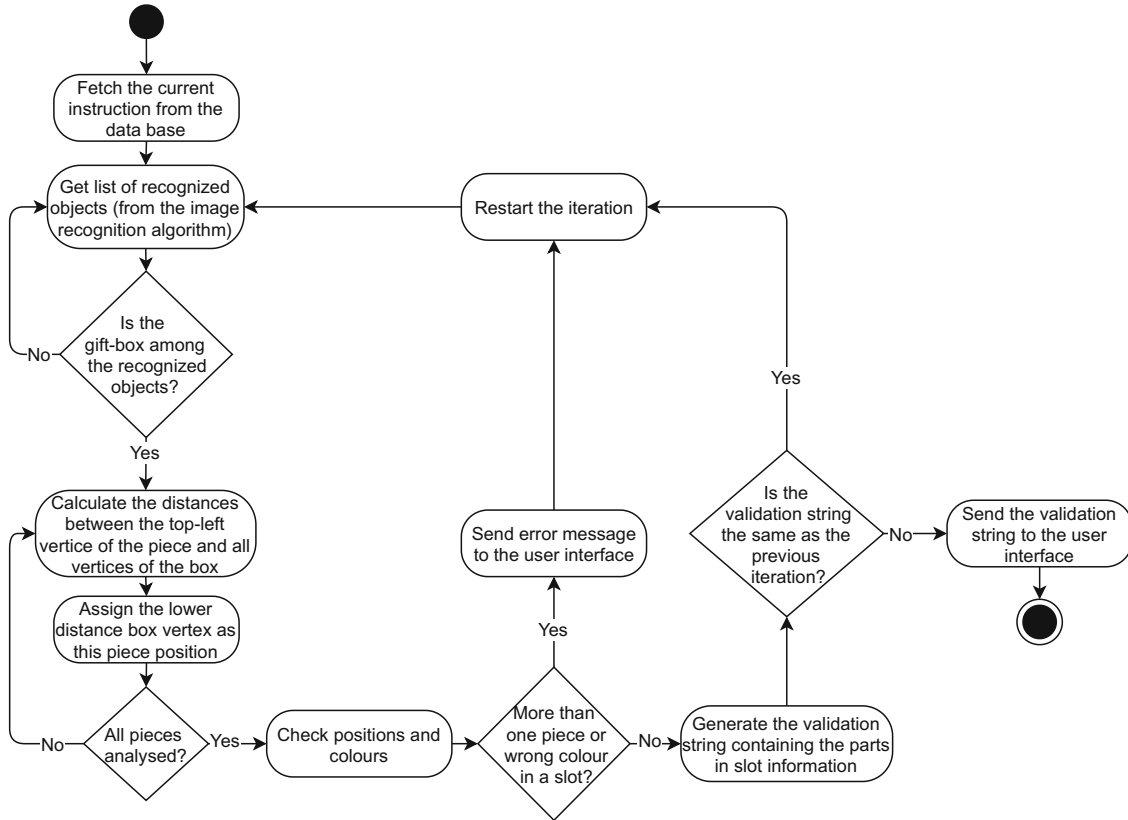


Fig. 4. Verification algorithm for the gift-box assembly.

select only the pieces that are inside the box. The algorithm identifies the contour of the box, and then, knowing its position, it is possible to measure the Euclidean distance between the other pieces and each corner of the box. Due to the geometry of the box, the piece that is placed in a slot will always be at a smaller distance from its respective corner, e.g., the piece that is in the upper right slot always has a smaller distance from its upper right corner compared to the others. This allows to assign the proper slot positions of the pieces by comparing with the received instruction. If two pieces are detected in the same position or if the colour of the piece in one of the slots does not match with the colour presented in the instruction, an alert error is generated. In this way, it is possible to have freedom during the assembly operation as the positions are all relative to the current gift-box position.

After validating the correctness of the performed assembly, the information is sent to the dashboard application that will show the results, and in case of incorrectness, indicates which slots of the gift-box are wrongly assembled.

4.3 Verification Algorithm for the Complex Assembly

In this scenario, the dashboard application guides the operator during the assembly of a complex product by showing the image of the complete assembly and the visual instructions (i.e. action, image and video) for the current assembly

step. After concluding the verification of correctness, the system indicates if the assembly step was completed or not with success.

Since the operation involves a three-dimensional assembly, besides the recognition of the colour and shape of the pieces, it is also required to get information about the height, which is possible by using the IR Stereo sensor of the Real Sense camera. To mitigate inaccuracies caused by the camera's mounting angle and uneven surface, the application initially saves the scene depth as a height map, so during the detection routine, the captured depth is subtracted with the map to obtain the height of the pieces relative to the working table. The verification algorithm for the complex assembly is illustrated in Fig. 5.

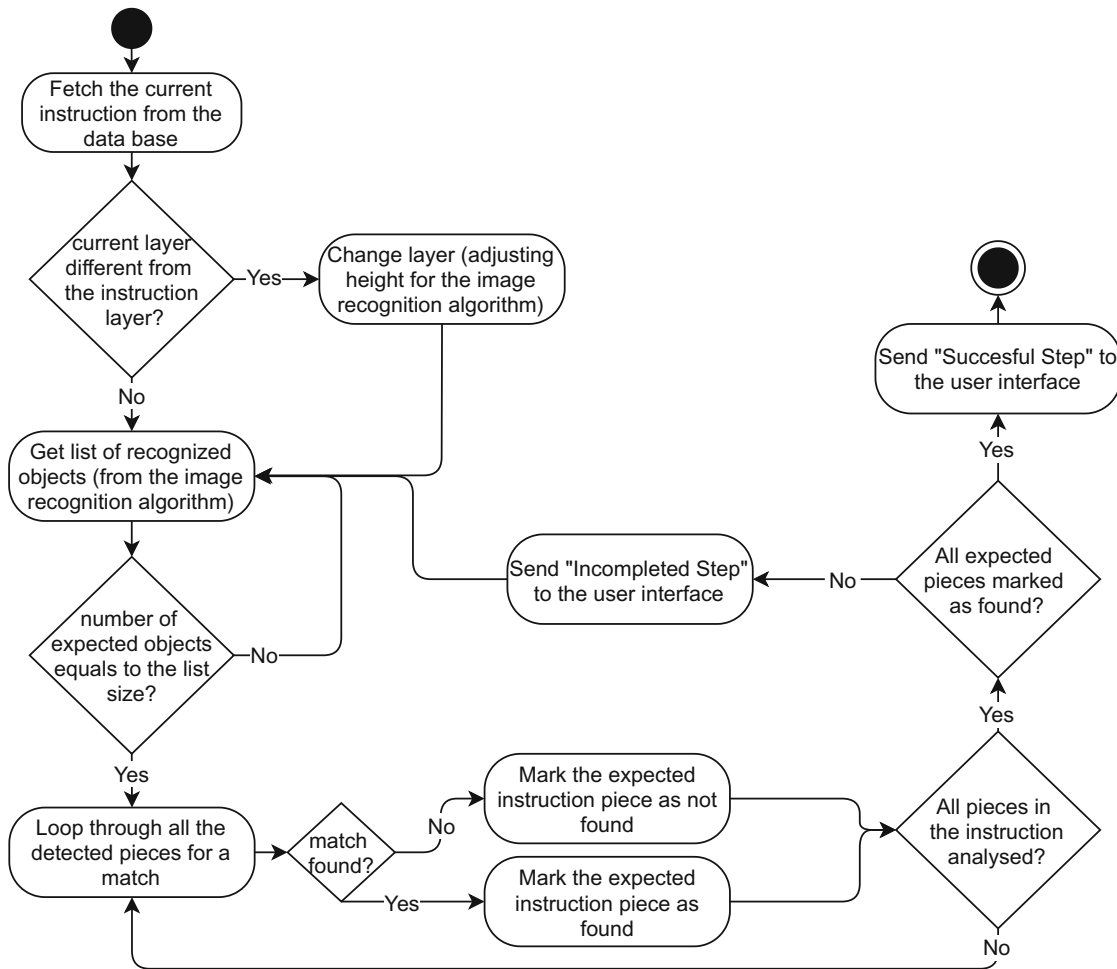


Fig. 5. Verification algorithm for the complex assembly.

To allow the assembly verification in this scenario, the first action is to fetch the active assembly and search for the respective instruction file for the current step. For all the instructions generated, the piece in the top left corner in relation to the rotation of the mounting surface, as illustrated in Fig. 6, is considered as a master piece, responsible for the basis of calculation to establish the position of the other pieces in scene. In scenarios that not require to use a box or a

basis to accommodate the pieces, the first piece placed in the working area, e.g., corresponding to the first step, is considered as the master piece, and all the others pieces placed later have their position related to the master piece.

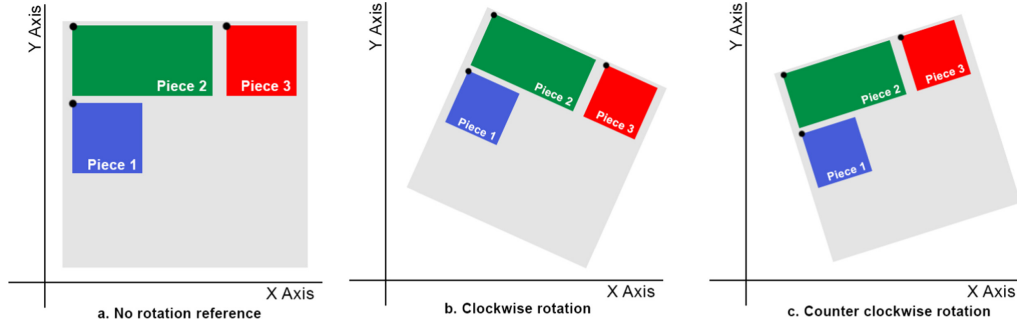


Fig. 6. Possible assembly rotations. (Color figure online)

The colour, orientation and shape of the piece are obtained directly from the image recognition algorithm. The assemblies were separated into layers of heights, to ensure that all pieces in the scene are analyzed, even those that are covered by another piece in a later step. Each layer has a master piece to serve as reference for other pieces in the same plane and a new layer is considered if any piece is mounted on top of another. It is important to remark a limitation in the assembly freedom since that the assembly area can not be moved when a layer change because this would change the stored reference position of the master piece used to calculate the distance and the reference point for the newly added piece.

In order to increase the stability of the verification correctness process, the assembly verification algorithm considers the last five performed detections and only confirms the assembly if they are equal. Note that this threshold value was empirically defined, with a small number leading to a reduced certainty and a high number increasing the response time.

By debugging the software, it was possible to observe that problems in detection may occur due to the positioning of the assembly in relation to the ambient lighting. To solve this problem, three solutions have been introduced: the reduction of the lighting intensity, the demarcation of an optimal area for assembly and the modification of the algorithm that returns the final detection.

5 Experimental Results

The developed IPA, and particularly the automatic system to verify the correctness of the assembly operation, was implemented in the workbench case study, and used by operators in their assembly operations' routines.

5.1 Accuracy of Developed Methods

Multiple running tests were performed using the intelligent assistant by operators performing assembly operations for the 2 case study scenarios.

Regarding the gift-box scenario, Fig. 7 illustrates an operator performing the assembly operation with the support of the intelligent assistant, as well as the output of the recognition algorithm to check the correctness of the performed operation.

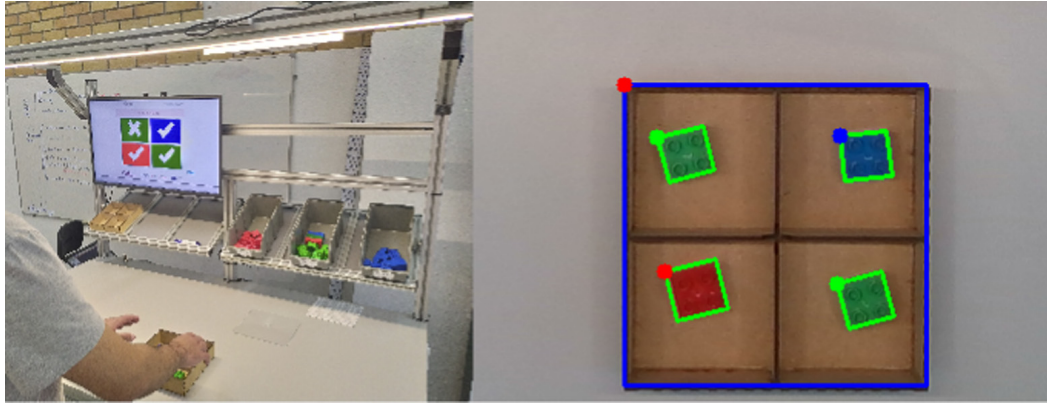


Fig. 7. Gift-box assembly in the IPA (right) with the recognition output (left).

It is clear the benefits of using the intelligent assistant to support the operator during the execution of customised assembly tasks, including the automatic presentation of the instructions to perform the operation and the automatic verification of the correctness of the performed operation, mitigating the possibility of human errors, e.g., due to fatigue, variability and error of judgement, thus increasing the efficiency of the process and the comfort of the operator.

The checking algorithm was intensively tested, including incorrect assemblies with the following situations to validate its accuracy: i) incorrect colour order within the box, ii) two pieces in the same box slot, and iii) pieces placed outside the box. No errors occurred during the tests, i.e. where the system output is correct although the real assembly is not. However, when the box was placed outside the detection area, some errors have occurred due to the light reflection. In particular, it was identified the incorrect detection of red pieces when they are very close to the box wall. This occurs since in some situations of low brightness, the HSV values for brown and red colours coincide, with the filter not being able to separate the two objects. This situation can be avoided with the improvement of the scene lighting and adjusting the filter threshold values to better classify the pieces' colours.

The response time to perform the recognition algorithm and to present the verification decision to the operator is approximately 3 s, which means a waiting time of 3 s to check the correctness of the performed operation's step. This implies the need to establish a cycle time for the assembly of gift-boxes that includes this additional time.

Regarding the second scenario, Fig. 8 shows the operator performing the assembly of a product and the output of the recognition algorithm. The black points presented in the algorithm's output are due to the layer system since as the distances are subtracted from the height map, it is possible to obtain negative values by oscillating the camera data, with the algorithm excluding these areas.

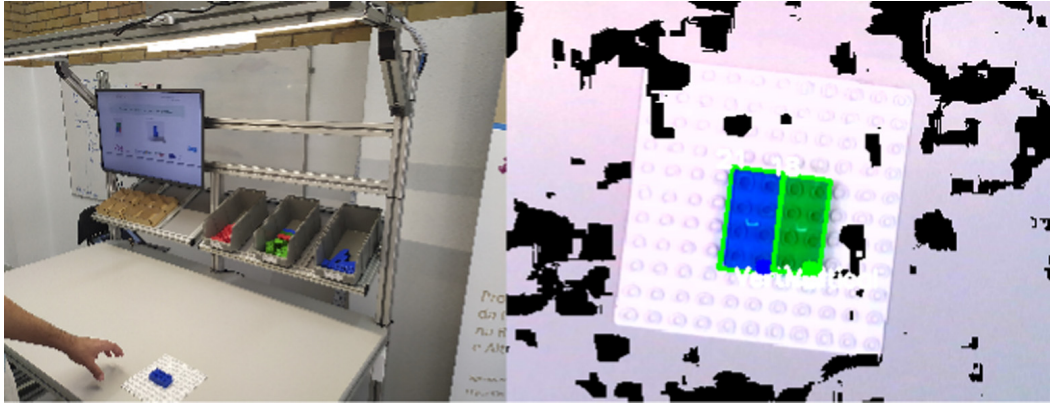


Fig. 8. Operator performing a complex product assembly (left) and the output of the recognition algorithm (right).

Similarly to the previous scenario, erroneous situations, e.g., switched colour or position, wrong orientation, pieces mounted in incorrect layers, movement of the mounting base in instructions of the same layer and removal of previous pieces, were included to the testing experiment to identify possible errors in the recognition of the assembly steps. It was observed that during the experimental tests, no errors have occurred. One problem found was the insertion of pieces of the same colour as other pieces in lower layers. Although the performance of the algorithm when ignoring the layers not being worked on was satisfactory, the shape of lower pieces placed in the proximity of parts of the superior layer was detected, as observed in Fig. 9. Thus, when the colours of these pieces coincide, they are considered only one piece, causing the incorrect calculation of their edges and consequently unable to be confirmed by the algorithm.

It was also proven the theorized problem during the development of this application in which during the change of layers, if the pieces change their position on the working area, it is not possible to obtain the relation of the new piece and therefore it is not possible to confirm the assembly step. This problem can be solved by using another algorithm that can identify the position of the pieces, independently of the relations between the rest of the assembly.

Finally, the classification of the pieces' heights has been proven to be efficient by using a height map, since, through the debugging of the algorithm, it is possible to find the same height for pieces in the same plane. Since a height map technique is used, it is assumed that the recognition algorithm starts with no object above the table, otherwise it is necessary to clean it and restart the

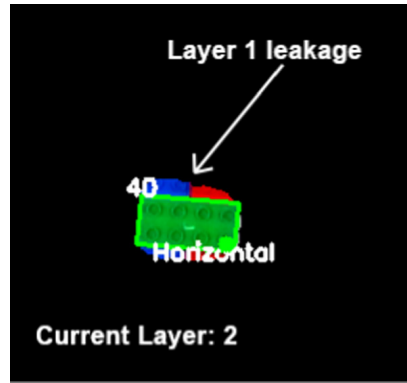


Fig. 9. Example of wrong inclusion of bottom layer pieces. (Color figure online)

detection procedure. Also, if the camera is misaligned perpendicularly to the working area, incorrect heights are obtained, being necessary to perform this verification ahead.

5.2 Comparing with Traditional Methods

An experimental use case test was performed to compare the time and efficiency of the IPA system against the traditional manual method, considering the second use case scenario. The time elapsed and the errors made during the setup, assembly and completion phases were analysed. For the conventional method, the operator follows a printed manual that describes the steps to be executed and fulfills a report containing the confirmation of the correct performance of the instructions. After the assembly through the printed manual, the participants used the workbench to perform a different assembly from the one performed previously, but with the same difficulty and number of steps, and the same metrics were calculated. Note that the order in which the methods are carried out does not influence the result as the set of parts used and the assembly process itself change, which does not allow the operator to become more skilled after executing an assembly process. Table 1 summarises the obtained results with four operators performing the assembly using the two different methods (conventional and IPA), each one performing a setup and 5 assembly steps.

Table 1. Average assembly time (seconds)

	Conventional method	IPA method
Setup	84.25	15.75
Steps	97.75	62.00
Total	182.00	77.75

It can be observed that the biggest difference between the two methods is related to the setup time, which is composed by the selection of the assembly

procedure and the pre-filling of the report, where, in the IPA, the information is filled automatically and uploaded to the database accordingly. The time taken to complete all the 5 steps when performed using the intelligent assistant shows a reduction of 36,6% in relation to the conventional methods. Through the use of assembly recognition associated to the IPA method, it is ensured the certainty that the instruction was correctly executed, while in the conventional method this function depends of the operator performance, thus introducing the possibility of human errors. These benefits will be as higher as more complex and longer is the assembly procedure.

6 Conclusions and Future Work

In Industry 4.0, humans are considered the most flexible piece in an automated system, being crucial their symbiotic integration. The use of intelligent assistants contribute for this integration, particularly to support humans during the execution of complex and/or customised operations.

This paper presents the development of an IPA to support the integration of humans in cyber-physical systems, particularly acting as mentoring of operators in the execution of their assembly operations. A key issue in this IPA system is the use of machine vision techniques to automatically verify the correctness of the performed operations, allowing to reduce the operators errors and improve the product quality.

The application of a workbench equipped with an intelligent personal assistant demonstrates, through the use of two different scenarios, how emergent ICT technologies can be applied to help operators to perform assembly tasks faster and efficiently. In fact, the developed solutions presented high levels of accuracy, a reduction of the operators errors and a reduction of the execution time, as well as excellent levels of acceptance from operators.

In this sense, IPA directly contributes to increasing productivity, quality and efficiency in the tasks performed, highlighting the importance of adopting Industry 4.0 in traditional manufacturing companies through the interaction of humans with intelligent assistants.

Future work includes the use of more robust detection algorithms to handle more complex parts, and AI techniques to provide better action plans along the assembly process. Also, it is planned to perform tests with more operators, including a statistical study with the variability of the assembly execution time.

Acknowledgments. This work has been supported by FCT- Fundação para a Ciência e Tecnologia within the Project Scope: UIDB/05757/2020.

References

1. Abidi, M., Al-Ahmari, A., Ahmad, A., Ameen, W., Alkhalefah, H.: Assessment of virtual reality-based manufacturing assembly training system. *Int. J. Adv. Manuf. Technol.* **105**, 3743–3759 (2019)

2. de Barcelos Silva, A., et al.: Intelligent personal assistants: a systematic literature review. *Expert Syst. Appl.* **147**, 113193 (2020)
3. Fantini, P., et al.: Exploring the Integration of the human as a flexibility factor in cps enabled manufacturing environments: methodology and results. In: *Proceedings of the 42nd Annual Conference of IEEE Industrial Electronics Society (IECON 2016)*, pp. 5711–5716 (2016)
4. Frigo, M.A., da Silva, E.C., Barbosa, G.F.: Augmented reality in aerospace manufacturing: a review. *J. Ind. Intell. Inf.* **4**(2), 125–130 (2016)
5. Gilchrist, A.: *Industry 4.0: The Industrial Internet of Things*. Springer, Heidelberg (2016)
6. Hauswald, J., Laurenzano, M.A., Zhang, Y., et al.: Sirius: an open end-to-end voice and vision personal assistant and its implications for future warehouse scale computers. In: *20th International Conference on Architectural Support for Programming Languages and Operating Systems*, pp. 223–238 (2015)
7. Hoedt, S., Claeys, A., Landeghem, H.V., Cottyn, J.: The evaluation of an elementary virtual training system for manual assembly. *Int. J. Prod. Res.* **55**(24), 7496–7508 (2017)
8. Krupitzer, C., et al.: A survey on human machine interaction in industry 4.0. *CoRR abs/2002.01025* (2020)
9. Leitão, P., Colombo, A.W., Karnouskos, S.: Industrial automation based on cyber-physical systems technologies: prototype implementations and challenges. *Comput. Ind.* **81**, 11–25 (2016)
10. Mantovani, G.: VR Learning: Potential and Challenges for the Use of 3D. *Towards Cyberpsychology: Mind, Cognitions, and Society in the Internet Age*, pp. 208–225 (2003)
11. Mohd Ali, N., Md Rashid, N.K.A., Mustafah, Y.M.: Performance comparison between RGB and HSV color segmentations for road signs detection. In: *Advances in Manufacturing and Mechanical Engineering. Applied Mechanics and Materials*, vol. 393, pp. 550–555. Trans Tech Publications Ltd (2013)
12. Morgado, M., Miguel, L.: Ergonomics in the industry 4.0: virtual and augmented reality. *J. Ergon.* **08** (2018)
13. Pierdicca, R., Frontoni, E., Pollini, R., Trani, M., Verdini, L.: The use of augmented reality glasses for the application in industry 4.0. In: *Proceedings of the International Conference on Augmented Reality, Virtual Reality and Computer Graphics*, pp. 389–401 (2017)
14. Romero, D., et al.: Towards an operator 4.0 typology: a human-centric perspective on the fourth industrial revolution technologies. In: *Proceedings of the Int'l Conference on Computers and Industrial Engineering*, pp. 1–11 (2016)
15. Webel, S., Bockholt, U., Engelke, T., Gavish, N., Olbrich, M., Preusche, C.: Augmented reality training for assembly and maintenance skills. *Robot. Auton. Syst.* **61**(4), 398–403 (2013)
16. Zhu, Z., et al.: AR-mentor: augmented reality based mentoring system. In: *Proceedings of the IEEE International Symposium on Mixed and Augmented Reality (ISMAR 2014)*, pp. 17–22 (2014)