Intelligent Haptic Perception for Physical Robot Interaction

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PhD Thesis Dissertation
2020

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UNIVERSIDAD DE MÁLAGA

Doctorado en Ingeniería Mecatrónica
Departamento de Ingeniería de Sistemas y Automática
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EDITA: Publicaciones y Divulgación Científica. Universidad de Málaga

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Málaga, 8 de enero de 2020

....
Dr. D. Jesús Manuel Gómez de Gabriel

....
Dr. D. Alfonso José García Cerezo

To my parents.

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Abstract

The idea of intelligent robots, conceived as the merge of Robotics and Artificial Intelligence (AI) fields, has gained momentum over the last years. The dream of having robots living among us is coming true thanks to the recent advances in these areas. The gap that still exists between that dream and reality will be filled by scientific research, but manifold challenges are yet to be addressed. Handling the complexity and uncertainty of unstructured, real world scenarios is still the major challenge in robotics nowadays. In this respect, novel AI methods are giving the robots the capability to learn from experience and therefore to cope with real life situations. Moreover, we live in a physical world in which physical interactions are both vital and natural. Thus, those robots that are being developed to live among humans must perform tasks that require physical interactions. Haptic perception, conceived as the idea of feeling and processing tactile and kinesthetic sensations, is essential for making this physical interaction possible. This research is inspired by the dream of having robots among us, and therefore, addresses the challenge of developing robots with haptic perception capabilities that can operate in a real, unstructured and physical world. This thesis is based on the application of novel AI methodologies to enhance haptic perception for physical robot interaction problems.

This general concept can be studied from many points of view such us dexterous manipulation, physical Human-Robot Interaction (pHRI) or estimation of humans' intention, among others. This PhD thesis tackles the problems related to physical robot interaction by employing machine learning techniques. In particular, three AI solutions are proposed for different physical robot interaction challenges: i) Grasping and manipulation of humans' limbs; ii) Tactile object recognition; iii) Control of Variable-Stiffness-Link (VSL) manipulators. The ideas behind these research work has potential robotic applications such as search and rescue, healthcare or rehabilitation. This dissertation consists of a compendium of publications comprising as main body a compilation of previously published scientific articles. The baseline of this research is composed by a total of five papers published in prestigious peer-reviewed scientific journals and international robotics conferences. The three challenges aforementioned are critical for physical robot interaction and are addressed in chapters 2, 3 and 4.

Chapter 2 presents two works about human limbs manipulation. A robot capable of directly manipulating the human body has not been developed so far. In this chapter, the study of adaptive grippers and AI-based methods for the robotic manipulation of human limbs is addressed, and validated based on experimental results. Machine and deep learning techniques are applied to this problem to provide a stable grasping of a human forearm, estimating the roll angle of the grasped arm for precise location and safe manipulation, and distinguishing between inert objects and human body parts. The resulting methodologies provide robust and precise grasping, tolerant to location inaccuracy with inexpensive sensors, and a method to identify human body parts by tactile perception only. This is one of the very first works on the robotic human-body manipulation.

In chapter 3, the problem of tactile object recognition is further analysed. Two methodologies based on 2D and 3D Convolutional Neural Networks (CNN) are used for static and dynamic in-hand object recognition. A high-resolution tactile sensor installed at the end-effector of a robotic manipulator is used to collect a dataset composed by pressure images of several objects. In the static case, single pressure images are used, while for the dynamic case, a novel representation of tactile information as 3D tactile tensors is defined. TactNet is presented as a set of 2D and 3D CNN-based architectures designed for tactile object recognition. The different architectures of TactNet are compared to each other and to the most relevant works of the state-of-the-art.

Finally, chapter 4 includes an article that proposes the application of learning-based techniques to enhance position control of VSL manipulators. The integration of variable stiffness elements in collaborative robots allow inherently safe interaction. This way, the performance of VSL manipulators has been previously studied, demonstrating the potential for pHRI tasks and promising safety improvements in the event of unintentional collisions. However, position control of these type of robotic manipulators is essential and challenging for critical task-oriented motions. Traditional model-based kinematics are not able to accurately control the position of the end-effector: the position error increases with higher loads and lower pressures inside the links. Therefore, a hybrid, learning-based kinematic modelling approach is proposed to compensate this error, and then improve the performance of traditional model-based controllers for a modular, collaborative VSL robot.

Resumen

Introducción

Visión general

La robótica y la inteligencia artificial (Artificial Intelligence o AI) son dos de los temas de investigación más relevantes en la actualidad. El concepto de robots inteligentes, o sistemas robóticos inteligentes, ha cogido fuerza en las últimas décadasno solo en la comunidad científica o la industria, si no en la sociedad en general. Sin duda, se ha avanzado mucho en el campo de la robótica industrial en los últimos años, obteniéndose grandes beneficios para la sociedad, pero las aspiraciones actuales en el campo de la robótica apuntan a robots que puedan convivir con humanos, robots asistenciales y colaborativos. ¿Quién no ha soñado alguna vez con un robot que realice las tareas del hogar? Atrás quedaron los típicos robots industriales que aparecen en vídeos de fábricas y cadenas de montaje. La robótica que se investiga y desarrolla hoy en día pretende ir un paso más allá, aspira a cumplir el sueño de tener robots conviviendo entre nosotros.

En este sentido, la inteligencia artificial aplicada a la robótica juega un papel fundamental. Gracias a los avances en inteligencia artificial de los últimos años y, especialmente, el impacto del aprendizaje profundo o deep learning, podemos decir que los robots inteligentes y autónomos son una realidad que tenemos al alcance de nuestra mano. Sin embargo y a pesar de estos avances, aún hay severos desafíos que resolver antes de que veamos robots entre nosotros. Uno de esos grandes desafíos es el estudio de las interacciones de los robots con el entorno. El paradigma de interacción en robótica es, en sí mismo, un concepto muy amplio cuya investigación requiere la división en temáticas más reducidas. En este sentido, esta tesis se centra en el estudio de las interacciones físicas de los robots desde el punto de vista de la percepción háptica. Así, para entender la contribución de esta tesis hay que definir los conceptos de interacción física y percepción háptica.

La interacción física es una forma natural de efectuar tareas compartidas entre humanos, desde corregir movimientos y desplazamientos hasta manipular objetos de forma conjunta. Nos permite realizar tareas complejas y es imprescindible en algunas de ellas como ayudar o guiar a otras personas, o la atención a personas dependientes. Sin embargo, la interacción física en robótica actualmente está muy limitada y no es habitual entre humanos y robots para estos cometidos. El motivo es que para que una interacción de este tipo se lleve a cabo, aún hay muchos campos de investigación abiertos, como diseños de robots ligeros, sistemas de percepción háptica, o la capacidad de predecir las intenciones de los colaboradores humanos, entre otros.

La palabra háptico, del griego ἁπτικός haptikós, hace referencia a aquello que se puede sentir a través del sentido del tacto. En concreto, las sensaciones hápticas se pueden dividir en dos: táctiles y kinestésicas. Las sensaciones táctiles son aquellas que se reciben de forma externa a través del contacto de la piel con el entorno, como temperatura, presión, textura, etc. Por otro lado, las sensaciones kinestésicas son las que se perciben de forma interna y nos permiten, por ejemplo, conocer la posición espacial de nuestro cuerpo o percibir fuerzas. Por lo tanto, definimos la percepción háptica robótica como el conjunto de los sistemas, métodos, y técnicas que permiten a un robot obtener y procesar información a través de sensores que perciben sensaciones hápticas.

Interacción física robot-humano

Dentro del campo de estudio de las interaccones de los robots con el entorno existe un caso particular de gran interés para la comunidad científica: la interacción de robots con humanos (Human-Robot Interaction o HRI). Los sistemas robóticos de interacción con humanos más desarrollados se basan en el estudio de la interacción social entre máquinas y personas, aunque sin contacto (Social Robotics) [1].

Sin embargo, existe un subgrupo dentro del campo de estudio de HRI que estudia las interacciones de los robots con los humanos cuando existe contacto físico entre ellos (physical Human-Robot Interaction o pHRI). En este sentido, los sistemas robóticos que estudian el contacto físico entre personas y robots más comunes consideran métodos de acomodación, control compartido y colaborativo [2], pero no consideran el contacto iniciado por un robot. Este contacto es estudiado desde el punto de vista de sus efectos sociales (Social Touch) [3], aunque los aspectos físicos no son considerados. Podemos encontrar múltiples estudios en el campo de estudio de robótica social desde el punto de vista de la interacción con personas sin contacto [4, 5], como por ejemplo, el acercamiento a las personas de forma amigable. En [6, 7], se estudian los efectos de abrazar y ser abrazado por un robot, encontrándose mejoras sobre la conducta social de las personas.

La interacción física entre robots y humanos es aún muy limitada. Existen sistemas robóticos que actúan en contacto con las personas en tareas de rehabilitación, como prótesis [8] o exoesqueletos [9], que se colocan o instalan en personas, pero no disponemos de sistemas capaces de ayudar a los humanos con robots que actúen sobre nosotros o nos toquen, es decir, que el robot tenga participación activa en la interacción, mediante un contacto físico intencionado. Es por ello que en la actualidad los robots sociales y personales rara vez interactúan físicamente con los humanos con los que trabajan, y requieren extensiva supervisión que puede llegar hasta el control completamente teleoperado.

Las primeras aplicaciones en las que existe contacto físico con robots aparecieron con los dispositivos teleoperadores y de manipulación bilateral [10]. Estos sistemas han resultado en el desarrollo de dispositivos hápticos, que se usan como interfaz para teleoperar o interactuar con entornos virtuales [11]. La gran mayoría de los sistemas robóticos que interactúan con el cuerpo humano están basados en exoesqueletos [12] o en dispositivos especializados que, siguen los movimientos del humano para, por ejemplo, ayudarle a levantar cargas con un menor esfuerzo muscular [13]. No obstante, todas estas aplicaciones son iniciadas por un humano o requieren de una instalación previa de los dispositivos en el cuerpo de la persona.

Por otro lado, podemos encontrar también gran variedad de robots asistenciales, algunos de los cuales están pensados para poder realizar tareas en las que exista contacto físico con las personas. Sin embargo, lo más común es encontrar robots asistenciales semiautónomos de telepresencia cuyo objetivo es ayudar a personas mayores [14, 15]. Estos robots, al no tener brazos, poseen una interacción limitada y no pueden llevar a cabo tareas que requieran interacción física. Gran parte de las aplicaciones de los robots asistenciales limitan su interacción a intercambiar objetos con una persona, como el caso del robot ASIBOT [16, 17], que se emplea para dar de comer o de beber, sin entrar directamente en contacto, o como un sistema robótico asistencial para la colocación de un zapato en el pie de una persona [18]. El robot de asistencia doméstica Care-O-bot 4 [19] posee dos brazos y puede agarrar objetos y colocarlos en una bandeja en la que los intercambia con el usuario.

Dentro del campo de los robots asistenciales, también podemos encontrar robots para ayudar a mover personas como RIVA [20], que ayuda a levantar pacientes de la cama, aunque no sin la colaboración de otras personas. En [21] se presenta una propuesta para robótica de rescate de difícil implementación, en la que se proponen unas garras auto-bloqueantes que podrían ser colocadas por un pequeño robot en las extremidades de una persona en una situación de emergencia, para arrastrarla fuera de la zona de peligro. Entre las escasas aplicaciones de pHRI asistencial en las que un robot toca a un humano, se encuentra un robot para experimentos de limpieza de las extremidades de personas con discapacidad física o de manipulación de las extremidades de humanos con un actuador no prensil [22] y control de impedancia mediante control predictivo basado en modelos [23].

En otros trabajos se están desarrollando efectores finales para aplicaciones con robots asistenciales, como aplicar inyecciones de atropina o morfina, colocación de respiradores, y realización de torniquetes [24]. Aunque existen muchos terminales de fijación especiales [25], es necesario crear herramientas o manos que permitan al robot realizar el agarre automático de manera segura [26], pero con la firmeza suficiente para manejar las extremidades de una persona de forma precisa. En [27] se presentan actuadores de impedancia variable para pinzas de pHRI.

El uso de pinzas adaptativas permite obtener un mejor agarre reduciendo la presión máxima sobre los objetos. Los mecanismos flexibles, sin embargo, reducen la capacidad de manipulación precisa. Existen para ello diseños basados en manos robóticas articuladas subactuadas que se adaptan automáticamente como las del proyecto de código abierto de la Universidad de Yale, OpenHand [28], construibles mediante fabricación híbrida mediante impresión 3D de modelado por deposición fundida (Fused Deposition Modeling o FDM) y moldeado de goma de poliuretano, con unas capacidades de manipulación muy prometedoras. Otros diseños de garras subactuadas poseen una estructura rígida pero adaptable como el sistema PaCome, diseñada para usos industriales que podría adaptarse para pHRI [29]. Sin embargo, este tipo de pinza no se ha utilizado para tareas de pHRI iniciadas por el robot. De hecho, el único estudio encontrado de la interacción entre una pinza robotizada y extremidades humanas es muy reciente [30], y se basa en un análisis de simulación con elementos finitos.

Los casos de pHRI en los que el robot toma la iniciativa e inicia el contacto resultan de gran interés y tienen multitud de aplicaciones. Sin embargo, es un campo que aún está muy inmaduro y prácticamente no existen trabajos debido a la complejidad y a la cantidad de problemas que aún hay que resolver. En esta tesis se presentan contribuciones al diseño de pinzas adaptativas y subactuadas para el agarre y manipulación de las extremidades humanas utilizando técnicas de inteligencia artificial y percepción háptica, con aplicaciones directas a la robótica asistencial y robótica de rescate.

Percepción táctil en robótica

Al igual que ocurre con los seres humanos [31], las interacciones físicas en robótica, incluyendo tareas de manipulación, exploración háptica o pHRI, se deberían poder llevar a cabo incluso cuando los objetos no están a la vista del robot, sin perjudicar la destreza con la que se realizan. De hecho, se ha demostrado científicamente que, en comparación con otros sentidos como el oído o la vista, el tacto es más relevante cuando se trata de procesar las características superficiales y la forma de los objetos [32]. Sin embargo, llevar a cabo este tipo de tareas utilizando visión únicamente, sin percepción háptica, implicaría trabajar en un entorno estructurado o tener modelos áltamente robustos del entorno. Desafortunadamente, el mundo real es muy desestructurado y difícil de predecir, y no se puede pretender conocer con total exactitud, especialmente en los entornos habitados por seres humanos [33] en los que la interacción física es esencial.

El sentido del tacto es una fuente de información irremplazable para los seres humanos. Como se ha explicado anteriormente, los humanos percibimos información de diversos tipos a través del sentido del tacto como presión, vibraciones o temperatura, entre otras, que nos permiten percibir el entorno para poder realizar funciones básicas en el día a día y evitar posibles lesiones [34]. En este sentido, es esencial que los robots dispongan de un avanzado sentido del tacto para poder interactuar físicamente con el entorno, tanto para evitar contactos no intencionados, como para poseer información para tareas como la manipulación de objetos. Por lo tanto, es necesario investigar nuevos métodos basados en el desarrollo de algoritmos de inteligencia artificial y sensores táctiles para poder controlar las interacciones físicas. En las últimas décadas, se han desarrollado diversas soluciones en cuanto a sensores y algoritmos de percepción táctil [35–37]. Los sensores táctiles existentes se pueden clasificar de múltiples formas según la magnitud a percibir [38], los métodos de fabricación empleados [39] y los principios de transducción [40].

De entre todas las opciones disponibles, el uso de sensores táctiles basados en matrices de sensores de presión es uno de las más extendidos [41]. Este tipo de sensor permite obtener imágenes de presión de las superficies en contacto, lo que ofrece múltiples posibilidades a los investigadores en cuanto al desarrollo de robots que puedan explorar, reconocer y manipular objetos. Dentro de los sensores matriciales de presión, existen varios sensores táctiles comerciales, como el sistema TactArray de Pressure Profile Systems (PPS) [42], el sistema sensorial de Tekscan [43], y los sensores táctiles multimodales BioTac de SynTouch [44]. También existen otros tipos de sensores táctiles en desarrollo como es el caso de los sensores GelSight [45] o TacTip [46].

El procesamiento de los datos táctiles obtenidos mediante sensores matriciales de presión suele estar inspirado en técnicas de visión por computador de extracción de características, donde cada unidad sensorial, también conocida como tactel, sensel o taxel, se trata como un píxel de una imagen [47, 48], de ahí que la salida del sensor sea denominada imagen táctil o imagen de presión. Los datos extraídos de las imágenes de presión contienen información sobre la forma, características de los materiales, y posición y orientación del objeto respecto del sensor. La forma de tratar esos datos extraídos de las imágenes de presión depende de la tarea, y son de gran utilidad para tareas de manipulación de objetos [49], detección de deslizamientos [50] o control y estabilidad del agarre [51].

El desarrollo de métodos para la interpretación y extracción de características a partir de imágenes de presión no está tan extendido en la literatura, en comparación con el avance de la tecnología de sensores táctiles. La evolución de dichos sensores unido a los avances tecnológicos en unidades de procesamiento gráfico (Graphics Processing Unit o GPU) y los avances científicos de los algoritmos de deep learning, establecen un entorno ideal para aplicar técnicas de deep learning al procesamiento de imágenes de presión. En este bloque de la tesis nos centramos en el desarrollo y aplicación de este tipo de métodos para el reconocimiento táctil de objetos. En concreto, se presentan contribuciones con dos enfoques a este problema: i) reconocimiento táctil estático, es decir, utilizando una única imagen de presión; ii) reconocimiento táctil dinámico o activo, en el que se utiliza un conjunto de imágenes obtenidas a lo largo del tiempo conforme el agarre se realiza.

Robots seguros de rigidez variable:

Dentro del campo de estudio de aplicaciones pHRI, podemos encontrar también trabajos en el que se desarrollan sistemas robóticos seguros para que, en el caso de que haya una colisión no intencionada, no se produzcan lesiones sobre la persona. Los casos más comunes son aquellos en los que el robot realiza una acomodación de sus movimientos (compliance) gracias al control de impedancia [52] o de admitancia [53] según el tipo de robot, que le permite controlar la fuerza de interacción con el entorno [54]. Existen métodos que adaptan los parámetros de dicha impedancia [55] en función del tipo de movimiento o prediciendo los desplazamientos [56], para seguir y ayudar al humano.

En los últimos años se ha incrementado el interés en un nuevo campo de la robótica que persigue el desarrollo de estructuras y materiales para robots inherentemente seguros. Es decir, que aunque se disponga de técnicas como las descritas anteriormente, en caso de fallo y posible colisión no intencionada, el daño producido por el robot hacia la persona sea el mínimo posible. En este sentido, las características más deseadas para este tipo de robots es que sean flexibles, blandos o de dureza variable. Actualmente podemos encontrar diversos enfoques a este problema: desde robots que son completamente blandos [57], hasta robots completamente rígidos con articulaciones o actuadores que presentan comportamientos elásticos [58], pasando por robots flexibles tipo serpiente [59]. De entre los más prometedores y recientes estudios de investigación en robótica se encuentra el desarrollo de robots manipuladores blandos inherentemente seguros [7, 60].

La robótica blanda promete grandes avances en las aplicaciones de la robótica a tareas que antes eran impensables, he ahí el incremento del interés en este campo. Actualmente se pueden encontrar múltiples estudios que presentan manipuladores construídos con silicona, plásticos deformables u otros materiales blandos que permiten a un robot alcanzar posiciones y orientaciones complejas [61], realizar movimientos con todo el cuerpo de forma continua [62] y movimientos articulares con estructuras simples [63].

La mayoría de robots que se basan en estructuras de silicona se mueven mediante el uso de actuadores neumáticos, de forma que tienen una serie de cámaras de aire que pueden ser actuadas de forma independiente [64] o conectadas en forma de red [65]. En este sentido, al aumentar y disminuir la presión en las cámaras se produce una deformación de la estructura de silicona y, por tanto, se produce un movimiento a lo largo del cuerpo del robot. El principal inconveniente de este tipo de actuación es la deformación máxima que puede soportar la estructura del robot al aumentar la presión interna de las cámaras. Como consecuencia, la fuerza máxima y la rigidez que puede tener el robot también está limitada. Asimismo, al estar la rigidez máxima limitada, el problema de control de posición de este tipo de robots es muy complejo, especialmente cuando se aplican fuerzas externas que producen grandes deformaciones y suponen grandes errores de posición.

Para contrarrestar estos errores, se han presentado varias contribuciones a un nuevo concepto de robot blando con elementos neumáticos de presión variable [66, 67]. La idea consiste en disponer de una estructura interior de silicona recubierta de una capa externa de material poco elástico. El objetivo de esta última capa es minimizar las deformaciones de la capa interna de silicona al no permitir que esta se deforme. Siguiendo con esta línea de investigación, se han publicado trabajos más recientes en los que se presenta un nuevo tipo de eslabón inflable para robots manipuladores basado en estructuras de silicona cuya rigidez se puede controlar mediante actuadores neumáticos [68]. En un trabajo posterior, los mismos investigadores presentaron el primer prototipo de un robot manipulador antropomórfico construído con esta tecnología, denominada desde entonces Eslabones de Rogidez Variable (Variable Stiffness Link o VSL) [69]. Sin embargo, pese a las mejoras introducidas por los VSL, los problemas del control de posición en este tipo de robots aún no se ha resuelto. Aunque se hayan reducido los errores de posición debido a fuerzas externas, éstos aún son demasiado grandes como para que este tipo de robot pueda ser empleado en aplicaciones reales. Por tanto, en esta tesis se presentan contribuciones al control de robots basados en VSL.

Contribuciones

Dentro del amplio abanico de problemas y desafíos descritos anteriormente, la presente tesis aborda el estudio de los contactos físicos de los robots con su entorno haciendo uso de técnicas de inteligencia artificial. En concreto, las contribuciones de esta tesis se pueden dividir en tres bloques, y se presentan de esta forma en los capítulos 2, 3, y 4.

- **Métodos para interacción física robot-humano:** Esta contribución se centra en el desarrollo de interfaces robóticas inteligentes para aplicaciones de pHRI en las que el robot realiza un contacto físico sobre la persona de forma intencionada. Presentándose así técnicas para el agarre, la manipulación y las recolocación de las extremidades humanas superiores para personas tumbadas utilizando pinzas subactuadas; y mejoras en la percepción de pinzas adaptativas para el reconocimiento táctil de objetos y personas.

- **Percepción táctil robótica:** Estudio de métodos de inteligencia artificial basados en el uso de redes neuronales convolucionales profundas (*Convolutional Neural Network - CNN*, o *Deep Convolutional Neural Network - DCNN*) para clasificación de objetos utilizando únicamente sensores táctiles. Se presentan así dos casos: Por un lado el uso de las CNNs 2D, que permiten extraer características de las imágenes táctiles de forma estática y, por otro lado, el uso de las CNN 3D, que permiten extraer información temporal conforme se lleva a cabo el agarre.

- **Control de robots con elementos neumáticos de presión variable:** El uso de robots blandos, inherentemente seguros, es de especial interés cuando se producen colisiones no intencionadas. Sin embargo, el control de posición de estos robots es una tarea compleja. Este capítulo presenta el desarrollo de los modelos cinemáticos para el control en bucle abierto de robots antropomórficos basados en VSL, combinando técnicas basadas en redes neuronales profundas y basadas en modelos.

Publicaciones que avalan la tesis

En el marco de trabajo de esta tesis, definido por las contribuciones descritas anteriormente, se han publicado los siguientes trabajos:

Revistas

- J.M. Gandarias, Y. Wang, A. Stilli, A.J. García-Cerezo, J.M. Gómez-de-Gabriel, H.A. Wurdemann “Open-loop position control in collaborative, modular Variable-Stiffness-Link (VSL) robots", IEEE Robotics and Automation Letters, 2020.

- F. Pastor, J.M. Gandarias, A.J. García-Cerezo, J.M. Gómez-de-Gabriel, “Using 3D convolutional neural networks for tactile object recognition with robotic palpation", Sensors, vol. 19(24), 5356, 2019. (Q1, T1).

- J.M. Gandarias, A.J. García-Cerezo, and J.M. Gómez-de Gabriel, “CNN-based methods for object recognition with high-resolution tactile sensors," IEEE Sensors Journal, 2019. (Q1, T1).

- J.M. Gandarias, J.M. Gómez-de Gabriel, and A.J. García-Cerezo, “Enhancing perception with tactile object recognition in adaptive grippers for human–robot interaction," Sensors, vol. 18, no. 3, p. 692, 2018. (Q1, T1).

Conferencias

- J.M. Gandarias, F. Pastor, A.J. Muñoz-Ramírez, A.J. García-Cerezo, J.M. Gómez-de- Gabriel, “Underactuated Gripper with Forearm Roll Estimation for Human Limbs Manipulation in Rescue Robotics", IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2019.

Marco y Evolución de la Tesis

En abril de 2017 comencé mi trabajo como investigador en formación dentro del programa de ayudas para la Formación de Personal Investigador (FPI) del Ministerio de Ciencias y Universidades del Gobierno de España. El trabajo presentado en esta tesis ha sido desarrollado dentro del Grupo de Robótica y Mecatrónica, del departamento de Ingeniería de Sistemas y Automática de la Universidad de Málaga, más concretamente en el marco de los proyectos nacionales FIRST-ROB (DPI-2015-65186-R) y TRUST-ROB (RTI2018-093421-B-100), cuyos objetivos se describen a continuación:

FIRST-ROB: El proyecto FIRST-ROB empieza en el año 2015 y finaliza en 2019, y se centra en el desarrollo y puesta en marcha de un equipo de multi-robots para el apoyo a los equipos de primera respuesta en situaciones de desastre. El equipo está compuesto por vehículos terrestres y aéreos con el objeto de obtener información del estado de la situación, tanto a nivel de entorno con técnicas de fotogrametría o mapas de elevación, como a nivel de víctimas para facilitar la valoración anticipada del estado de salud y la prioridad de atención.

TRUST-ROB: El proyecto TRUST-ROB empieza en el año 2019, y se centra en el desarrollo de sistemas robóticos resilientes y robustos en un equipo heterogéneo de vehículos robóticos que cooperan en escenarios de desastre. En concreto, el equipo está formado por, al menos, dos vehículos terrestres no tripulados (Unmanned Ground Vehicle o UGV), uno de los cuales posee un brazo robótico colaborativo que permite la interacción y asistencia a víctimas, y dos vehículos aéreos no tripulados (Unmanned Aerial Vehicle o UAV), uno de los cuales incorpora un manipulador para la interacción con las víctimas y el entorno.

Los primeros años de doctorado se dedicaron al estudio de técnicas de inteligencia artificial basadas en el uso de redes neuronales y su aplicación a los problemas percepción táctil. En concreto, se pretendía estudiar las interacciones físicas de los robots con el entorno, con el objeto de responder a cuestiones sobre cómo puede un robot obtener información de alto nivel a partir de los contactos, cómo se puede representar y procesar esa información y cuáles son sus aplicaciones. En primer lugar, se probaron y adaptaron distintas técnicas usualmente utilizadas en visión por computador para extracción de características (como los descriptores SIFT y SURF), a la interacción física con sensores táctiles y, más tarde, se desarrollaron métodos para reconocimiento táctil de objetos basados en redes neuronales convolucionales.

Posteriormente, el marco de la tesis se extendió para abarcar el estudio de las interacciones físicas de robots con personas. En este caso, existen dos posibilidades: que el contacto sea no intencionado, o que sea intencionado, teniendo el robot una participación activa en la interacción. Se decidió abordar ambos problemas de forma independiente. En concreto, se han desarrollado métodos para robótica asistencial e interacción con víctimas en situaciones de desastre, debido al carácter de los proyectos a los que se encuentra asociada esta tesis.

El tercer campo temático de esta tesis versa en el estudio de robots blandos o Soft Robotics, uno de los campos de mayor interés para la comunidad robótica en la actualidad. Las contribuciones de este bloque se llevaron a cabo en colaboración el Soft Haptics & Robotics Laboratory del Departamento de Ingeniería Mecánica del University College London (UCL), liderado por el Dr. Helge A. Wurdemann. Dicho laboratorio constituye una referencia en el campo de robótica blanda, habiendo presentado trabajos previos sobre el desarrollo de robots con elementos neumáticos de presión variable. Se llevó a cabo una estancia de investigación de cautro meses en dicho laboratorio. Gracias a dicha estancia, se realizaron aportaciones que se centran en métodos basados en modelos cinemáticos y modelos híbridos que combinan la cinemática con técnicas de aprendizaje profundo para mejorar el control de posición de este tipo de robots.

Además de los trabajos publicados que avalan la tesis, se han publicado otros trabajos y llevado a cabo otras actividades complementarias y colaboraciones que, de una forma u otra, están relacionadas con el trabajo que aquí se presenta. A continuación se enumeran dichas publicaciones y actividades:

Publicaciones

Revistas

- J.M. Gómez-de-Gabriel, J. Ballesteros, J.M. Gandarias, F. Pastor, A.J. García-Cerezo, C. Urdiales, “Sensorless force estimation for human upper-limb manipulation with underactuated grippers", IEEE Sensors Journal, Under review. (Q1, T1).

Conferencias

- F. Pastor, J.M. Gandarias, A.J. García-Cerezo, J.M. Gómez-de-Gabriel, “Grasping Angle Estimation of Human Forearm with Underactuated Grippers Using Proprioceptive Feedback", ROBOT 2019: Fourth Iberian Robotics Conference, Springer, 2019.

- J.M. Gandarias, F. Pastor, A.J. García-Cerezo, J.M. Gómez-de-Gabriel, “Active Tactile Recognition of Deformable Objects with 3D Convolutional Neural Networks", IEEE World Haptics Conference (WHC), 2019.

- T. Sánchez-Montoya, J.M. Gandarias, F. Pastor, A.J. Muñoz-Ramírez, A.J. García-Cerezo, J.M. Gómez-de-Gabriel,“Diseño de una pinza subactuada híbrida soft-rigid con sensores hápticos para interacción física robot-humano", XL Jornadas de Automática, 2019.

- J.M. Gómez-de-Gabriel, J.M. Gandarias, F.J. Pérez-Maldonado, F.J. García-Núñez, E.J. Fernández-García, A.J. García-Cerezo, “Methods for Autonomous Wristband Placement with a Search-and- Rescue Aerial Manipulator", IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2018.

- A.J. Muñoz-Ramírez, J.M. Gómez-de-Gabriel, J.M. Gandarias, J. Cárdenas, J. Molina, A. Mandow,“Uso de Google Classroom como repositorio de robótica práctica: PieroAcademy" XXXIX Jornadas de Automática, 2018.

- F.J. Ruíz-Ruíz, J.M. Gandarias, A.J. Muñoz-Ramírez, A.J. García-Cerezo, F. Pastor, J.M. Gómez-de-Gabriel, “Monitorización de víctimas con manipuladores aéreos en operaciones de búsqueda y rescate", XXXIX Jornadas de Automática, 2018.

- J.M. Gandarias, J.M. Gómez-de-Gabriel, A.J. García-Cerezo, “Tactile Sensing and Machine Learning for Human and Object Recognition in Disaster Scenarios", ROBOT 2017: Third Iberian Robotics Conference, Springer, 2017.

- J.M. Gandarias, J.M. Gómez-de-Gabriel, A.J. Garcia-Cerezo, “Human and object recognition with a high-resolution tactile sensor", IEEE Sensors, 2017.

- J.M. Gandarias, J.M. Gómez-de-Gabriel, A.J. García-Cerezo, “Clasificación de información táctil para la detección de personas", XXXVIII Jornadas de Automática, 2017.

- J.M. Gandarias, A.J. Muñoz-Ramírez, J.M. Gómez-de-Gabriel, “Uso del Haptic Paddle con aprendizaje basado en proyectos", XXXVIII Jornadas de Automática, 2017.

- F. Pastor, J.M. Gandarias, J.M. Gómez-de-Gabriel, “Cinemática y prototipado de un manipulador paralelo con centro de rotación remoto para robótica quirúrgica", XXXVIII Jornadas de Automática, 2017.

- J.M. Gandarias, S. Akbari-Kalhor, J.M. Gómez-de-Gabriel, “Diseno y uso de una paleta háptica para prácticas de teleoperación con simulink", XXXVII Jornadas de Automática, 2016.

Patentes

- J.M. Gómez-de-Gabriel, A.J. MuñozRamírez, J.M. Gandarias, F. Pastor, J. Ballesteros, A.J. García-Cerezo. “Dispositivo, sistema y método de fijación controlable mediante un brazo mecánico," *Solicitud de protección a nivel mundial (paises PCT).*

Otras actividades

Además, se han realizado otras actividades relacionadas con la investigación como la asistencia a talleres o workshops, la asistencia al Third Summer School in Cognitive Robotics en la University of Southern California, la publicación de dos trabajos en progreso o Work-In-Progress (WIP) en el IROS 2018 y IEEE WHC 2019, o la revisión de artículos en las siguientes conferencias internacionales y revistas de prestigio: IEEE Transactions on Haptics (2020), IEEE Robotics and Automation Letters (2020), IEEE Sensors Journal (2018, 2019 y 2020) IEEE/RSJ International Conference on Intelligent Systems and Robots (2018 y 2019), IEEE World Haptics Conference (2019), IEEE International Conference on Robotics and Automation (2020).

Por otro lado, se han llevado a cabo tareas docentes en las siguientes asignaturas: Sistemas Robotizados (2018/2019), Regulación Automática (2019/2020), y Control de Sistemas Ferroviarios (2018/2019 y 2019/2020), del Grado en Ingeniería en Tecnologías Industriales (GITI) y Grado en Ingeniería Electrónica, Robótica y Mecatrónica (GIERM). Asimismo, se han cotutorizado 6 Trabajos de Fin de Grado (TFG) en dichos grados.

Organización de la Tesis

Esta tesis está organizada en 5 capítulos. En el capítulo 1 se presenta una introducción global al tema de investigación, las contribuciones y actividades realizadas durante la tesis, y la estructura de la misma. En los capítulos 2, 3, y 4, se encuentran las tres principales contribuciones referentes a métodos para interacción física robot-humano, percepción táctil en robótica, y control de robots con eslabones inflables de dureza variable, respectivamente. Finalmente, en el capítulo 5 se describen las conclusiones globales de la tesis y las líneas de trabajo futuro.

Conclusiones

En esta tesis se han abordado distintos problemas relacionados con las interacciones físicas en robots. Los contribuciones introducidas por la presente han sido publicados en revistas y conferencias internacionales de prestigio. El uso de métodos de percepción háptica basados en algoritmos de inteligencia artificial es el hilo conductor de los trabajos que se han presentado. En concreto, se han usado estos métodos para llevar a cabo tareas de reconocimiento táctil de objetos tanto estático como dinámico, para desarrollar aplicaciones de pHRI en las que un robot puede manipular y recolocar las extremidades superiores de una persona y reconocer si está agarrando una parte del cuerpo deseada o no, y finalmente, mejorar el control en bucle abierto de robots VSL. A continuación se describen las conclusiones individuales de los trabajos presentados.

- En el capítulo 2 se presentan dos trabajos sobre aplicaciones de pHRI para la manipulación de las extremidades superiores de personas. El primer trabajo expone métodos para el agarre y la recolocación del brazo de una persona que se encuentra tumbada. Utilizando técnicas de inteligencia artificial y los sensores propioceptivos de una pinza subactuada, un robot es capaz de realizar un agarre estable y manipular el brazo de una persona tumbada. El segundo trabajo presenta la integración de métodos de percepción táctil y pinzas adaptativas para pHRI. Se comparan pinzas rígidas, semirígidas y flexibles con sensores táctiles para la manipulación de objetos y extremidades humanas y se discute, en función a resultados experimentales con datos reales, qué tipo de pinza es mejor para cada situación y tipo de objeto.

- En el capítulo 3 se presentan dos trabajos. Por un lado, se ha presentado el uso de redes neuronales convolucionales de dos dimensiones para reconocer objetos utilizando únicamente sensores tácitles, obteniéndose índices de reconocimiento superiores a la mayoría de trabajos del estado del arte. Aunque ha sido difícil llevar a cabo esta comparación debido a la variedad en el tipo de sensores y datos, se ha presentado una discusión que sitúa el trabajo en el estado del arte. A pesar de los buenos resultados obtenidos, las CNNs de dos dimensiones no permiten utilizar toda la información obtenida durante el agarre e impide obtener altos índices de clasificación con objetos blandos o de dureza variable. Por este motivo se ha presentado un segundo trabajo en el que se describe el uso de CNNs de a lo largo del tiempo que utilizan toda la infromación táctil obtenida durante el agarre para clasificar objetos muy similares, y mezclando objetos rígidos con objetos blandos. En ese trabajo, además, se comparan los resultados obtenidos con los métodos presentados en el trabajo anterior, demostrando que las CNNs 3D obtienen mejores resultados, especialmente cuando se tienen pocos datos de entrenamiento o se trata con objetos blandos o con rigidez variable.

- En el capítulo 4 se presentan mejoras en los sistemas de control, de actuación y sensoriales de un robot VSL. Se han implementado dos métodos para el control de posición en bucle abierto de este tipo de robots, uno basado en los modelos cinemáticos tradicionales de robots antropomórficos y otro híbrido, que mezcla el modelo anterior junto con algoritmos de deep learning. Los resultados demuestran que los errores de posición son considerablemente mejores al empleaar un modelo híbrido frente al modelo cinemático tradicional. Además, se demuestra que los errores de posición cuando se utiliza el modelo híbrido en un robot VSL son menores que los obtenidos por un robot de las mismas características pero completamente rígido.

Se puede decir que la interacción física de los robots con el entorno es uno de los grandes desafíos de la robótica hoy en día, especialmente cuando esa interacción se produce entre humanos y robots. Sin embargo, para habilitar el uso de robots que ayuden en las tareas diarias o a personas con discapacidad, se debe profundizar en este campo de estudio.. A pesar de los recientes avances, alguno de los cuales se presentan en esta tesis, aún queda un largo recorrido para cumplir ese sueño, y a continuación se exponen algunos problemas que aún se tienen que resolver:

- Integración de técnicas de percepción visual con percepción táctil. Existen multitud de trabajos que se centran, o bien en percepción visual, o bien en percepción táctil, pero los trabajos que utilizan y fusionan ambos tipos de información son menos comunes.

- Diseño de pinzas sensorizadas basadas en robótica blanda. Existen muchos trabajos y proyectos que están trabajando en el desarrollo de manos robóticas blandas o flexible, los cuales se centran en investigar mecanismos de actuación que permitan controlar esas pinzas, sin embargo, muy pocos se centran en desarrollar los sistemas sensoriales.

- Desarrollo de métodos e interfaces para pHRI. A pesar de los avances en robótica e inteligencia artificial y los beneficios que puede tener para la sociedad, el campo de pHRI está prácticamente inexplorado, especialmente en los casos en que un robot interacciona con una persona de forma intencionada.

- Implementación de robots VSL en aplicaciones reales. El primer paso para poder utilizar este tipo de robots en aplicaciones reales consiste en construir robots con un mayor número de grados de libertad y de mayor tamaño. Además, es necesario reducir los efectos dinámicos de este tipo de robots, ya sea mediante el uso de modelos dinámicos, diferentes estructuras de los enlaces o ambos.

ACKNOWLEDGMENTS

First and foremost, I would like to express my special appreciation and thanks to my supervisors, Prof. Jesús Gómez de Gabriel and Prof. Alfonso García Cerezo. They wisely guided and inspired me through all of the stages of my PhD. Alfonso, thanks for your support and trust. Jesús, thanks for being my mentor and supervising me throughout my Bachelor, Master, and PhD studies. This work was only possible thanks to your support. Your sharp supervision and advises have been invaluable.

This PhD has also been possible thanks to the amazing working environment in our laboratory at the University of Málaga. I have to mention Manuel Castellano, Dahui, Manuel Toscano, Fran, Juan, Pablo, Manuel Sánchez, Javier, Antonio, Ricardo and Gonzalo, thanks for being that amazing. I would like to thank all the professors and researchers of the Systems Engineering and Automation Department for their help and advises. I would also like to thank Prof. Helge Wurdemann, for his valuable comments and recommendations on my work. For inviting me to stay at the University College London and make me feel at home. I will always remember farmers' market on Thursdays with Erin, Yongjing and all the amazing people from UCL.

Undoubtedly, there is a special place for Curro here. I know you from long time ago. You have always been there in good and bad moments, and I cannot tell you how grateful I am. Your friendship and trust is invaluable. Of course, I would not be here if I had not met Dani. I always say that I passed my BS thanks to you. Now, I can also say that I became a Doctor thanks to you. Thanks for your advice, and for always putting me in the right direction.

I would like to thank my family and friends for being there. I would like to thank my parents and sister for all their trust and unconditional support. I am who I am because of you. Helena, you know how sharp was this mountain better than anyone. You have been there with me in every single moment, and I could not have made it without your support. I will be eternally grateful to you. I love you.

Finally, I would like to thank Angela Faragasso and Klaus Janschek for their valuable comments and reviews, and to the members of the Jury, Anthony Mandow, Aníbal Ollero, and Manuel Fernández for helping in the evaluation of this Doctoral Thesis.

Juan M. Gandarias
Málaga, March 2020

This thesis was partially supported by the European Commission under grant agreement BES-2016-078237, and by the Spanish projects FIRST-ROB: Multi-Robot System for Cooperation with First Response Human and Canine Rescue Teams in Catastrophe Scenarios (DPI2015-65186-R) and TRUST-ROB: Towards Resilient UGV and UAV Manipulator Teams for Robotic Search and Rescue Tasks (RTI2018-093421-B-I00), funded by the Spanish Government.

Chapter 1

Introduction

1.1 Motivation and Bachground

Robotics and Artificial Intelligence (AI) are two of the most relevant research topics nowadays. The concept of intelligent robots, or intelligent robotic systems, has gained momentum over the last decade, not only in the scientific community or industry, but in society. Undoubtedly much progress has been made in the field of industrial robotics in recent years, obtaining great benefits for society, but current aspirations in the field of robotics aim to develop robots that can live among humans: social and collaborative robots. Who has not ever dreamed of having a robot that performs household tasks? Classic industrial robots for factories and assembly lines are past. The robots that are being researched and developed today are to go one step further, they are aimed to fulfill the dream of having robots living among us.

This way, the application of AI techniques to robotics plays an important role. Thanks to the advances in AI in the last years and, especially to the impact of deep learning, intelligent and autonomous robots are a reality today. In spite of these advances, there are still several challenges to address before we can see robots around us. One of them is the study of robotics interactions with their environment. The topic of robotic interactions constitutes such a broad concept that it is to be split in smaller technical problems to research about. This thesis focuses on the study of physical robot interaction from the point of view of haptic perception. Hence, to understand the contributions of this work, the concepts of physical interaction and haptic perception have to be defined.

Physical interactions are a natural way to carry out shared tasks between human beings, from adapting movements and displacements to manipulate objects in a collaborative way. It offers high possibilities in behalf of helping, training or guiding people, and is essential in many tasks such as healthcare or rehabilitation. However, physical robotic interactions are still limited, and it is not usual between humans and robots for this kind of tasks. To realize successful physical interactions between humans and robots, manifold challenges are yet to be addressed, namely the design of light robots, haptic perception systems, or the ability to predict human intentions.

One can categorize the active participation of a robot's interaction based on whether the contact was intentional or not. This work addresses both cases independently. On the one hand, intentional situations have been less studied by the robotics community despite the potential applications to the fields of assistance robotics, search and rescue, or rehabilitation. This way, collaborative robots are a revolutionary advance for healthcare robotics and physical Human-Robot Interaction (pHRI), since they integrate safety restrictions and allow the existence of a shared workspace with humans. Collaborative robots can also be used to carry out tasks in which the robot intentionally touches or manipulates a human. On the other hand, in the event of an unintentional collision, safety is even more critical than in the previous case. In this respect, the integration of soft and variable stiffness elements in robots' structure promises improvements that cannot be achieved by traditional rigid robots. However, current position control methods for these types of robots are yet too primitive for real applications. Practical solutions for this problem are to be found before considering the use of these robots in industrial environments.

The word haptic can be defined as every aspect that is related to the sense of touch. In particular, haptic sensations are divided in two groups: tactile and kinesthetic. Tactile sensations are those perceived through the skin such as temperature, pressure, textures, etc. Kinesthetic sensations are those that are perceived internally and allow us to know the spatial configuration of our body or to sense forces. Therefore, robotic haptic perception is conformed by the set of systems, methods and techniques that allow a robot to perceive and process information through artificial haptic sensors. Haptic perception is essential for robotics as long as it is for human beings. Carrying out complex manipulations tasks dexterously requires advanced haptic perception capabilities. The integration of AI methods and tactile sensing in robots' hands is an open challenge that promises great advances in robotic manipulation problems.

1.2 Objectives and Aims

Many challenges related to this research are yet to be solved, and addressing all of these challenges in one particular thesis is impracticable, e.g., Figure 1.1 summarizes several of these challenges in a pHRI task. Within the wide range of the aforementioned challenges, this thesis addresses the study of haptic perception methodologies for physical robot interaction using AI methods, which forms the connecting link of the contributions of this dissertation. Hence, this thesis contributes to several of these problems according to the aims proposed below.

1. Development of intelligent robotic systems for intended, physical interactions between robots and humans. In particular, considering those situations in which a robot has an active role. This thesis aims to develop adaptive grippers, considering rigid and flexible

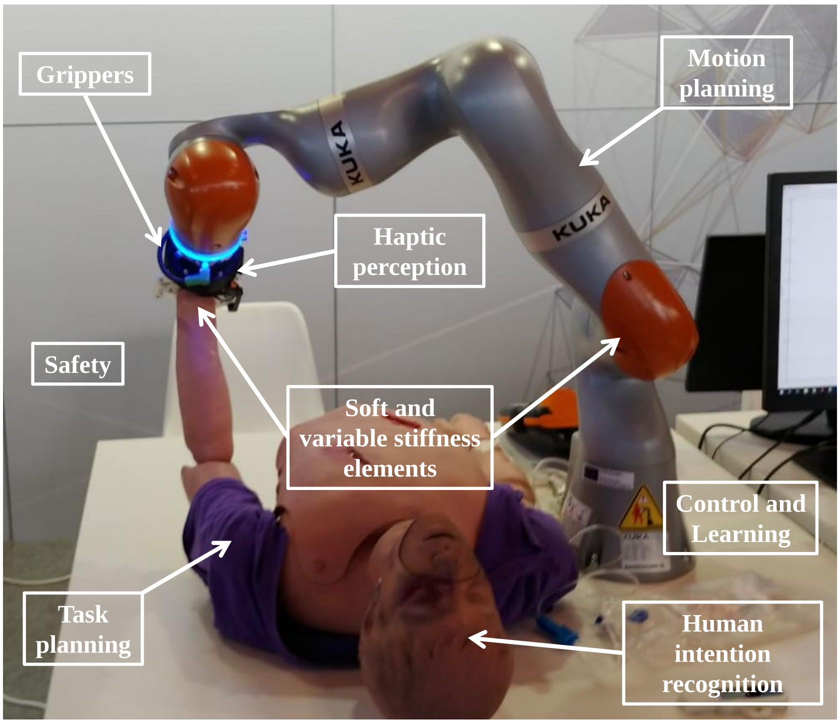

Figure 1.1: Representation of several problems and challenges related to physical robot interaction. The picture was taken during the European Robotics Forum (ERF2020) held in Malaga in March 2020. The author of this thesis participated in a demonstration of pHRI in collaboration with the robotics company KUKA.

materials, and AI-based methodologies for safety and autonomous manipulation of human limbs.

2. Enhancement of robotic tactile perception capabilities. Touch sense is essential for manipulation and other tasks that requires physical interactions. In fact, human beings are able to manipulate and distinguish objects using tactile sensations only. However, providing robots with artificial touch sense is still a challenge that has not been solved. This thesis focuses on designing AI methods to classify grasped objects.

3. Development of robotic manipulators for pHRI that can cope with unintentional collisions, and can be used in real tasks. The integration of inflatable, Variable-Stiffness-Links (VSL) in robotics manipulators improves safety in the event of a collision. However, the performance of traditional model-based controllers is not good enough for task-oriented motions. This thesis aims to develop novel control methods that outperforms traditional controllers and makes these robots suitable for real applications.

1.3 Contributions

The contributions of this thesis are split in the three main categories presented in chapters 2, 3, and 4.

- **Methods for physical Human-Robot Interaction (pHRI):** This contribution focuses on the development of intelligent robotic interfaces for pHRI applications in which a robot makes intentional physical contact with a person. This thesis contributes to this topic with two works. The first work is described in section 2.2 and presents methods for grasping, manipulation and relocation of the upper human limbs for people lying down using underactuated grippers are presented. The second work (section 2.3) focuses on the enhancement on haptic perception of adaptive grippers for distinguishing between human and inert objects.

- **Tactile perception in robotics:** The study of AI methods based on Convolutional Neural Networks (CNNs) or Deep Convolutional Neural Networks (DCNNs) for object classification using tactile sensors only. Two contributions are included: i) The use of 2D CNNs to extract features from a single tactile image (section 3.2); ii) The use of 3D CNNs to obtain temporal tactile information while a robot grasps an object (section 3.3).

- **Control of Variable-Stiffness-Link (VSL) robots:** This thesis contributes to the problem of position control of VSL robots. Section 4.2 presents the development and integration of hybrid kinematic models for open-loop control of VSL anthropomorphic robots combining traditional model-based kinematics and deep learning.

1.4 Publications that support the thesis

This PhD thesis consists of a compendium of publications in the frame of the contributions of this work. The references of these publications are included below along with a comment to describe the author contributions to each work.

1.4.1 Journal articles

- J.M. Gandarias, Y. Wang, A. Stilli, A.J. García-Cerezo, J.M. Gómez-de-Gabriel, H.A. Wurdemann “Open-loop position control in collaborative, modular Variable-Stiffness-Link (VSL) robots", IEEE Robotics and Automation Letters, vol. 5(2), pp. 1772-1779, 2020. [70]

  The author’s contributions are as follows: Conceptualization of the idea, validation of the research and methodology, software and electronics, visualization of the results, and writing of the different versions of the manuscript.

- F. Pastor, J.M. Gandarias, A.J. García-Cerezo, J.M. Gómez-de-Gabriel, “Using 3D convolutional neural networks for tactile object recognition with robotic palpation", Sensors, vol. 19(24), 5356, 2019. (Q1, T1). [71]

  The author’s contributions are as follows: Conceptualization of the idea, validation of the research and methodology, software, experimentation, visualization of the results, and writing of the different versions of the manuscript.

- J.M. Gandarias, A.J. García-Cerezo, and J.M. Gómez-de Gabriel, “CNN-based methods for object recognition with high-resolution tactile sensors," IEEE Sensors Journal, vol. 19(16), pp.6872-6882, 2019. (Q1, T1). [72]

  The author’s contributions are as follows: Conceptualization of the idea, validation of the research and methodology, software and dataset creation, experimentation, visualization of the results, and writing of the different versions of the manuscript.

- J.M. Gandarias, J.M. Gómez-de Gabriel, and A.J. García-Cerezo, “Enhancing perception with tactile object recognition in adaptive grippers for human–robot interaction," Sensors, vol. 18(3), pp. 692, 2018. (Q1, T1). [73]

  The author’s contributions are as follows: Conceptualization of the idea, validation of the research and methodology, software and dataset creation, experimentation, characterization of the gripper configurations, and writing of the different versions of the manuscript.

1.4.2 Refereed conference articles

- J.M. Gandarias, F. Pastor, A.J. Muñoz-Ramírez, A.J. García-Cerezo, J.M. Gómez-de- Gabriel, “Underactuated Gripper with Forearm Roll Estimation for Human Limbs Manipulation in Rescue Robotics", IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2019. [74]

  The author’s contributions are as follows: Validation of the research and methodology, software and dataset creation, experimentation, visualization of the results, and writing of the different versions of the manuscript.

1.5 Research Activities and Timeline

In November 2016, this thesis is conceived and takes off within the framework of the Robotics and Mechatronics Group [1] at the Department of Systems Engineering and Automation o the University of Málaga. During this time, and in addition to the articles that support this thesis, other publications, complementary activities and collaborations have been carried out in the

[1]https://www.uma.es/robotics-and-mechatronics/

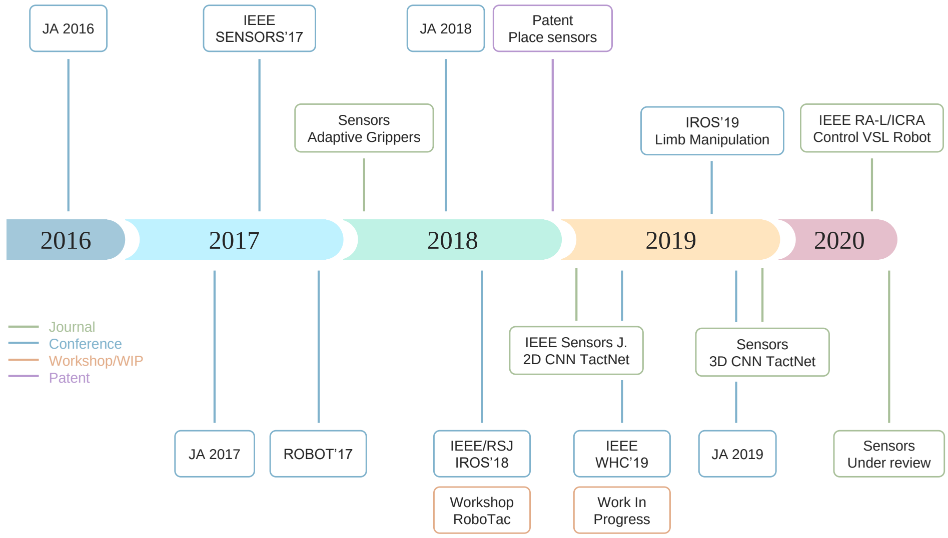

Figure 1.2: Timeline of the research achievements of this thesis.

bosom of this work. A summary of these activities are listed below, and a graphical timeline including all the research achievements is shown in Figure 1.2.

1.5.1 Other Publications

1.5.1.1 Journal articles

- J.M. Gómez-de-Gabriel, J. Ballesteros, J.M. Gandarias, F. Pastor, A.J. García-Cerezo, C. Urdiales, "Proprioceptive estimation of forces using underactuated fingers for pHRI tasks", Sensors, Under review. (Q1, T1).

1.5.1.2 Refereed conference articles

- F. Pastor, J.M. Gandarias, A.J. García-Cerezo, J.M. Gómez-de-Gabriel, "Grasping Angle Estimation of Human Forearm with Underactuated Grippers Using Proprioceptive Feedback", ROBOT 2019: Fourth Iberian Robotics Conference, Springer, 2019. [75]

- J.M. Gandarias, F. Pastor, A.J. García-Cerezo, J.M. Gómez-de-Gabriel, "Active Tactile Recognition of Deformable Objects with 3D Convolutional Neural Networks", IEEE World Haptics Conference (WHC), 2019. [76]

- T. Sánchez-Montoya, J.M. Gandarias, F. Pastor, A.J. Muñoz-Ramírez, A.J. García-Cerezo, J.M. Gómez-de-Gabriel,"Diseño de una pinza subactuada híbrida soft-rigid con sensores hápticos para interacción física robot-humano", XL Jornadas de Automática, 2019. [77]

- J.M. Gómez-de-Gabriel, J.M. Gandarias, F.J. Pérez-Maldonado, F.J. García-Núñez, E.J. Fernández-García, A.J. García-Cerezo, "Methods for Autonomous Wristband Placement with a Search-and- Rescue Aerial Manipulator", IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2018. [78]

- A.J. Muñoz-Ramírez, J.M. Gómez-de-Gabriel, J.M. Gandarias, J. Cárdenas, J. Molina, A. Mandow,"Uso de Google Classroom como repositorio de robótica práctica: PieroAcademy" XXXIX Jornadas de Automática, 2018. [79]
- F.J. Ruíz-Ruíz, J.M. Gandarias, A.J. Muñoz-Ramírez, A.J. García-Cerezo, F. Pastor, J.M. Gómez-de-Gabriel, "Monitorización de víctimas con manipuladores aéreos en operaciones de búsqueda y rescate", XXXIX Jornadas de Automática, 2018. [80]
- J.M. Gandarias, J.M. Gómez-de-Gabriel, A.J. García-Cerezo, "Tactile Sensing and Machine Learning for Human and Object Recognition in Disaster Scenarios", ROBOT 2017: Third Iberian Robotics Conference, Springer, 2017. [81]
- J.M. Gandarias, J.M. Gómez-de-Gabriel, A.J. Garcia-Cerezo, "Human and object recognition with a high-resolution tactile sensor", IEEE Sensors, 2017. [82]
- J.M. Gandarias, J.M. Gómez-de-Gabriel, A.J. García-Cerezo, "Clasificación de información táctil para la detección de personas", XXXVIII Jornadas de Automática, 2017. [83]
- J.M. Gandarias, A.J. Muñoz-Ramírez, J.M. Gómez-de-Gabriel, "Uso del Haptic Paddle con aprendizaje basado en proyectos", XXXVIII Jornadas de Automática, 2017. [84]
- F. Pastor, J.M. Gandarias, J.M. Gómez-de-Gabriel, "Cinemática y prototipado de un manipulador paralelo con centro de rotación remoto para robótica quirúrgica", XXXVIII Jornadas de Automática, 2017. [85]
- J.M. Gandarias, S. Akbari-Kalhor, J.M. Gómez-de-Gabriel, "Diseno y uso de una paleta háptica para prácticas de teleoperación con simulink", XXXVII Jornadas de Automática, 2016. [86]

1.5.2 Patents

- J.M. Gómez-de-Gabriel, A.J. MuñozRamírez, J.M. Gandarias, F. Pastor, J. Ballesteros, A.J. García-Cerezo. "Dispositivo, sistema y método de fijación controlable mediante un brazo mecánico," *Solicitud de protección a nivel mundial (paises PCT).*

1.5.3 Other activities

During this thesis, the author has been granted the chance to participate in several research activities such as the Third Summer School in Cognitive Robotics at the University of Southern California, the publication of two Work-In-Progress papers at IROS 2018 and IEEE WHC 2019, or the participation as reviewer for the following international conferences and scientific journals: IEEE Transactions on Haptics (2020), IEEE Robotics and Automation Letters (2020), IEEE Sensors Journal (2018, 2019 y 2020) IEEE/RSJ International Conference on Intelligent Systems and Robots (2018 y 2019), IEEE World Haptics Conference (2019), IEEE International Conference on Robotics and Automation (2020).

Besides, teaching tasks were realized at the University of Málaga in the following subjects in the field of mechatronics, robotics and automation: Robotic Systems (Sistemas Robotizados) (2018/2019), Automatic Control (Regulación Automática) (2019/2020), and Railway Systems Control (Control de Sistemas Ferroviarios) (2018/2019 y 2019/2020), from the Bs degree of Engineering in Industrial Technologies (Grado en Ingeniería en Tecnologías Industriales or GITI), and the Bs degree in Electronics, Robots and Mechatronics (Grado en Ingeniería Electrónica, Robótica y Mecatrónica or GIERM). Besides, 6 undergraduate students were supervised to accomplish their Bachelor thesis.

1.6 Methodological Frame

The application of machine and deep learning methods to robotics is probably the hottest topic in the field. This aspect is stated in the large amount of publications described by this keyword in flagship conferences such as IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) [87] or IEEE International Conference on Robotics and Automation (ICRA) [88]. The application of these learning techniques to physical robot interaction problems conform the methodological frame of this thesis. This methodology is generally used in other areas such as computer vision, and it is becoming more popular for other fields such as haptic perception. In this thesis, this learning-based methodology have been used to process haptic-based information in the form of tactile images and proprioceptive information measured from sensory systems.

1.6.1 Machine Learning

The term machine learning is defined by the set of algorithms and techniques that refer to the recognition of patterns in data. This methodology has become a powerful tool in any task that requires to extract and process information from datasets [89]. In the terminology of machine learning, the wide concept of learning has branched into three main sub-types: i) Supervised learning; ii) Unsupervised learning; iii) Reinforcement learning. Supervised learning is the most common approach [90], and it is also the one addressed in this thesis. A schematic representation of this approach is shown in Figure 1.3. Models trained under the supervised learning approach learn from experience: A set of labeled data that contains significant information (experience) is used to train a model. This model acquires the expertise and is aimed to predict missing information of unlabeled datasets.

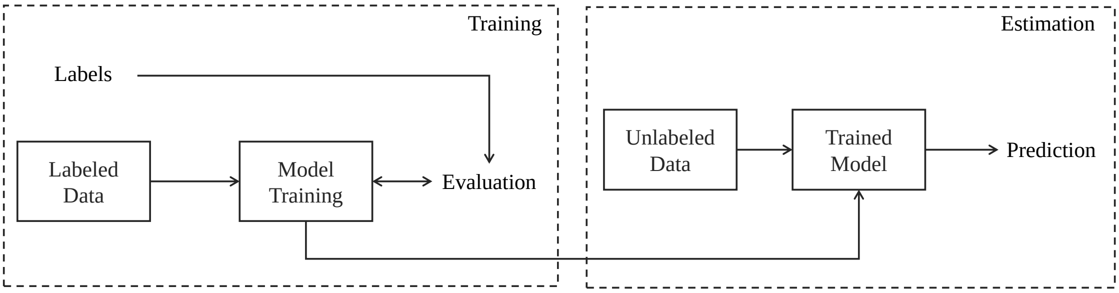

Figure 1.3: Schematic representation of the supervised machine learning methodology.

Machine learning techniques have been used to solve problems from multiple domains such as image classification [91], error modelling [92], bioinformatics [93], or GNSS positioning [94], among others. In this terminology, classification is treated as an instance of pattern recognition, and is also considered an example of supervised learning, i.e., identifying labels of unseen data from experience acquired from previous seen data [95]. On the other hand, regression models aim to predict a continuous value, i.e., estimating the expected value from an input dataset [96]. The publications that support this thesis propose methodologies within the framework of classification (sections 2.3, 3.2, and 3.3) and regression (sections 2.2 and 4.2).

1.6.2 Deep Learning

Deep learning is a specific set of methods and techniques within the broad frame of machine learning. These methods are based on deep artificial neural networks, which are formed by layers of artificial neurons that emulate the behavior of biological neurons. The word “deep" refers to the presence of one or more hidden layers in the model [97].

There are multiple deep learning architectures, such as CNNs, deep belief networks or recurrent neural networks [98]. These models have been applied to a broad variety of fields including computer vision [99], natural language processing [100], or medical image analysis [101], among others. Several deep learning architectures are applied in this dissertation. In particular, chapters 2 and 3 exploit the capabilities of CNNs to classify tactile images.

1.6.2.1 Convolutional Neural Networks

A Convolutional Neural Network (CNN or ConvNet) is a common architecture of deep neural network which is generally applied to process visual information [102]. The word “convolution" refers to the eponymous mathematical operation. CNNs present the same layer-based structures that traditional fully connected neural networks, but using convolutions in place of general matrix multiplication. Generally, the first convolutional layers of the network learn to extract features form input data, while the last layers are usually simple fully connected layers and are used learn to classify these features. This structure can be seen in Figure 1.4, extracted

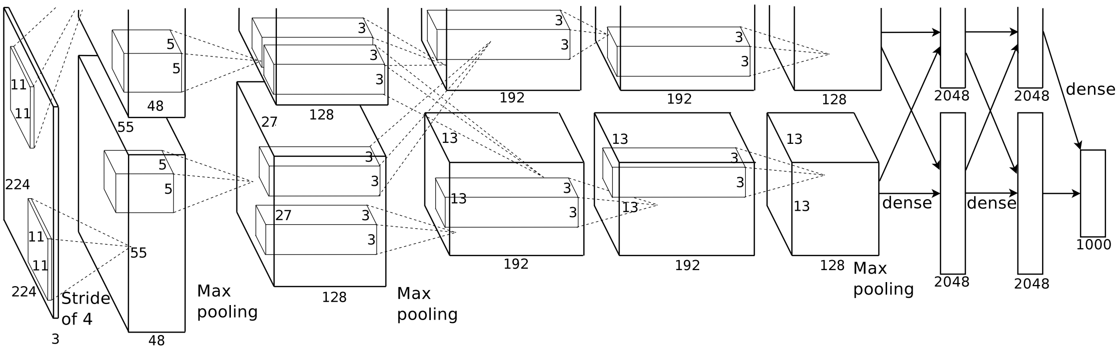

Figure 1.4: Structure of AlexNet. (Source: [99]).

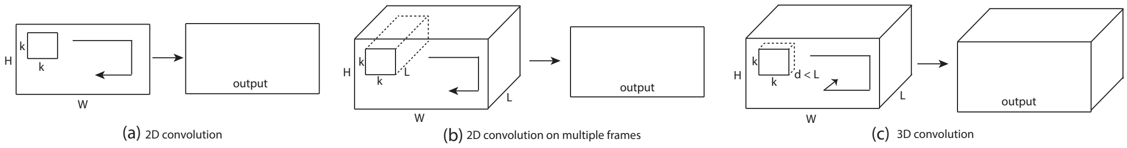

Figure 1.5: Differences of 2D and 3D convolutional layers. (Source: [104]).

from[99], which presents the structure of AlexNet, one of the most popular CNNs. This and other CNN-based structures are used in this thesis in section 3.2.

A particular class of CNNs are 3D CNNs, which were designed to improve the identification of time-series of data and 3D images. A good explanation of the differences between 2D and 3D CNN layers is described in [103]. The different structures of 2D and 3D layers are presented in Figure 1.5, extracted from [104]. Despite of their good performance in many applications such as medical imaging [105] or object recognition [106], they are still an immature technology due to its novelty and complexity. 3D CNNs are used in this thesis in section 3.3 for distinguishing objects by processing series of tactile data acquired during the grasping.

1.6.2.2 Transfer Learning

Transfer learning is a particular technique in the broad family of machine learning. This technique focuses on applying the experience learned while solving one specific task, to a different but related problem [107]. There are three main transfer learning approaches: i) Inductive transfer learning; ii) Unsupervised transfer learning; iii) Transductive transfer learning. This thesis only addresses the latter, which is specially useful when dealing with small datasets. In the terminology of deep learning, it consists of using a neural network previously trained in a specific source domain (S), for a different target domain (T). The schematic representations of transductive transfer learning is presented in Figure 1.6. This idea takes advantage of the particular functions of each part of the network, i.e., the first convolutional layers act as a features extractor ($\mathscr{E}$), while the last fully-connected layers act as a classifier for the source domain ($\mathscr{C}_S$). Then, the

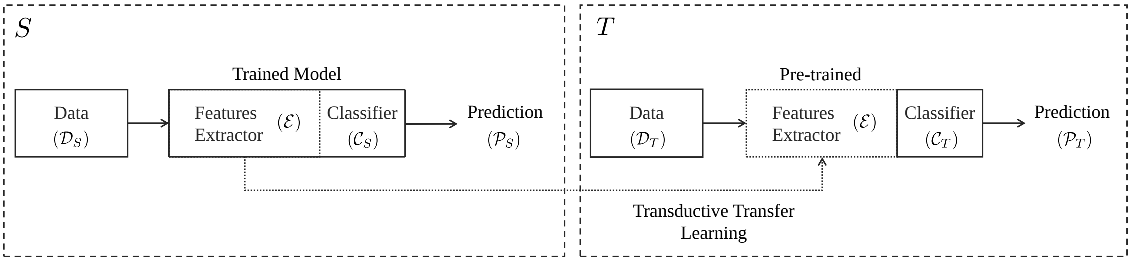

Figure 1.6: Schematic representation of transductive transfer learning.

features extractor previously trained to extract features from the source domain data ($\mathscr{D}_S$), can be used to extract features from a target domain data ($\mathscr{D}_T$). Finally, these extracted features can be processed with a specific classifier ($\mathscr{C}_T$) for the target domain. This thesis exploit this technique (see section 3.2) to use networks that have been trained in large datasets of common images for the tactile object recognition problem.

1.7 Thesis Outline

As represented in Figure 1.7, this thesis is organised in 5 chapters. The main body of this dissertation is formed by a compendium of articles that have been published in prestigious peer-reviewed scientific journals and international robotics conferences.

Chapter 1 gives a general scope to the research topic, and presents the contributions of the thesis, the methodological frame, and the research activities developed during this period.

Chapter 2 presents the contributions to pHRI applications. In particular, this chapter addresses two fundamental challenges of this area: i) Manipulation of human upper limbs; ii) Tactile perception in adaptive grippers for pHRI. The contributions to these problems are respectively presented in sections 2.2 and 2.3.

Chapter 3 further analyses the problem of tactile perception in robotics and includes the contributions to this problem. In particular, the contributions of this chapter face the challenges of tactile object recognition considering both static (section 3.2) and dynamic (section 3.3) cases.

Chapter 4 addresses the problem of position control of VSL collaborative robots. This chapter includes the contribution of this work to this problem.

Chapter 5 summarizes the highlights and the main achievements of this research, as well as the limitations leading to suggestions for future work.

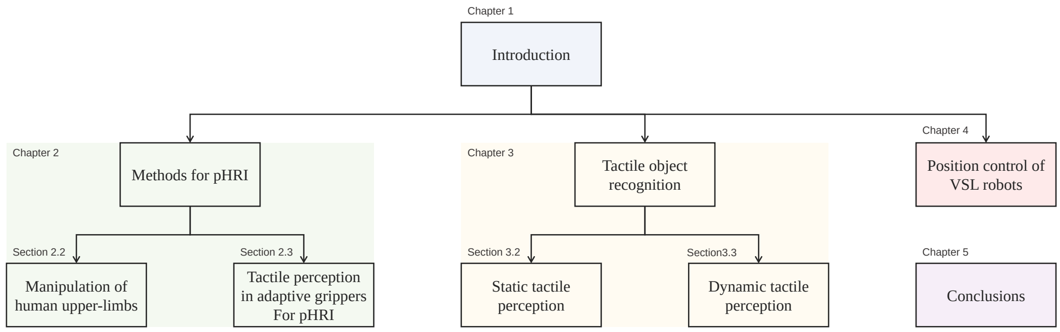

Figure 1.7: Graphical representation of the thesis organization.

CHAPTER 2

METHODS FOR PHYSICAL HUMAN-ROBOT INTERACTION

2.1 Background

Research devoted to interactive robotic systems have been mainly focused on the social human-machine interactions, without incurring on the physical contact [1]. PHRI is a particular and interesting case of Human-Robot Interaction (HRI). Most research studies in this field focus on developing compliance, collaborative and shared control methods [2]. Nonetheless, the study of contacts initiated by the robot remains an interesting niche. This contact is studied from the point of view of the social effects (Social Touch) [3], but the physical aspects of the interaction are not considered. In literature, there are multiple research studies in the field of social robotics from non-contact HRI perspective [4, 5]. These studies often focus on tasks such as approaching people in a friendly way. In [6, 7], the effects of hugging and being hugged by a robot are presented, finding improvements on people's social behavior.

Physical interactions between robots and humans are still very limited. Existing approaches present robotic systems that have physical contact with people for rehabilitation such as prostheses [8] or exoskeletons [9], that are mounted on people. However, there are not solutions based on robots that manipulate people to help them, having an active participation in the interaction through an intentional physical contact from the robot to the human. Therefore, existing social and assistance robots rarely interact physically with people they work with, and extensive supervision or fully teleoperated systems are required.

The first application involving physical contacts between robots and humans appeared with teleoperation devices and bilateral manipulation [10]. These systems have led to the development of haptic devices that are used as interfaces to teleoperate and interact with virtual environments [11]. Most of the robotic systems that interact with human bodies are based on exoskeletonss [12] or special devices that follow the movements of the user to help them to carry heavy loads with low physical effort [13]. Nevertheless, all these applications are initiated by a human or require a previous installation of the systems on the human's body.

Moreover, great variety of assistance robots, some of which are designed to perform tasks with physical contact with people, are found. It is most common to find semi-autonomous telepresence care robots that aim at helping eldery people [14, 15]. These robots do not usually have arms so their interaction capabilities are very limited and are not able to perform tasks that require physical interactions. Many of the applications of assistance robots limit their interaction to exchanging objects with a person, as in the case of the ASIBOT robot [16, 17], which is used for feeding, without coming into direct contact. Another example is introduced in [18], for which a robotic assistant system is used for placing a shoe on a person's foot. The housekeeping robot Care-O-bot 4 [19] has two arms and can grasp and hold objects and place them in a tray where they are exchanged with the user.

Other assistance robots are made to realize actions requiring direct physical contact for helping to move people like robot RIVA [20], that helps to lift patients out of bed with the cooperation of other people. Among the few applications of assistance pHRI in which a robot manipulates a human, there is an experimental robot designed to clean or manipulate human limbs of people with physical disabilities with a non-prensil actuator [22] and Impedance, Model Predictive Control (MPC)s [23].

Other works are developing end-effectors for assistance robots to deliver atropine or morphine injections, placement of ventilators, and implementation of tourniquets [24]. Although there is a large variety of special end-effectors [25], it is still necessary to create tools or hands that allow a robot to perform autonomous gripping safely [26] but firmly enough to handle a person's limb accurately. Variable-impedance actuators for pHRI grippers are presented in [27].

The use of adaptive grippers allows for a better grip by reducing the maximum pressure on the objects. Flexible mechanisms, however, reduce the capacity for precise manipulation. There are designs based on underactuated robotic hands that adapt to the in-hand object automatically, such as those presented in Yale University's open source project OpenHand [28]. These grippers are built by hybrid manufacturing using 3D printing (Fused Deposition Modeling or FDM) and polyurethane rubber moulding, exhibiting promising handling capabilities. Other underactuated gripper designs are based on rigid but adaptive structures as the PaCome system [29], designed for industrial purposes that could be adapted for pHRI. However, this kind of grippers has not been used for robot-initiated pHRI tasks. In fact the only study found about the interaction between a robotic gripper and human limbs is very recent, and is based on a simulation analysis with finite elements [30].

To summarize, those cases of pHRI where the robot takes the initiative and initiates contact are of great interest and have many applications. However, it is a field that is still very immature and there are practically no works due to the complexity and the number of problems that still need to be solved. This chapter presentsthe following contributions to the problems aforementioned:

1. The development of an underactuated gripper and a grasping strategy for manipulating laying people's upper limbs. The design of a two-finger underactuated gripper with two passive joints each proprioceptive sensors is presented. The robot takes advantage of the interaction with the environment to perform a stable grasping of the forearm. Besides, a machine learning method fed by proprioceptive data from the gripper is used to estimate the roll-angle of the grasped arm for precise and safe manipulation.

2. The integration of a flexible tactile sensor in adaptive grippers for object recognition based on CNNs. Three types of grippers (rigid, semi-rigid, and flexible) are evaluated when performing a tactile recognition tasks with a total of 15 classes, including human body parts and inert objects. Finally, a two-level neural network is used to provide both object-type and human/non-human recognition.

2.2 Manipulation of human upper-limbs

Published as:

J.M. Gandarias, F. Pastor, A.J. Muñoz-Ramírez, Alfonso J. García-Cerezo, Jesús M. Gómez-de-Gabriel, "Underactuated Gripper with Forearm Roll Estimation for Human Limbs Manipulation in Rescue Robotics", IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 5937–5942, 2019 DOI: 10.1109/IROS40897.2019.8967953

Abstract

The emergence of new robotic technologies such as compliant control and soft robotics, has contributed to safe physical Human-Robot Interaction (pHRI) mainly for assistive applications. However, a robot capable of directly manipulating the human body, which is key for the implementation of autonomous rescue robots, has not been developed so far. In this section, the development of a gripper and methods for the robotic manipulation of a laying victim's forearm, initiated by the robot is addressed, and validated based on experimental results. An underactuated gripper with added proprioceptive sensors has been designed, with environment sensing and tactile recognition capabilities. This method provides a stable grasping of a human forearm that lays on a surface and is capable of estimating the roll angle of the grasped arm for precise location and safe manipulation. The roll-angle estimation method is based on Machine Learning and has been trained with experimental data obtained from experiments with human volunteers. The resulting method provides robust and precise grasping, tolerant to location inaccuracy with inexpensive sensors. This is one of the very first works on the robotic human-body manipulation.

2.3 Tactile Perception in Adaptive Grippers for pHRI

Published as:
J.M. Gandarias, J.M. Gómez-de-Gabriel, A.J. García-Cerezo, "Enhancing perception with tactile object recognition in adaptive grippers for human–robot interaction", Sensors, vol. 18(3), 692, 2018.
DOI: 10.3390/s18030692

Abstract

The use of tactile perception can help first response robotic teams in disaster scenarios, where visibility conditions are often reduced due to the presence of dust, mud, or smoke, distinguishing human limbs from other objects with similar shapes. Here, the integration of the tactile sensor in adaptive grippers is evaluated, measuring the performance of an object recognition task based on Deep Convolutional Neural Networks (DCNNs) using a flexible sensor mounted in adaptive grippers. A total of 15 classes with 50 tactile images each were trained, including human body parts and common environment objects, in semi-rigid and flexible adaptive grippers based on the fin ray effect. The classifier was compared against the rigid configuration and a Support Vector Machine classifier (SVM). Finally, a two-level output network has been proposed to provide both object-type recognition and human/non-human classification. Sensors in adaptive grippers have a higher number of non-null tactels (up to 37% more), with a lower mean of pressure values (up to 72% less) than when using a rigid sensor, with a softer grip, which is needed in physical human–robot interaction (pHRI). A semi-rigid implementation with 95.13% object recognition rate was chosen, even though the human/non-human classification had better results (98.78%) with a rigid sensor.

CHAPTER 3

TACTILE PERCEPTION IN ROBOTICS

3.1 Background

Physical robot interactions including manipulation, haptic exploration or object recognition, should be able to take place even when objects are not visible. Thus, a robot should be able to perform these tasks without compromising the dexterity, imitating human beings' performance [31]. It has been demonstrated that touch sense is more relevant when processing surface features and shape of objects in comparison to other senses [32]. Renouncing haptic perception solely in favor of vision is possible, although it limits the operability to very structured environments and reliable models of the surrounding [174]. Considering the complexity of predicting real world surroundings and given the limited sensing capabilities of robots, haptic perception is essential, especially in human-inhabited environments [33].

Touch sense is an irreplaceable source of information for human beings. As aforementioned, humans perceive information of diverse nature through sense of touch such as pressure, vibrations or temperature among others. This human capability allows realizing physical contacts with the environment to be able to carry out basic functions in our daily life and avoid possible injuries [34]. Thus, it is indispensable endowing robots with advanced touching sense to physically interact with the environment, to both avoid unintentional collisions and derive additional information. Novel methods based on AI algorithms are to be researched, along with tactile sensors so that physical robot interactions can be controlled. In the last decades, several solutions have been proposed in the fields of sensors and tactile perception algorithms [35–37]. Existing tactile sensors can be categorized in multiple ways depending on different factors such as the sensation to be sensed [38], manufacturing methodologies [39], and transduction principles [40].

Among the available options, the use of tactile sensors based on pressure sensor arrays is one of the most extended [41]. These sensors obtain pressure images from the contacting surfaces, which offers many options to build robots that can explore, recognize and manipulate objects. Some commercial sensors already offer this kind of solution, such as the TactArray system from Pressure Profile Systems (PPS) [42], the Tekscan sensory system [43], or the BioTac multimodal sensors from SynTouch [44]. Besides, other types of tactile sensors that use different technology based on computer vision are currently under development, e.g., GelSight [45] or TacTip [46]).

Processing tactile data obtained from arrays of pressure sensors is usually inspired by computer vision techniques for feature extraction. Each sensor unit –also denoted sensel, tactel or taxel– is treated as a pixel in an image [47, 48], that is the reason why the output of these sensors is called tactile or pressure image. Features extracted from pressure images have information about the shape, material and pose of the object in contact. Processing tactile images is conditioned on the final application, as shown for in-hand manipulation [49], slippage detection and grasp control [50].

The development of methods for interpreting and extracting features from tactile images is not so extended in literature, in comparison with the advanced of tactile sensors technologies. Besides, the last technological breakthroughs on Graphics Processing Units (GPUs) and scientific advances on deep learning algorithms, set an ideal background for processing pressure images. This chapter focuses on the implementation of CNN-based methods for tactile object recognition. In particular, two approaches are proposed: static tactile recognition with a single pressure image and 2D CNNs, and dynamic or active tactile perception using sets of tactile data obtained while a robot grasps an object.

3.2 Static Tactile Perception with 2D CNNs

Published as:

J.M. Gandarias, A.J. García-Cerezo, J.M. Gómez-de-Gabriel, "CNN-based Methods for Object Recognition with High-Resolution Tactile Sensors", IEEE Sensors Journal, vol. 19(6), 6872 - 6882, 2019. DOI: 10.1109/JSEN.2019.29129682

Abstract

Novel high-resolution pressure-sensor arrays allow treating pressure readings as standard images. Computer vision algorithms and methods such as Convolutional Neural Networks (CNN) can be used to identify contact objects. In this section, a high-resolution tactile sensor has been attached to a robotic end-effector to identify contacted objects. Two CNN-based approaches have been employed to classify pressure images. These methods include a transfer learning approach using a pre-trained CNN on an RGB-images dataset and a custom-made CNN (TactNet) trained from scratch with tactile information. The transfer learning approach can be carried out by retraining the classification layers of the network or replacing these layers with an SVM. Overall, 11 configurations based on these methods have been tested: 8 transfer learning-based, and 3 TactNet-based. Moreover, a study of the performance of the methods and a comparative discussion with the current state-of-the-art on tactile object recognition is presented.

3.3 Dynamic Tactile Perception with 3D CNNs

Published as:

F. Pastor, J.M. Gandarias, A.J. García-Cerezo, J.M. Gómez-de-Gabriel, "Using 3D Convolutional Neural Networks for Tactile Object Recognition with Robotic Palpation", Sensors, vol. 19(24), 5356, 2019. DOI: 10.3390/s19245356

Abstract

In this section, a novel method of active tactile perception based on 3D neural networks and a high-resolution tactile sensor installed on a robot gripper is presented. A haptic exploratory procedure based on robotic palpation is performed to get pressure images at different grasping forces that provide information not only about the external shape of the object, but also about its internal features. The gripper consists of two underactuated fingers with a tactile sensor array in the thumb. A new representation of tactile information as 3D tactile tensors is described. During a squeeze-and-release process, the pressure images read from the tactile sensor are concatenated forming a tensor that contains information about the variation of pressure matrices along with the grasping forces. These tensors are used to feed a 3D Convolutional Neural Network (3D CNN) called 3D TactNet, which is able to classify the grasped object through active interaction. Results show that 3D CNN performs better, and provide better recognition rates with a lower number of training data.

CHAPTER 4

CONTROL OF VARIABLE-STIFFNESS-LINK ROBOTS

4.1 Background

Within the field of pHRI applications, a relevant topic is the development of robotic systems that, in the event of an unintentional collision, do not cause injuries to a human. The most common cases are those in which the robot performs an accommodation of its movements (compliance) thanks to impedance or admittance control [52], which allows it to control the force of interaction with the environment [54]. There are methods that adapt the parameters of this general impedance [55] according to the type of movement or predicting the displacements [56] to follow and help the human.

In the recent years, a growing interest towards inherently safe robots is being experienced. This involves the development of new structures and materials that, even in the case of control failure and collision, the harm done is reduced. Hence, the most desirable characteristics for safe robots are to be flexible, soft or with variable stiffness. Currently, one can find a plethora of approaches: from completely soft robots soft [57], through flexible snake-like robots [59], to completely rigid robots with joints or actuators that present an elastic behavior [58]. Among the most promising and recent research studies in robotics is the development of inherently safe soft manipulator robots [7, 60].

Soft robotics promises great advances in the application of robotics to tasks that were previously unimaginable, which has entailed the increased interest of the robotics community in this field. Multiple studies have demonstrated that manipulators built of silicone, deformable rubbers or other soft materials that allow a robot to reach complex poses [61], perform displacements with the whole body continuously [62], and perform joint movements with simple structures [63].

Most of robots based on silicone structures are pneumatically actuated, presenting a series of chambers that can be operated independently [64] or connected in a network [65]. The internal pressure of the chambers increases and decreases, resulting in a deformation of the silicone structure and a movement along the body of the robot. The main disadvantage of this type of actuation is the maximum deformation that the robot structure can tolerate when the internal pressure of the chambers increases. As a consequence, the maximum force and stiffness of the robot are also limited. Besides, since the maximum stiffness is limited, the position control problem of this type of robot is very complex, especially when external forces are applied, which produce large deformations and imply large position errors.

To overcome these errors, several contributions to a new soft robot concept with pneumatic variable pressure elements have been presented [66, 67]. The idea consists on having an inner silicone structure covered with an outer layer of low-elasticity material. The purpose of this outer layer is to minimize the deformation of the inner silicone layer by not allowing it to deform. Following this line of research, a recent works presented a new type of inflatable link for robotic manipulators based on silicone structures pneumatically controllable stiffness [68]. In their next work, the same researchers presented the first prototype of an anthropomorphic robotic manipulator built with this technology, called Variable Stiffness Link (VSL) since then [69]. However, despite the improvements made by VSLs, the position control problems for this type of robot have not been solved so far, and although the position errors due to external forces have been reduced, they are still too large for using this type of robot in real applications. This chapter presents contributions to the control of VSL-based robots. The actuation, control and sensing system of the VSL robot presented in [69] have been improved. Besides, two approaches for open-loop position control are presented: i) traditional, model-based kinematics; ii) hybrid, learning-based kinematics. The hybrid method uses the outputs from the traditional kinematic model to feed a deep learning algorithm that compensates the error produced by high loads and low internal pressures. The performance of the robot is evaluated using both control methods, under different conditions of loads, internal pressures and trajectories.

4.2 Open-Loop Position Control of VSL Robots

Published as:

J.M. Gandarias, Y. Wang, A. Stilli, A.J. García-Cerezo, J.M. Gómez-de-Gabriel, H.A. Wurdemann, "Open-loop position control in collaborative, modular Variable-Stiffness-Link (VSL) robots", IEEE Robotics and Automation Letters, vol. 5(2), pp. 1772–1779, 2020. DOI: 10.1109/LRA.2020.2969943

Abstract

Collaborative robots open up new avenues in the field of industrial robotics and physical Human-Robot Interaction (pHRI) as they are suitable to work in close approximation with humans. The integration and control of variable stiffness elements allow inherently safe interaction: Apart from notable work on Variable Stiffness Actuators, the concept of Variable-Stiffness-Link (VSL) manipulators promises safety improvements in cases of unintentional physical collision. However, position control of these type of robotic manipulators is challenging for critical task-oriented motions. In this section, we propose a hybrid, learning based kinematic modelling approach to improve the performance of traditional open-loop position controllers for a modular, collaborative VSL robot. We show that our approach improves the performance of traditional open-loop position controllers for robots with VSL and compensates for position errors, in particular, for lower stiffness values inside the links: Using our upgraded and modular robot, two experiments have been carried out to evaluate the behaviour of the robot during task-oriented motions. Results show that traditional model-based kinematics are not able to accurately control the position of the end-effector: the position error increases with higher loads and lower pressures inside the VSLs. On the other hand, we demonstrate that, using our approach, the VSL robot can outperform the position control compared to a robotic manipulator with 3D printed rigid links.

Chapter 5

Conclusions

In this thesis, several problems related to physical robot interaction have been addressed. The works presented here have been published in prestigious scientific journals and international conferences. The use of haptic perception methods based on machine learning algorithms is the common thread of these works. In general, these methods have been used to: i) Develop pHRI applications in which a robot can manipulate and relocate humans' upper limbs and recognize whether it is grasping a desired body part or not; ii) Perform static and dynamic tactile object recognition tasks; iii) Improve the open-loop control of VSL robots. The specific outcomes and conclusions of these works have been presented at the end of each section. The general highlights of this thesis are described below.

- Two papers on applications of pHRI for manipulating the upper limbs of people have been presented. The first work has described methods for grasping and repositioning the arm of a person who is lying down. Using AI techniques and the measurements from proprioceptive sensors of an underactuated gripper, a robot is able to perform a stable grasping and manipulate the arm. The second contribution has exposed the integration of tactile perception methods and adaptive grippers for pHRI. The performance of rigid, semi-rigid and flexible grippers with tactile sensors for manipulating inert objects and humans' upper limbs has been compared. A discussion based on experimental results was included to deliberate which type of gripper is more adequate for each situation and type of object.
- Regarding the tactile perception problem, two publications have been included. Firstly, the use of 2D CNNs to recognize objects using only tactile sensors has been presented, obtaining recognition rates higher than most works of the state of the art. Despite the good results obtained, 2D CNNs do not allow to exploit all the information obtained during

the grasping, and prevents obtaining high classification rates with deformable objects. Secondly,the other paper has described the use of 3D CNNs that employs all the tactile data obtained during the grasping to distinguish very similar objects. This work also compared the results obtained with the methods presented in the previous work, showing that 3D CNNs obtain better results, especially when there are little training data or when dealing with deformable objects.

- The control, actuation and sensory systems of a VSL robot were improved. Besides, two methods for the open-loop position control of this type of robot have been proposed: i) traditional kinematic models of anthropomorphic robots; ii) hybrid, learning based modelling, which mixes the previous model together with deep learning algorithms. The results exposed that the position errors when using the hybrid model are much lower than those of the traditional kinematic model. In fact, it has been demonstrated that the position errors when using the hybrid model are lower than when using a robot with the same configuration and size but completely rigid.

One can say that physical robot interaction is one of the most interesting problem in robotics today, especially when that interaction occurs between humans and robots. Despite the recent advances, some of which are presented in this thesis, many challenges are yet to be faced. Below, some promising future research lines based on the outcomes of this thesis are described:

- Integration of visual perception techniques with tactile perception. There are many research studies that focus either on visual perception or on tactile perception, but the synergistic use of both remains almost unexplored.

- Design of sensorized grippers based on soft robotics. Numerous works and projects are developing soft or flexible robotic hands. However, these works are focused on developing actuation mechanism for controlling the gripper, while just a few studies focus on developing sensory systems for soft hands. Integrating tactile perception in soft hands is an important step in this field.

- Development of methods and interfaces for pHRI. Despite the advances in robotics and AI, and the benefits it has for society, the field of pHRI is almost unexplored, especially in cases where a robot interacts with a person on purpose. Novel robotics systems, methods, and applications will be considered in future work for intended pHRI tasks.

- Implementation of VSL robots in real applications. The first step for being able to use VSL robots in real applications is to build robots with higher degrees of freedom and larger sizes. Furthermore, it is necessary to reduce or compensate the dynamic effects of these robots.

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