Advances in Intelligent Systems and Computing

Volume 693

Series editor

Janusz Kacprzyk, Polish Academy of Sciences, Warsaw, Poland
e-mail: kacprzyk@ibspan.waw.pl

About this Series

The series “Advances in Intelligent Systems and Computing” contains publications on theory, applications, and design methods of Intelligent Systems and Intelligent Computing. Virtually all disciplines such as engineering, natural sciences, computer and information science, ICT, economics, business, e-commerce, environment, healthcare, life science are covered. The list of topics spans all the areas of modern intelligent systems and computing.

The publications within “Advances in Intelligent Systems and Computing” are primarily textbooks and proceedings of important conferences, symposia and congresses. They cover significant recent developments in the field, both of a foundational and applicable character. An important characteristic feature of the series is the short publication time and world-wide distribution. This permits a rapid and broad dissemination of research results.

More information about this series at http://www.springer.com/series/11156

Anibal Ollero · Alberto Sanfeliu
Luis Montano · Nuno Lau
Carlos Cardeira
Editors

ROBOT 2017: Third Iberian Robotics Conference

Volume 1

Springer

Editors
Anibal Ollero
Escuela Técnica Superior de Ingeniería
Universidad de Sevilla
Sevilla
Spain

Alberto Sanfeliu
Institut de Robòtica I Informàtica Industrial (CSIC-UPC)
Universitat Politècnica de Catalunya
Barcelona
Spain

Luis Montano
Departamento de Informática e Ingeniería de Sistemas, Escuela de Ingeniería y Arquitectura
Instituto de Investigación en Ingeniería de Aragón
Zaragoza
Spain

Nuno Lau
Institute of Electronics and Telematics Engineering of Aveiro (IEETA)
Universidade de Aveiro
Aveiro
Portugal

Carlos Cardeira
IDMEC, Instituto Superior Técnico de Lisboa
Universidade de Lisboa
Lisbon
Portugal

ISSN 2194-5357 ISSN 2194-5365 (electronic)
Advances in Intelligent Systems and Computing
ISBN 978-3-319-70832-4 ISBN 978-3-319-70833-1 (eBook)
https://doi.org/10.1007/978-3-319-70833-1

Library of Congress Control Number: 2017957985

© Springer International Publishing AG 2018
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, express 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.

Printed on acid-free paper

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

Preface

This book contains a selection of papers accepted for presentation and discussion at "Robot 2017: Third Iberian Robotics Conference," held in Seville, Spain, November 22–24, 2017. Robot 2017 is part of a series of conferences that are a joint organization of Sociedad Española para la Investigación y Desarrollo de la Robótica/Spanish Society for Research and Development in Robotics (SEIDROB) and Sociedade Portuguesa de Robótica/Portuguese Society for Robotics (SPR). The conference organization had also the collaboration of several universities and research institutes, including University of Seville, Polytechnic University of Catalonia, University of Zaragoza, University of Aveiro, and University of Lisbon.

Robot 2017 builds upon several successful events, including three biennial workshops (Zaragoza–2007, Barcelona–2009, and Sevilla–2011) and two Iberian Robotics Conferences (Madrid–2013 and Lisbon–2015).

The conference is focused on the robotics scientific and technological activities in the Iberian Peninsula, although open to research and delegates from other countries.

Robot 2017 featured three plenary talks by:

- Oussama Khatib, Director of Stanford Robotics Lab, Stanford University, USA, President of the International Foundation of Robotics Research (IFRR)
- Dario Floreano, Director of the Laboratory of Intelligent Systems, EPFL, Switzerland, Director of the Swiss National Center of Competence in Robotics, Switzerland
- Alin Albu-Schäffer, Head of the Institute of Robotics and Mechatronics at the German Aerospace Center (DLR), Germany.

Robot 2017 featured 27 special sessions, four of them with two slots in the Conference Program, plus 5 sessions coming from the General Track. The conference had an industrial track with four sessions. The main purpose of this track is to present industrial needs and recent achievements in robotic industrial applications looking to promote new collaborations between industry and academia. Six papers of the industrial track have been included in this book.

The Special Sessions were about Aerial Robotics for Inspection, Agricultural Robotics and Field Automation, Autonomous Driving and Driver Assistance Systems, Challenges in Medical Robotics in the Frame of Industry 4.0, Cognitive Architectures, Communication-Aware Robotics, Cooperative and Active Perception for Robotics, Educational Robotics, Legged Locomotion Robots, Machine Learning in Robotics, Marine Robotics, Ontologies and Knowledge Representation for Robotics, Rehabilitation and Assistive Robotics, Robotics and Cyber-Physical Systems for Industry 4.0, Robotic and Unmanned Vehicles for Security, Robot Competitions, Robots Cooperating with Sensor Networks, Robots for Health care, Sensor Technologies oriented to Computer Vision Applications, Simulation in Robotics, Vision and Learning for Robotics, and Visual Perception for Robotics.

Additionally, the four industrial Special Sessions were about Application of Robotics to Manufacturing Processes in the Aeronautic Industry, Application of Robotics to Shipbuilding, Integration of Drones in Low Altitude Aerial Space, and Robotics Solutions for Flexible Manufacturing.

Finally, the sessions in the General Track were about the following topics: Aerial Robotics (double slot), Manipulation, Mobile Robotics, and Mobile Robotics Applications.

The Robot 2017 Call for papers received 201 papers. After a careful review process with at least three independent reviews for each paper, 141 of them have been selected to be included in this book. There are over 500 authors from 21 countries including Australia, Brazil, Colombia, Croatia, Czech Republic, Denmark, Ecuador, Finland, France, Germany, Ireland, Italy, Luxembourg, Macao, Mexico, Poland, Portugal, Spain, United Arab Emirates, UK, and USA.

We would like to thank all Special Sessions' organizers for their hard work on promoting their special session, inviting the Program Committee, organizing the Special Session review process, and helping to promote the ROBOT 2017 Conference. This acknowledgment goes especially to the members of the Program Committee, Organizers of the Special Sessions, and Reviewers for the hard work required to prepare this volume as they were crucial for ensuring the high scientific quality of the event and to all the authors and delegates whose research work and participation made this event a success. The work of the Local Organizing Committee was also crucial to produce the Robot 2017 Program and this book.

Last but not the least, we acknowledge and thank our editor, Springer, that was in charge of these proceedings, and in particular to Dr. Thomas Ditzinger.

November 2017

Anibal Ollero
Alberto Sanfeliu
Luis Montano
Nuno Lau
Carlos Cardeira

Organization

General/Program Chairs

Anibal Ollero	University of Sevilla, Spain
Alberto Sanfeliu	Polytechnical University of Catalonia, Spain
Luis Montano	University of Zaragoza, Spain
Nuno Lau	University of Aveiro, Portugal
Carlos Cardeira	University of Lisbon-IST, Portugal

Organizing Committee

The following members of the Organizing Committee of Robot 2017 have contributed to the preparation of this book and its dissemination:

Alberto Sanfeliu	Polytechnical University of Catalonia, Spain
Ángel Rodríguez	University of Sevilla, Spain
Anibal Ollero	University of Sevilla, Spain
Arturo Torres	University of Sevilla, Spain
Carlos Cardeira	University of Lisbon-IST, Portugal
Carlos Rodríguez	University of Sevilla, Spain
Francisco Real	University of Sevilla, Spain
Iván Maza	University of Sevilla, Spain
Jesús Capitán	University of Sevilla, Spain
José Ángel Acosta	University of Sevilla, Spain
José Antonio Cobano	University of Sevilla, Spain
Luis Montano	University of Zaragoza, Spain
Nuno Lau	University of Aveiro, Portugal
Pablo Ramón	University of Sevilla, Spain
Pedro Sánchez	University of Sevilla, Spain

Robot 2017 Program Committee

Agapito Ledezma Espino	University Carlos III Madrid
Alexandre Bernardino	University of Lisbon, Portugal
Angel Pasqual del Pobil	University Jaume I
Alfonso Garcia Cerezo	University of Malaga, Spain
Alícia Casals	Polytechnical University of Catalonia, Spain
Anders Christensen	University Institute of Lisbon, Portugal
Andry Pinto	University of Porto, Portugal
Ángel García Olaya	University Carlos III Madrid, Spain
Aníbal Matos	University of Porto, Portugal
Antidio Viguria	FADA-CATEC, Spain
Antonio Barrientos	CAR CSIC-UPM, Spain
Antonio Jesús Bandera	University of Málaga, Spain
António Paulo Moreira	University of Porto, Portugal
António Pedro Aguiar	University of Porto, Portugal
Armando Jorge Sousa	University of Porto, Portugal
Artur Pereira	University of Aveiro, Portugal
Arturo Morgado	University of Cadiz, Spain
Bernardo Cunha	University of Aveiro, Portugal
Begoña C. Arrue	University of Sevilla, Spain
Brígida Mónica Faria	Polytechnic Institute of Porto, Portugal
Carlos Cerrada	UNED, Spain
Carlos Vazquez Regueiro	University A Coruña, Spain
Carme Torras	Institut de Robotica i Informatica Industrial (CSIC-UPC), Spain
Cristina Santos	University of Minho, Portugal
Danilo Tardioli	University of Zaragoza, Spain
Estela Bicho	University of Minho, Portugal
Francisco J. Rodríguez	University of Luxembourg, Luxembourg
Fernando Fernández	University Carlos III de Madrid, Spain
Fernando Lasagni	FADA-CATEC, Spain
Fernando Ribeiro	University of Minho, Portugal
Filipe Santos	University of Porto, Portugal
Filomena Soares	University of Minho, Portugal
Guillermo Heredia	University of Sevilla, Spain
Ismael García Varea	University of Castilla-La Mancha, Spain
Javier Civera	University of Zaragoza, Spain
Jesús Capitán	University of Sevilla, Spain
João Calado	Polytechnic Institute of Lisbon, Portugal
João Sequeira	University of Lisbon, Portugal
Jon Agirre Ibarbia	TECNALIA, Spain

Jorge Dias	University of Coimbra, Portugal
Jorge Lobo	University of Coimbra, Portugal
Jorge Martins	University of Lisbon, Portugal
José Barata	University of Lisbon, Portugal
José A. Castellanos	University of Zaragoza, Spain
José L. Villarroel	University of Zaragoza, Spain
José Luis Azevedo	University of Aveiro, Portugal
José Luis Lima	Polytechnic Institute of Bragança, Portugal
José Luis Pons	Instituto Cajal-CSIC, Spain
José María Cañas	University Rey Juan Carlos, Spain
Josep Amat	Polytechnical University of Catalonia, Spain
Juan Andrade	Institut de Robotica i Informatica Industrial (CSIC-UPC), Spain
Juana Mayo	University of Sevilla, Spain
Lino Marques	University of Coimbra, Portugal
Lluís Ribas Xirgo	Autonomous University of Barcelona, Spain
Luis Almeida	University of Porto, Portugal
Luis Correia	University of Lisbon, Portugal
Luis Merino	University Pablo Olavide, Spain
Luis Moreno	University Carlos III de Madrid, Spain
Luis Paulo Reis	University of Minho, Portugal
Manuel Armada	CAR CSIC-UPM, Spain
Manuel Ferre	CAR CSIC-UPM, Spain
Manuel Silva	Polytechnic Institute of Porto, Portugal
Micael Couceiro	University of Coimbra, Portugal
Miguel Oliveira	University of Porto, Portugal
Miguel A. Cazorla	University of Alicante, Spain
Nicolás García-Aracil	University of Miguel Hernández, Spain
Nuno Cruz	University of Porto, Portugal
Oscar Reinoso	University of Miguel Hernández, Spain
Pablo Bustos	University of Extremadura, Spain
Pascual Campoy	Polytechnical University of Madrid, Spain
Paulo Costa	University of Porto, Portugal
Paulo Gonçalves	Polytechnic Institute of Castelo Branco, Portugal
Paulo Jorge Oliveira	University of Lisbon, Portugal
Pedro Costa	University of Porto, Portugal
Pedro Fonseca	University of Aveiro, Portugal
Pedro Lima	University of Lisbon, Portugal
Ramiro Martinez de Dios	University of Sevilla, Spain
Raul Cano	FADA-CATEC, Spain
Raul Morais	UTAD, Portugal
Raul Suarez	Polytechnical University of Catalonia, Spain
Rodrigo Ventura	University of Lisbon, Portugal
Rui Araújo	University of Coimbra, Portugal

Rui Rocha	University of Coimbra, Portugal
Thierry Keller	TECNALIA, Spain
Vicente Feliú	University of Castilla-La Mancha, Spain
Vicente Matellán	University of León, Spain
Vitor Santos	University of Aveiro, Portugal

Special Sessions' Organizers

Aerial Robotics for Inspection

Guillermo Heredia	University of Seville, Spain

Agricultural Robotics and Field Automation

Raul Morais Santos	UTAD, Portugal
Filipe Neves dos Santos	INESC-TEC, Portugal

Application of Robotics to Manufacturing Processes in the Aeronautic Industry

Raúl Cano	FADA-CATEC, Spain

Application of Robotics to Shipbuilding

Arturo Morgado	Universidad de Cádiz, Spain

Autonomous Driving and Driver Assistance Systems

Vitor Santos	Universidade de Aveiro, Portugal
Angel Sappa	CVC Barcelona and ESPOL Guayaquil, Spain
Miguel Oliveira	INESC-TEC, Portugal
Arturo de la Escalera	Universidad Carlos III de Madrid, Spain

Challenges in Medical Robotics in the Frame of Industry 4.0

Josep Amat	UPC, Spain
Alicia Casals	UPC, Spain

Cognitive Architectures

Vicente Matellán	Universidad de León, Spain

Communication Aware Robotics

Danilo Tardioli	CUD Zaragoza, Spain
Alejandro R. Mosteo	CUD Zaragoza, Spain
Luis Riazuelo	Universidad de Zaragoza, Spain

Cooperative and Active Perception in Robotics

Eduardo Silva	ISEP/IPP, Portugal
Jesús Capitán	Universidad de Sevilla, Spain
Luis Merino	Universidad Pablo de Olavide, Spain

Educational Robotics

Armando Sousa	FEUP, Portugal
Fernando Ribeiro	Universidade do Minho, Portugal

Integration of Drones in Low Altitude Aerial Space

Antidio Viguria	FADA-CATEC, Spain

Legged Locomotion Robots

Manuel Silva	ISEP/IPP and INESC-TEC, Portugal
Cristina Santos	University of Minho and Centro ALGORITMI, Portugal
Manuel Armada	CSIC-UPM, Spain

Machine Learning in Robotics

Guillem Aleny	Institut de Robotica Informatica Industrial (CSIC-UPC), Spain
Brígida Mónica Faria	ESS-PP, Portugal
Luis Merino	UPO, Spain
Carme Torras	Institut de Robotica i Informatica Industrial (CSIC-UPC), Spain

Marine Robotics

A. Pedro Aguiar	FEUP, Portugal
António Pascoal	IST, Portugal
João B. Sousa	FEUP, Portugal
Fernando Lobo Pereira	FEUP, Portugal

Ontologies and Knowledge Representation for Robotics

Paulo Gonçalves	IPCB and IDMEC/Universidade de Lisboa, Portugal
Julita Bermejo-Alonso	UPM, Spain
Ricardo Sanz	Autonomous Systems Laboratory (ASLab), UPM, Spain

Rehabilitation and Assistive Robotics

Luis Paulo Reis	University of Minho, Portugal
Brígida Mónica Faria	P.Porto, Portugal

Robotic and Unmanned Vehicles for Security

A. García-Cerezo	Universidad de Málaga, Spain

Robotics and Cyber-Physical Systems for Industry 4.0

José Lima	INESC-TEC, Portugal
Germano Veiga	INESC-TEC, Portugal
Paulo Leitão	IPB, Portugal

Robotics Solutions for Flexible Manufacturing

Jon Agirre Ibarbia	Tecnalia Research & Innovation, Spain

Robot Competitions

Bernardo Cunha	University of Aveiro, Portugal
José Luis Azevedo	University of Aveiro, Portugal

Robots Cooperating with Sensor Networks

J. Ramiro Martinez de Dios	University of Sevilla, Spain

Robots for Health Care

Raquel Fuentetaja Pizán	Universidad Carlos III de Madrid, Spain
Angel García Olaya	Universidad Carlos III de Madrid, Spain

Sensor Technologies Oriented to Computer Vision Applications

Carlos Cerrada	UNED, Spain

Simulation in Robotics

Luis Paulo Reis	University of Minho, Portugal
Artur Pereira	University of Aveiro, Portugal

Vision and Learning for Robotics

Miguel Cazorla	Universidad de Alicante, Spain
Oscar Reinoso	Universidad Miguel Hernández, Spain

Visual Perception for Robotics

B.C. Arrue	University of Sevilla, Spain

Sessions Program Committee

Aamir Ahmad
Abdelghani Chibani
Abdulla Al-Kaff
Ahmed Hussein
Alberto Olivares-Alarcos
Alberto Sanfeliu
Alejandro Linares-Barranco
Alejandro R. Mosteo
Alejandro Suarez
Alexandre Bernardino
Alfonso García-Cerezo
Alicia Casals
Alicja Wasik
Ana Lopes

Anais Garrell
Anders Christensen
Andre Dias
Andrea Alessandretti
Andry Pinto
Angel Garcia Olaya
Ángel Manuel Guerrero-Higueras
Angela Ribeiro
Angelos Amanatiadis
Anthony Mandow
Antidio Viguria
Antonio Adan
Antonio Agudo
Antonio Bandera
Antonio Barrientos
Antonio Morales
António Neves
Antonio Paulo Coimbra
António Paulo Moreira
Antonio Valente
Armando Sousa
Artur Pereira
Arturo Bertomeu-Motos
Arturo Morgado
Arturo Torres-González
Augusto Tavares
Begoña C. Arrue
Belén Curto
Benoit Landry
Brígida Mónica Faria
Bruno J.N. Guerreiro
Camino Fernández
Cándido Otero
Carlos Cardeira
Carlos Hernández Corbato
Carlos Miguel Costa
Carlos Rizzo
Carlos Vázquez Regueiro
Carme Torras
Claudio Rossi
Clauirton Siebra
Craig Schlenoff
Daniel Gutierrez Galan
Daniel Silva
Danilo Tardioli
David Alejo
David Valiente
Dimitrios Paraforos
Domenec Puig
Denes Nagy
Duarte Valério
Edson Prestes
Eduardo Ferrera
Eduardo Mendes
Eduardo Molinos Vicente
Enrique Valero
Estela Bicho
Eugenio Aguirre Molina
Eugenio Marinetto
Eurico Pedrosa
Felipe Jimenez
Fernando Caballero
Fernando Fernández
Fernando Garcia
Fernando Gomez-Bravo
Fernando Ribeiro
Filipe Neves Dos Santos
Filomena Soares
Francisco Alarcón
Francisco Bonnín
Francisco Gomez-Donoso
Francisco J. Rodríguez Lera
Francisco Javier Badesa
Francisco Madrigal
Francisco Martín Rico
Francisco Ramos
Francisco Rodríguez-Sedano
Frederic Lerasle
Gary Philippe Cornelius
Gil Lopes
Guillermo Heredia
Iñaki Diaz
Ismael Garcia-Varea
Ivan Armuelles
Ivan Maza
J.M. Aguilar
Jaime Duque Domingo
Javier Perez Turiel
Jesús Balsa
Jesus Capitan

Jesus Fernandez-Lozano
Joao Calado
Joao Fabro
João Macedo
João Sequeira
Joel Carbonera
Jon Agirre Ibarbia
Jorge De León Rivas
Jorge Díez
Jorge Lobo
Jorge Martins
Jose A. Castellanos
José Antonio Cobano
José Barbosa
José Carlos Rangel
Jose Eugenio Naranjo
Jose García Rodríguez
Jose Javier Anaya
Jose Joaquin Acevedo
Jose Lima
José Luis Villarroel
José M. Cogollor
José Manuel Cañas
José María Armingol
José María Cañas Plaza
José María Catalán Orts
Josenalde Oliveira
Josep Amat
Joshue Pérez
Josu Larrañaga Leturia
Juan Andrade Cetto
Juan Barios
Juan Braga
Juan Jesús Roldán Gómez
Juan Pedro Bandera Rubio
Julián Estévez
Julita Bermejo-Alonso
Justyna Gerłowska
Leopoldo Rodriguez
Lluis Ribas Xirgo
Luis Almeida
Luis Correia
Luis Costa
Luis Evaristo Caraballo de La Cruz
Luis Garrote
Luis Gomes
Luis Merino
Luis Montano
Luis Moreno
Luis Oliveira
Luis Paulo Reis
Luis Riazuelo
Luis Rocha
Manuel Armada
Manuel Ferre
Manuel Garcia
Manuel Jesus Dominguez Morales
Manuel Pérez
Manuel Silva
Marcelo Borges Nogueira
Marcelo Petry
Marco Ceccarelli
Margarita Bachiller
Martin Rico Francisco
Micael Couceiro
Miguel Ángel Conde
Miguel Angelo Sotelo
Miguel Cazorla
Miguel Trujillo
Mohammad Rouhani
Natalia Ayuso
Nicolas García Aracil
Nicolas Jouandeau
Nieves Pulido
Noé Pérez-Higueras
Nuno Cruz
Nuno Lau
Oscar Lima
Oscar Reinoso
Oscar Sipele
P. Javier Herrera
Pablo Bustos
Pablo Jiménez
Pablo Ramon Soria
Paulo Costa
Paulo Dias
Paulo Gonçalves
Paulo Menezes
Paulo Oliveira
Paulo Peixoto

Pedro Costa
Pedro Fonseca
Pedro Lima
Pedro Neto
Pedro Pedro Costa
R. Praveen Kumar Jain
Rafael Barea
Ramiro Martinez de Dios
Raquel Fuentetaja
Raul Cano
Raul Morais Santos
Raul Suarez
Ricardo Pascoal
Ricardo Sanz
Rita Cunha
Robert Fitch
Roberto Arroyo
Rui Araujo
Rui Gomes
Rui Rocha
Sedat Dogru
Stephen Balakirsky
Tiago Nascimento
Valter Costa
Veera Ragavan
Vicente Feliú
Vicente Matellán
Víctor Vaquero
Vítor Carvalho
Vitor Santos
Yaroslav Marchukov

Contents

Mobile Robotics

Mobile Robotics Applications

Marine Robotics

Agricultural Robotics and Field Automation

Cooperative and Active Perception in Robotics

Robots for Healthcare

Ontologies and Knowledge Representation for Robotics

Simulation in Robotics

Vision and Learning for Robotics (I)

Vision and Learning for Robotics (II)

Aerial Robotics for Inspection

Aerial Robotics (I)

Aerial Robotics (II)

Robotic and Unmaned Vehicles for Security

Movement Direction Estimation Using Omnidirectional Images in a SLAM Algorithm

Yerai Berenguer(✉), Luis Payá, Oscar Reinoso, Adrián Peidró,
and Luis Miguel Jiménez

Departamento de Ingeniería de Sistemas y Automática,
Miguel Hernández University, Alicante, Spain
`{yberenguer,lpaya,o.reinoso,apeidro,luis.jimenez}@umh.es`
`http://arvc.umh.es`

Abstract. This work presents a method to estimate the movement direction of a mobile robot using only visual information, without any other additional sensor. This visual information is provided by a catadioptric system mounted on the robot and formed by a camera pointing towards a convex mirror. It provides the robot with omnidirectional images that contain information with a field of view of 360° around the camera-mirror axis. A SLAM algorithm is presented to test the method that estimates the movement direction of the robot. This SLAM method uses two different global appearance descriptors to calculate the orientation of the robot and the distance between two different positions. The method to calculate the movement direction is based on landmarks extraction, using SURF features. A set of omnidirectional images has been considered to test the effectiveness of this method.

Keywords: SLAM · Omnidirectional images · Vision systems · Image description

1 Introduction

Nowadays many robots can be found to solve some day to day tasks, and the number of them is increasing year to year. Many of these robots are mobile, due to their flexibility, as they are able to change their position during operation. Usually, these robots have to solve a task autonomously in an unknown environment, so the robot must estimate its position and orientation to be able to arrive to the target point avoiding obstacles. To solve this task, two fundamental steps must be carried out. On the one hand, it must create an internal representation of the unknown environment (map) and on the other hand it must be able to estimate its position within the map. The robot uses the information extracted from the environment by the different sensors that it is equipped with. This information is compared with the data stored in the map to estimate the position of the robot. There are many kinds of sensors that provide useful information to the robot, such as touch sensors, encoders, laser or vision sensors.

A. Ollero et al. (eds.), *ROBOT 2017: Third Iberian Robotics Conference*, Advances in Intelligent Systems and Computing 693, https://doi.org/10.1007/978-3-319-70833-1_52

Vision sensors have some properties that make them very useful in mobile robotics because they have many possible configurations, relative low cost and they provide the robot with very rich information from the environment. This images permit carrying out other high-level tasks. In this work we use the omnidirectional configuration [17].

In the field of the Simultaneous Localization and Mapping (SLAM), omnidirectional images have many advantages because they contain information with a field of view of 360° around the mirror axis. We can find many previous works that use omnidirectional images in mapping and localization tasks. For example, Valiente et al. [16] present a comparison between two different visual SLAM methods using omnidirectional images and Garcia-Fidalgo and Ortiz [6] make a survey of vision-based topological mapping and localization methods.

The classic developments in mobile robotics using visual sensors are based on the extraction and description of some landmarks from the scenes. These landmarks can be either natural or artificial and some methods are available, such as SIFT (Scale-Invariant Feature Transform) [12] and SURF (Speeded-Up Robust Features) [1].

More recently, some works propose using the global appearance to describe the scenes, creating a unique descriptor per image. These techniques have demonstrated to be a good option to solve the localization and navigation problems when the movement of the robot is contained in the floor plane. For example, Chang et al. [3] presents a vision-based navigation and localization system using the gist descriptor, Payá et al. [14] use a descriptor based on the Fourier signature in Monte Carlo localization tasks, and Wu et al. [18] propose an efficient visual loop closure detection method. In [13], several methods to obtain global descriptors from panoramic scenes are analyzed and compared to demonstrate their validity in map building and localization. The majority of these global appearance descriptors can be used in real time because the computational time to calculate and handle them is low, and they usually lead to more straightforward mapping and localization algorithms.

Sometimes, the mapping process produces an error that tends to increase as new positions are added to the map due to the iterative calculation of new poses of the robot. This can be a big problem in extensive environments when the robot has to calculate many new poses. This uncertainty can be reduced by detecting loop closures and using optimization algorithms to relocate each previous pose. This problem is thoroughly studied in this work.

The contribution of this work is the creation of a method to calculate the movement direction of the robot using only visual information. Also, a SLAM method is presented to test this movement direction algorithm as a fundamental step of it. This SLAM method consists of three different steps: calculating the pose of the robot (position and orientation), detecting loop closures (by comparing global appearance descriptors) and optimizing the map. The optimization algorithm used in the presented paper is named G2O and it was presented by Kümerle et al. [11].

The experiments have been carried out with a set of images captured while the robot traversed a real working environment. It has been captured following a real path including several rooms in a building.

The remainder of this paper is structured as follows. Section 2 introduces some preliminary concepts about image description and graph optimization. Section 3 describes our movement direction estimation algorithm and the SLAM method. Section 4 describes the database used to carry out the experiments and presents the experiments and results. At last, Sect. 5 outlines the conclusions.

2 Preliminaries

Along the paper, two methods are used to describe the global appearance of scenes: the Radon transform and the Histogram of Oriented Gradients (HOG). This section includes some information on them. Also, we present the fundamentals of the methods used to calculate the difference between two images captured from different locations. At last, we describe the optimization algorithm used to recalculate the previous map positions after detecting loop closures.

2.1 Global Appearance Descriptors

Methods based on the global appearance of the scenes constitute a robust alternative compared with methods based on landmarks extraction. The key is that the global appearance descriptors represent the environment through high-level features that can be interpreted and handled easily, and with a reasonably low computational cost.

When designing a new description method, we should take several features into account. This descriptor should have a compression effect in the image information. Also, there should be a correspondence between the distance between two descriptors and the distance between the two positions where the images were captured. The computational cost to calculate and compare them should be low, so that this descriptor can be used in real time. Furthermore, it should provide robustness against noise, illumination changes, occlusions and position changes of the objects in the environment. Finally, it should contain information on the orientation the robot had when it captured the image.

This subsection presents two different image descriptors we have used in the SLAM method to describe the omnidirectional images. Both of them are based on global appearance, without any segmentation or local landmark extraction. Also, a descriptor based on the landmark extraction is used to carry out the movement direction estimation.

Radon Transform. The Radon transform was initially described in [15]. It has been used in some computer vision tasks, such as shape description and segmentation, such as [7,8].

The Radon transform in 2D consists in calculating the integral of a 2D function along a set of straight lines (line-integral projections). This transform is invertible. The inverse Radon transform reconstructs an image from its line-integral projections. By this reason it was initially used in medical imaging (such as CAT scan and Magnetic Resonance Imaging (MRI)).

The Radon transform of a 2D function $f(i, j)$ can be defined mathematically as:

$$\mathcal{R}\{f(i,j)\} = \lambda_f(p,\phi) = \iint_{-\infty}^{+\infty} f(i,j)\delta(p - \overrightarrow{r}\widehat{\overrightarrow{p}})\partial i \partial j \tag{1}$$

Where δ is the Dirac delta function ($\delta(x) = 1$ when $x = 0$, and $\delta(x) = 0$ elsewhere). The integration line is specified by the radial vector $\overrightarrow{p}$ that is defined by $\overrightarrow{p} = \widehat{\overrightarrow{p}} \cdot p$ where $\widehat{\overrightarrow{p}}$ is a unitary vector in the direction of $\overrightarrow{p}$. p is the $\overrightarrow{p}$ magnitude:

$$p = |\overrightarrow{p}| \tag{2}$$

The line-integral projections, evaluated for each azimuth angle ϕ, produce a 2D polar function λ_f, that depends on the radial distance p and the azimuth angle ϕ. $\overrightarrow{r}$ is a cluster of points which is perpendicular to $\overrightarrow{p}$.

The Radon transform of an image $im(i, j)$ along the line $c_1(d, \phi)$ can be expressed more clearly by the following equivalent expression:

$$\mathcal{R}\{im(i,j)\} = \int_{\mathbb{R}} im(i' \cos\phi - j' \sin\phi, i' \sin\phi + j' \cos\phi)\ ds \tag{3}$$

where

$$\begin{bmatrix} i' \\ j' \end{bmatrix} = \begin{bmatrix} \cos\phi & \sin\phi \\ -\sin\phi & \cos\phi \end{bmatrix} \cdot \begin{bmatrix} i \\ j \end{bmatrix} \tag{4}$$

When the Radon transform is applied to images, it calculates the image projections along the specified directions through a cluster of line integrals along parallel lines in this direction. The distance between the parallel lines is usually one pixel.

Histogram of Oriented Gradients (HOG). HOG has been used traditionally as a description method in the field of object detection. It was initially described by [4]. They used it in people detection tasks. However, there are several works in which this description method has been enhanced, such as [19], who improve the accuracy and the computational cost.

The basic implementation consists in dividing the image into small connected cells and the histogram of gradient orientations is calculated in each cell. Then, the descriptor is composed by arranging of these histograms in a single vector.

Fernandez et al. [5] analyze this kind of descriptor in outdoor localization tasks. Furthermore, they make a comparative analysis between several methods to describe outdoor panoramic images.

2.2 POC (Phase Only Correlation)

In this subsection we present the method we use to compare the Radon transform of two images.

POC (Phase Only Correlation), proposed in [10], is an operation made in the frequency domain that provides a correlation coefficient between two images [9]. In our case we compare two Radon transforms but this does not affect the POC performance because the Radon transform can be interpreted as an image. In general, it permits obtaining both the relative orientation between two different Radon transforms and a similitude coefficient between them, as shown in [2].

The correspondence between two images $im_1(i,j)$ and $im_2(i,j)$ calculated by POC is given by the following equation:

$$C(i,j) = \mathcal{F}^{-1}\left\{\frac{\mathbf{IM}_1(u,v)\cdot\mathbf{IM}_2^*(u,v)}{|\mathbf{IM}_1(u,v)\cdot\mathbf{IM}_2^*(u,v)|}\right\} \tag{5}$$

Where $\mathbf{IM}_1$ is the Fourier transform of the image 1 and $\mathbf{IM}_2^*$ is the conjugate of the Fourier transform of the image 2. $\mathcal{F}^{-1}$ is the inverse Fourier transform operator.

To estimate the distance between two images we have used the following expression:

$$dist(im_1, im_2) = 1 - max\{C(i,j)\} \tag{6}$$

$max\{(C(i,j)\}$ is a coefficient that takes values in the interval $[0,1]$ and it measures the similitude between the two images.

This operation is invariant against shifts along the i and j axes of the images. Furthermore, it is possible to estimate these shifts Δ_i and Δ_j along both axes by:

$$(\Delta_i, \Delta_j) = argmax_{(i,j)}\{C(i,j)\} \tag{7}$$

If we compare the Radon transforms of two omnidirectional images using POC, the value Δ_i is proportional to the relative orientation α of the robot when capturing the images according to Eq. (8).

$$\alpha = \frac{\Delta_i \cdot 2\pi}{N} \tag{8}$$

This way, POC is able to compare two images independently on the orientation and it is also able to estimate this change in orientation.

2.3 Optimization Algorithm: G2O

G2O is an optimization algorithm described in [11]. This method was created for optimizing graph-based nonlinear error functions.

In the field of SLAM, the robot has to calculate its pose when it takes every new image with respect to the previous poses included in the map. This operation has an error associated that increases in each pose calculation, so we need to correct the poses to decrease this deviation. G2O is able to recalculate each pose of the map using new pose restrictions. One of these restrictions can be obtained when loop closures between one pose of the existing map and the new pose of the robot occur. Then, G2O relocates each pose of the map gradually modifying them to fulfill the loop closure restriction. Then, the new pose is located in the same position than the equivalent pose stored in the map.

3 Movement Direction Estimation in a SLAM Method

In this section, we present our visual approach to estimate the movement direction of the robot inside a visual SLAM method. The robot goes through the environment and captures a set of images from some positions. Every time a new image arrives, the robot includes a new node inside the map. This map is formed by nodes. Then, the SLAM problem is solved, following these three steps:

First, the robot calculates two descriptors of the image: the Radon transform and the HOG descriptor; and stores them in the node. Then, the robot creates a new node and locates it inside the map calculating the position and orientation of the new node with respect to the previously added node, and both nodes are connected. This localization process is carried out by using only visual information.

Second, the robot checks the existence of possible loop closures comparing the new scene with the previous scenes stored in the map.

Finally, the map is optimized by using the G2O algorithm with the loop closures detected. This process is repeated in each new location. These steps are detailed in the next subsections.

3.1 Creating the Map

This subsection presents the method proposed to calculate the coordinates of each new node with respect to the previous one. The pose of the new node is estimated by calculating the distance, the orientation change and the movement direction. With this purpose, the Radon and the HOG descriptors of the omnidirectional images associated with the current and the previous node are used.

Figure 1 shows graphically the mapping process. It consist in calculating the (x_k, y_k) coordinates of each new node. These coordinates are calculated from the distance and the movement direction between poses.

The distance between consecutive locations is calculated using the Eq. 6. Which is an image distance, not a metric distance, i.e. this distance is expected to be proportional to the metric distance.

The orientation of the robot with respect to the previous node α_j, is calculated using the Eq. 8.

The calculation of the angle that forms the current node j with the x-axis β_j, is carried out following this process:

First, the robot calculates the orientation change α_j, between this image and the omnidirectional image of the previous node. Taking this orientation change

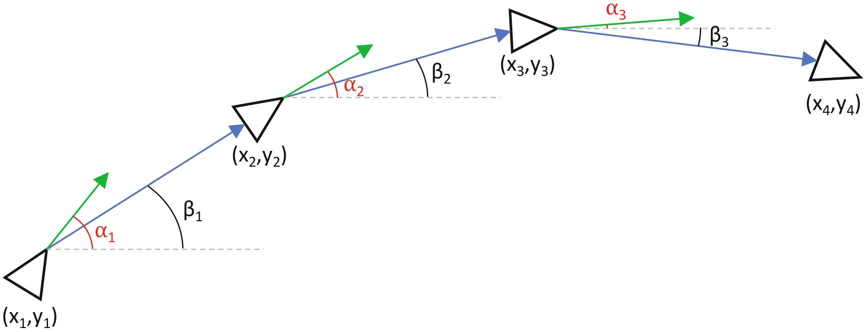

Fig. 1. Mapping process scheme.

into account, the previous image is rotated to have both images orientated in the same direction.

Second, both omnidirectional images are transformed into panoramic views.

Third, SURF features are extracted from both panoramic images and they are matched.

Fourth, the horizontal component of the displacement between matched features of both images is extracted. This 'horizontal displacement' is considered positive if it points towards the right of the image or negative otherwise.

Finally, a set of windows is defined. These windows have M rows and $0.5N$ columns, $W = \{W_1, W_2, ...\}$, which horizontal distance between them is one pixel. The quantity of landmarks with negative displacement inside each window and the number of landmarks with a positive displacement outside is counted, resulting the vector $\boldsymbol{n} = [n_1, n_2, ...]$. The maximum of this vector is extracted ($p_w = argmax(\boldsymbol{n})$). Then, the position p_w permits to estimate the searched angle using the Eq. 9.

$$\beta = \frac{p_w \cdot 2\pi}{N} \tag{9}$$

Figure 2 presents two different panoramic images superimposed, showing the matched SURF features between them. The red lines are the limits of the window of 180°. In that case the window is placed when the condition to calculate the movement direction of the robot is accomplished. It shows that all points inside the window have a negative displacement along the x axis and the points outside this window have a positive displacement along the same axis.

The new node coordinates (x_k, y_k) are calculated by these equations:

$$x_k = dist(im_{k-1}, im_k) \cdot cos(\beta_k) \tag{10}$$

$$y_k = dist(im_{k-1}, im_k) \cdot sin(\beta_k) \tag{11}$$

where $dist(im_{k-1}, im_k)$ is the POC distance between the Radon transform of the two consecutive images, calculated by using the Eq. 3, and β_k is the movement direction angle of the k node 9.

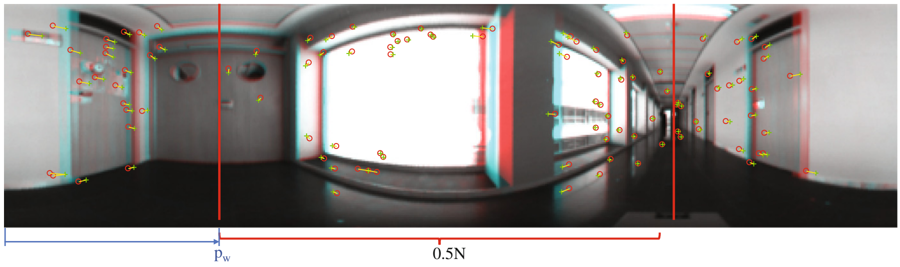

Fig. 2. Matches between SURF features of two consecutive panoramic images of the database.

3.2 Loop Closures

The next step of the algorithm consists in detect loop closures, i.e. comparing the HOG descriptor of the new image taken by the robot with the HOG descriptors stored in the map. To calculate the distance between HOG descriptors we use the cosine similarity between them to calculate the distance:

$$dist(\overrightarrow{d_1}, \overrightarrow{d_2}) = 1 - \frac{\overrightarrow{d_1} \cdot \overrightarrow{d_2}^T}{\sqrt{(\overrightarrow{d_1} \cdot \overrightarrow{d_1}^T)(\overrightarrow{d_2} \cdot \overrightarrow{d_2}^T)}} \tag{12}$$

where $\overrightarrow{d_1}$ and $\overrightarrow{d_2}$ are the HOG descriptors of two different images.

The loop closures have to be determined by defining a maximum threshold of distance, S (Eq. 13). This threshold is defined as a constant in the beginning of the SLAM process. If the distance is lower than this threshold, the two poses compared will be considered as the same location (x, y), but the orientation of the robot can be different.

$$if(dist(\overrightarrow{d_1}, \overrightarrow{d_2}) < S) \rightarrow loop\ closure \tag{13}$$

3.3 Optimization of the Map

Taking the detected loop closures into account, the robot uses this information to optimize the stored map. This optimization is made by using the G2O optimization algorithm.

When the robot detects a loop closure, it has to relocate all previous nodes to reduce the error associated to each node position. This process modifies all the node positions in the map to accomplish the new restriction calculated by the loop closure detection.

The modification of the position of the nodes is made by the G2O algorithm. It receive as input all the node positions of the map and the loop closure restriction. Then, G2O gives as an output the new recalculated node positions.

Therefore, the two nodes of the loop closure are localized in the same position and the coordinates of the rest of the map nodes are modified.

4 Experiments

This subsection presents the set of omnidirectional images used to test our method and the results obtained in these experiments.

4.1 Database

In order to check the performance of the proposed technique, a set of images captured by ourselves is used. This set was captured while the robot followed a tricky path through several rooms inside a building. Figure 3 shows a sample omnidirectional image of the environment.

This database has been created taking one new omnidirectional image every 40 cm approximately. It is formed by 515 omnidirectional images with 1280 × 960 pixels each one. The Fig. 4 shows the omnidirectional acquisition system used to capture the omnidirectional images, formed by the camera (model: DFK-41BF02) and the hyperbolic mirror (model: Eizo Wide70).

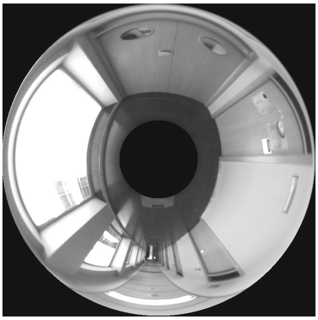

Fig. 3. Sample omnidirectional image of the database environment.

Fig. 4. Omnidirectional acquisition system

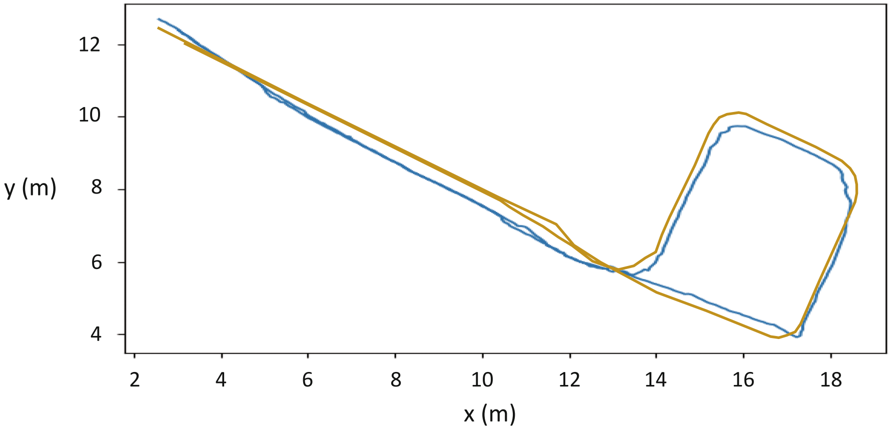

Fig. 5. Map created using the real path. The blue line is the map created using our SLAM algorithm. The yellow line is the ground truth.

4.2 Results

In this section the results of the experiments with our SLAM algorithm are shown. The database described in Sect. 4.1 has been used to carry out these experiments.

The maximum threshold of distance between HOG descriptors (Eq. 12) is an important parameter to tune. To do that, we have made some tests and chosen the best value to detect loop closures. After these tests we consider a threshold equal to 0.006 as a good value of distance between HOG descriptors.

Figure 5 shows the results of the SLAM algorithm after incorporating the final position of the first path. The blue line is the map created using our algorithm. The yellow line is the ground truth.

As for the computational time, the robot spends an average of 0.7 s in each iteration of the SLAM process. This time tends to increase in each iteration because the map is formed by larger amount of nodes and the loop closure detection needs to compare a higher number of HOG descriptors.

5 Conclusions

In this paper we have presented a SLAM method to estimate the position and orientation of a mobile robot in an environment estimating the movement direction of the robot using a method based on landmark extraction. We use two different global appearance descriptors and a method based on SURF features to carry out the SLAM process. The map is formed by these two global appearance descriptors of each image. At last, the algorithm has been tested with a set of images captured in an indoor environment.

The results have demonstrated the accuracy of the method, which is mainly thanks to the method to calculate the movement direction based on the behavior of the SURF features in both images.

The results presented in this paper show the effectiveness of the global appearance descriptors of omnidirectional images to do SLAM thanks to the richness of the information they contain. We are now working to test the method using new databases of different environments. Furthermore, we are implementing a clustering method to reduce the computational time to detect loop closures when the number of nodes considerably increases.

Acknowledgements. This work has been supported by the Spanish Government through the project DPI2016-78361-R (AEI/FEDER, UE) "*Creación de Mapas Mediante Métodos de Apariencia Visual para la Navegación de Robots*".

References

1. Bay, H., Tuytelaars, T., Gool, L.: Surf: speeded up robust features. In: Computer Vision at ECCV, vol. 3951, pp. 404–417 (2006)
2. Berenguer, Y., Payá, L., Ballesta, M., Reinoso, O.: Position estimation and local mapping using omnidirectional images and global appearance descriptors. Sensors **15**(10), 26368 (2015)
3. Chang, C., Siagian, C., Itti, L.: Mobile robot vision navigation and localization using gist and saliency. In: IROS 2010, International Conference on Intelligent Robots and Systems, pp. 4147–4154 (2010)
4. Dalal, N., Triggs, B.: Histograms of oriented gradients for human detection. In: 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2005), vol. 1, pp. 886–893, June 2005
5. Fernández, L., Payá, L., Reinoso, O., Jiménez, L., Ballesta, M.: A study of visual descriptors for outdoor navigation using google street view images. J. Sens. **2016** (2016)
6. Garcia-Fidalgo, E., Ortiz, A.: Vision-based topological mapping and localization methods: a survey. Robot. Auton. Syst. **64**, 1–20 (2015)
7. Hasegawa, M., Tabbone, S.: A shape descriptor combining logarithmic-scale histogram of radon transform and phase-only correlation function. In: 2011 International Conference on Document Analysis and Recognition (ICDAR), pp. 182–186, September 2011
8. Hoang, T., Tabbone, S.: A geometric invariant shape descriptor based on the radon, fourier, and mellin transforms. In: 20th International Conference on Pattern Recognition (ICPR), pp. 2085–2088, August 2010
9. Kobayashi, K., Aoki, T., Ito, K., Nakajima, H., Higuchi, T.: A fingerprint matching algorithm using phase-only correlation. IEICE Trans. Fundam. Electr. Commun. Comput. Sci. **E87–A**, 682–691 (2004)
10. Kuglin, C., Hines, D.: The phase correlation image alignment method. In: Proceedings of the IEEE, International Conference on Cybernetics and Society, pp. 163–165 (1975)
11. Kümmerle, R., Grisetti, G., Strasdat, H., Konolige, K., Burgard, W.: G2o: a general framework for graph optimization. In: 2011 IEEE International Conference on Robotics and Automation, pp. 3607–3613, May 2011

12. Lowe, D.: Object recognition from local scale-invariant features. In: ICCV 1999, International Conference on Computer Vision, vol. 2, pp. 1150–1157 (1999)
13. Payá, L., Amorós, F., Fernández, L., Reinoso, O.: Performance of global-appearance descriptors in map building and localization using omnidirectional vision. Sensors **14**(2), 3033–3064 (2014)
14. Payá, L., Fernández, L., Gil, L., Reinoso, O.: Map building and monte carlo localization using global appearance of omnidirectional images. Sensors **10**(12), 11468–11497 (2010)
15. Radon, J.: Uber die bestimmung von funktionen durch ihre integralwerte langs gewisser mannigfaltigkeiten. Berichte Sachsische Akademie der Wissenschaften **69**(1), 262–277 (1917)
16. Valiente, D., Gil, A., Fernández, L., Reinoso, O.: A comparison of EKF and SGD applied to a view-based SLAM approach with omnidirectional images. Robot. Auton. Syst. **62**(2), 108–119 (2014)
17. Winters, N., Gaspar, J., Lacey, G., Santos-Victor, J.: Omni-directional vision for robot navigation. In: IEEE Workshop on Omnidirectional Vision, pp. 21–28 (2000)
18. Wu, J., Zhang, H., Guan, Y.: An efficient visual loop closure detection method in a map of 20 million key locations. In: 2014 IEEE International Conference on Robotics and Automation (ICRA), pp. 861–866, May 2014
19. Zhu, Q., Yeh, M.-C., Cheng, K.-T., Avidan, S.: Fast human detection using a cascade of histograms of oriented gradients. In: 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2006), vol. 2, pp. 1491–1498 (2006)