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Review

Human–robot interaction in agriculture: A survey and current challenges

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Human–robot interaction (HRI) is an extensive and diverse research topic that has been gaining importance in last years. Different fields of study have used HRI approaches for solving complicated problems, where humans and robots interact in some way to obtain advantages from their collaboration. Many industrial areas benefit by applying HRI strategies in their applications, and agriculture is one of the most challenging of them. Currently, field crops can reach highly autonomous levels whereas speciality crops do not. In particular, crops such as fruits and vegetables are still harvested manually, and also some tasks such as pruning and thinning have long been considered to be too complex to automate completely. In addition, several countries face the problem of farm labour shortages. As a consequence, the production process is affected. In this context, we survey HRI approaches and ap-plications focused on improving the working conditions, agility, efficiency, safety, productivity and profitability of agricultural processes, in cases where manual labour cannot be replaced by but can be complemented with robots.

1. Introduction

Precision agriculture (PA) is one of the most important providers of livelihoods and has played a key role in the fight against poverty and hunger (FAO, 2015; Sud et al., 2015). However, according to the latest estimates, approximately 795 million people remain undernourished throughout the world, and 167 million of them correspond to the last decade. These results imply that one in nine people around the world cannot currently consume sufficient food to lead an active and healthy life (Marx, 2015). By 2050, the world population is projected to reach approximately 9.1 billion, which represents 34% more people than at present. Nearly all of this population increase will occur in developing countries. Urbanisation will continue to increase rapidly, and approximately 70% of the world's population will be urban (compared to 49% today). To feed this larger, more urban and richer population, food production must increase by 70% (FAO, 2009).

Currently, the growth rates of crop production have declined markedly in several countries such as the United States, Argentina, Chile and Ecuador (Cook & Frank, 2008; Donoso, 2016; Jokisch, 2002; Newell, 2009). One of the main reasons for this decrease is the migration of the labour workforce to other productive sectors, which affects the agricultural process and rural development. Some of the

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reasons why people migrate from rural to urban sectors are better employment opportunities, working conditions, access to education, social protection, credit, markets, etc (FAO, 2016). However, several studies indicate that a solution could be investing in agricultural research and development, which can generate extraordinary benefits that support and improve the process of eradicating hunger and poverty (FAO, 2009). Finding technological options should be one of the key points to address in the search of sustainable agricultural practises, which can help achieve better productivity and sustainability. If the productive process is improved, then a positive impact on the economy could be expected throughout the market chain, which goes from the producer to the consumer, in addition to the new areas of work that would bring the development and maintenance of these technologies. In this context, robotic solutions could be a key factor to improve crop production. At present, robotic systems are capable of sowing or harvesting in large fields. However, tasks such as harvesting and handling fruits constitute open and challenging problems that are still under study due to their complexity. In this work, the collaboration between humans and robots to face agricultural production process challenges is the main topic of study. In particular, Human–robot interaction (HRI) strategies and approaches in the agricultural field are reviewed. HRI is a multidisciplinary research area that investigates ways to understand, design, and evaluate robotic systems and their interactions with humans.

In this work, the main topic of study is the collaboration between humans and robots to face the challenges of the agricultural production process. In particular, the strategies and approaches of interaction among humans and robots (HRI) in the agricultural field are reviewed. HRI is a multidisciplinary research area that investigates ways of understanding, designing and evaluating robotic systems and their interactions with humans. This paper is aimed at studying the latest developments in HRI strategies applied to agricultural problems. In addition, we focus our analysis on health, safety and economic aspects such as productivity, profitability, and management.

This paper is organised as follows. Section 2 presents a brief review of the technologies used in agricultural robotics. Section 3 briefly describes the principles of human–robot interaction systems. Section 4 presents the human–robot interaction approaches in agricultural applications. Section 5 describes a health and safety perspective on HRI in agriculture. Section 6 presents a productivity, profitability and management analysis. Section 7 presents a classification of the most relevant works regarding HRI in agriculture, and an in-depth discussion of the challenges in this field. Finally, in section 8 conclusions are presented.

2. Robotics in agriculture

Currently, the field of robotic research is still changing and evolving (Boesl & Liepert, 2016). This growth has been possible due to the growing development of sensors, the reduction of equipment costs due to mass production, and the development of innovative control algorithms, computer vision and artificial intelligence, among others (Corollaro et al., 2014; Diels et al., 2016; Donis-González, Guyer, Fulbright, & Pease, 2014; Haff et al., 2013; Hashim, Adebayo, Abdan, & Hanafi, 2018; Kang, East, & Trujillo, 2008). As a result, robotics has been successfully implemented in many agricultural tasks and greenhouse applications, becoming an indispensable tool to reduce the workload and increase the productivity of agricultural processes as stated in (Moorehead, Wellington, Paulino, & Reid, 2010). However, the path that robotics must take to achieve a completely autonomous agricultural process is still long, especially because it requires significant investments, and most of the agricultural processes are complex (Sistler, 1987).

Agricultural robots are typically autonomous or semi-autonomous systems that can be operated in several stages of the process to solve demanding problems. Agricultural robots have been successfully implemented for repetitive tasks, trying to reduce the farmer's workload and optimise process times and costs, such as land preparation (Yaghoubi et al., 2013), water irrigation and spraying (Adamides et al., 2017a,b; Moreno, Cielniak, & Duckett, 2013; Oberti et al., 2013), pruning (Akbar, Chattopadhyay, Elfiky, & Kak, 2016), harvesting (Bac, Henten, Hemming, & Edan, 2014; De-An, Jidong, Wei, Ying, & Yu, 2011; Nuske, Achar, Bates, Narasimhan, & Singh, 2011; Nuske et al., 2011), monitoring and inspection (Corollaro et al., 2014; Donis-González, Guyer, & Pease, 2016; Lunadei et al., 2012; Munera et al., 2017; Pace, Cefola, Renna, & Attolico, 2011; Van Dael et al., 2017) and mapping (Cheein, Steiner, Paina, & Carelli, 2011).

Robots in greenhouse applications generally perform tasks such as grafting and cutting (Hassan, Ullah, & Iqbal, 2016; Van Henten, Bac, Hemming, & Edan, 2013), weeding (Slaughter, Giles, & Downey, 2008), harvesting and transplanting (Van Henten et al., 2013), precision spraying and irrigation (Rengifo & Preciado, 2016), fruit and crop harvesting and detection (Sa et al., 2017; Vitzrabin & Edan, 2016), mapping (Durmuş, Güneş, & Kırcı, 2016), and colour classification (Bergerman, Billingsley, Reid, & van Henten, 2016), among others. In some cases, a multi-purpose flexible robot can perform more than one task in a crop, improving horticultural and flower production (Belforte, Deboli, Gay, Piccarolo, & Aimonino, 2006) and harvesting processes (Arguenon, Bergues-Lagarde, Rosenberger, Bro, & Smari, 2006). To date, there are few commercial robots working on agricultural issues, since the vast majority are still being developed as prototypes (Bergerman et al., 2016).

Other development areas of agricultural robotics that have emerged in recent years are unmanned aerial vehicles (UAVs) or drones (Gogarty & Robinson, 2011). In particular, drones have been used in different applications, such as geographic area monitoring, natural resources mapping and surveying (Conesa-Muñoz, Valente, del Cerro, Barrientos, & Ribeiro, 2016; Krishna, 2016). Drones can be classified as semi-autonomous, autonomous or swarm drones depending on the level of automation. The type of flight craft is an important design selection criterion; examples include fixed-wing craft for applications that require high speed and multi-rotocopters. Agricultural drones are generally used to map natural resources and events using 2D, 3D, thermal or multispectral images of crops, terrain, and weeds, among others. All the information acquired by an unmanned aircraft can be used to monitor crop growth rates and nutrient deficiencies; detect weeds, pests or diseases; map soil and crops; detect and prevent water deficiencies; analyse the soil type and moisture; detect nitrogen deficiency; measure weather parameters; and spray fertiliser and pesticides (see (Krishna, 2016; Zikeli & Gruber, 2017) and the references therein).

The National Science Foundation (NSF) promotes initiatives for research into the next generation of collaborative robots (co-robots) working with human partners. A co-robot must be able to cooperate with people in a variety of applications such as co-workers, co-inhabitants, co-explorers, and co-defenders. According to this vision, co-robots will become useful companions for people in their daily activities and will be found in homes, schools, hospitals, factories, mines, and farms (National Science Foundation, 2017; National Robotics Initiative (NRI), 2014). The analysis in subsequent sections is motivated by the co-robot concept.

3. Human–robot interaction

Human–robot interaction (HRI) is an emerging research field focused on the study of physical, cognitive and social interaction among people and robots, which can extend and improve human capabilities and skills. It is focused on designing, understanding, and evaluating the interaction between humans and robots that can communicate and/or share physical space (Murphy, Nomura, Billard, & Burke, 2010; Yanco & Drury, 2002). The design of human–robot interaction strategies has been a challenging problem, partly because of the human complexity and the large number of different interactions that can be presented. Many approaches have been studied for different applications, such as: humanoids (Kanda, Miyashita, Osada, Haikawa, & Ishiguro, 2008), vehicle navigation (Mead & Mataríc, 2017), rescue robots (Murphy, 2004), assistant robots (Robins, Dautenhahn, Te Boekhorst, & Billard, 2005), and collaborative task robots (Kosuge & Hirata, 2004). HRI is a relatively new field that is still under development, and many of its guidelines and design considerations might depend on the context (Cavallaro, Facal, Pigini, Mast, & Blasi, 2013).

A brief guide to the fundamental aspects of HRI is presented as follows.

3.1. *Metrics in human–robot interaction*

Commonly, each HRI strategy focuses on metrics for its own task or particular model. However, some approaches present general metrics that have been studied for various scenarios (Burghart & Steinfeld, 2008; Olsen & Goodrich, 2003; Pina, Cummings, Crandall, & Della Penna, 2008; Steinfeld et al., 2006), as follows:

- Mission effectiveness: mission performance parameters, such as those presented in (Olsen & Goodrich, 2003; Pina et al., 2008).
- Human behaviour efficiency: attention allocation, problem recognition, decision making, action implementation and efficiencies, among others.
- Human cognitive indicators: accuracy of mental models, situation awareness, mental workload, trust in automation, self-confidence and emotional states.
- Human physiological indicators: physical workload, comfort and fatigue.
- Robot behaviour efficiency: error-proneness, robustness, autonomy, learnability, memorability, self-awareness, human awareness.
- Collaborative metrics: team behaviour action efficiency (coordination efficiency, collaborative problem recognition efficiency, collaborative decision-making efficiency, and collaborative action implementation efficiency), team cognition efficiency (team mental models, team situation awareness, workload distribution, and social patterns and roles) and robot collaboration efficiency.

3.2. *Human–robot interaction design concepts*

HRI concepts provide key strategies to help the designer solve challenging problems in different HRI scenarios (Adams, 2002; Forlizzi, DiSalvo, & Gemperle, 2004; Goodrich & Schultz, 2007; Kahn et al., 2008; Lee et al., 2007). Some of the most used concepts are shown below:

- Level of autonomy (LOA): This concept describes the degree of automation of a robot (Pang, Seet, & Yao, 2014). From an HRI autonomy perspective, one describes the level on which the human and the robot can interact and the degree of autonomy that each human and robot is capable of achieving. Mixed-initiative interaction strategies allow to interact in a flexible manner, in which the human and/or robot intervene when appropriate using the best-suited action. On the direct control side, the problem focuses on designing a user interface that can reduce the operator's cognitive load, but usually depends on the user's decisions, while on the dynamic autonomy side, the efforts are focused on the creation of robots with appropriate abilities and cognitive skills to interact in a natural, fluid and efficient way with their human partner (Durkop, Trsek, Otto, & Jasperneite, 2014; Endsley, 1999; Habib, Pacaux-Lemoine, & Millot, 2016; Sheridan, 2011).
- Nature of information exchange: this concept includes communication channels and protocols.
- Structure of the team: this concept illustrates how many humans and robots interact and their roles in the team.
- Adaptation: this concept studies how humans and robots can directly adapt, train and learn from the interaction.
- Task-shaping: this concept is focused on how the task is done, how it should be done, and how the HRI approach can shape the experience and processes. Examples include goal-directed process, task analysis, cognitive work analysis and ethnographic studies.

3.3. Human–robot interaction taxonomy

The integration of research and studies of HRI has allowed the creation of an HRI taxonomy in the last years (Yanco & Drury, 2002, 2004). Taxonomy categories allow the classification and comparison of various HRI architectures. A brief description of taxonomy categories for HRI is presented as follows:

- Task type: the task should be specified from a system classification point of view: a delivery robot, a rescue robot, a military robot, etc.
- Task criticality: this concept related to the importance of the task to be performed. For example, a robotic wheelchair could fail to detect stairs or any hazardous situation, which could provoke serious accidents. If a critical task is performed incorrectly, the life of a human being could be compromised.
- Robot morphology: it can be anthropomorphic (human-like appearance), zoomorphic (animal-like appearance) or functional (car-like, among others.).
- Ratio of people to robots: it is the relation between number of humans and robots that perform a task, which can be variable within the process.
- Composition of robot teams: it can be homogeneous (several robots of the same type) or heterogeneous (several robots of different types).
- Level of shared interaction: it analyses all the possible configurations of single or multiple humans and robots, acting as individuals or as a team (or various teams).
- Interaction roles: the roles that a human can adopt when interacting with a robot are the following: supervisor, operator, mechanic/programmer, peer, bystander, mentor, or information consumer (Goodrich & Schultz, 2007; Yanco & Drury, 2004).
- Type of human–robot physical proximity: modes of physical proximity such as avoiding, passing, following, approaching, and touching are analysed.
- Decision support: a key aspect to consider is the type of information that is provided to operators for decision support. This can be categorised according to pre-processing, available sensor information, sensor information provided, or type of sensor fusion, among others.
- Time-space taxonomy: it represents whether or not the human and the robot use the computing systems at the same time, the interaction can be synchronous or asynchronous.

3.4. Human factors and cognitive ergonomics

Human factors consider the abilities of humans and robots to develop systems capable of improving performance, safety and user satisfaction (Bouargane & Cherkaoui, 2015). Cognitive ergonomics approaches can improve work efficiency, decrease human error, and help to understand how humans process information during the interactions (Murata, 2000). Cognitive ergonomics are aimed at designing systems to support human mental process based on perception, memory, attention, mental workload, stress and mental models to improve human cognitive capabilities such as awareness, decision making, and problem solving (Bouargane & Cherkaoui, 2015; Tajri & Cherkaoui, 2015). Some of the most relevant parameters studied in human and cognitive factors are reviewed below:

- Mental workload: human workload measures decrease as the level of autonomy increases, which is a key consideration in human–robot interaction systems (Steinfeld et al., 2006).
- Situation awareness (SA): this concept is related to the conscience of the human and robot surroundings and the understanding of what information is useful to perform a task. SA can be separated into three levels: perception of the environment, comprehension of the current situation and projection of the future status (Endsley, 2001; Rossi, Staffa, & Rossi, 2017).
- Trust automation: this term refers to the level of confidence and the expectation that an individual has for the system to perform a particular action if it is required. The quality and fluidity of the interaction in HRI systems depend significantly on the trust level (Billings, Schaefer, Chen, & Hancock, 2012; Hoffman et al., 2009; Patacchiola & Cangelosi, 2016).
- Mental models: these describe how people's comprehension, prediction and problem-solving processes are performed, enabling efficient communication, understanding and collaboration between humans and robots (Bouargane & Cherkaoui, 2015; Goodrich & Schultz, 2007; Nagai, Abe, Nakamura, Oka, & Omori, 2015).

4. Human–robot interaction in agriculture

Currently, most agricultural processes are performed by human-operated machines and some autonomous robots that usually are able to work on large-scale fields. In small and medium agricultural fields, there are applications that are too difficult to be automated completely, and all the efforts in this direction appear to be on a long-term path.

HRI strategies in agriculture could provide solutions to complex problems, providing security, comfort, lower workload, and better process productivity. In particular, the advantages are evident for activities such as the detection of fruits and vegetables, grasping, detaching, and transport procedures (Bechar & Vigneault, 2016). It would appear that a viable solution to the HRI problem in agriculture can be summarised as obtaining models, systems or approaches focused on the interaction between the agents, which can be adapted to the needs of the process and the environment for each activity.

However, it is extremely difficult to model each environment, crop and task. Therefore, HRI strategies should be designed to enable the robot to learn and/or adapt to new tasks and working conditions (Van Henten et al., 2013) and take advantage of the human's and robot's skills to cooperate efficiently.

HRI approaches have been studied from different perspectives: interface de signs (Adamides, 2016; Adamides et al., 2017b,a; Berenstein, Edan, & Ben Halevi, 2012), interaction methods (Berenstein & Edan, 2012) and collaboration models (Oren, 2008), among others. However, the research field of robotics in agriculture is broad, and HRI architectures are still under development.

Some of the most relevant works in HRI are presented below.

The evaluation of different user interface modes for target recognition and spraying tasks from an HRI perspective is studied in (Adamides, 2016). This work presents an interface that allows a human to teleoperate (when necessary) a targeted pesticide-spraying robot, which is illustrated in (Fig. 1). The interface is able to command a robot that navigates along the rows of vineyards. The level of autonomy proposed is a semiautomatic teleoperation, which implies that the robot can work autonomously and remote manually if necessary. The latter can benefit human health since workers are not exposed to pesticides. Three different interface configurations which use a mouse, a Wiimote and a digital pen are proposed, as can be observed in (Fig. 2). Complementary works can be found in (Adamides et al., 2014; Adamides et al., 2017b, 2015; Berenstein & Edan, 2017; Berenstein et al., 2012); these works aim to specify the design guidelines of a user interface for semiautomatic teleoperation of an HRI system for vineyard spraying. Thus, awareness and other design principles for HRI interfaces are studied, such as visibility, safety, simplicity, feedback, extensibility and cognitive load reduction.

Situation awareness for an agricultural robot operator was analysed by (Adamides et al., 2014). It has the following two components: farmer- agricultural robot and agricultural-robot farmer. Farmer-agricultural robot is about the understanding that the farmer has regarding the location, surroundings, activities and status of the agricultural robot. Agricultural-robot farmer is related to the knowledge that the agricultural robot has of the operator status, his/her activities, surrounding limitations, and the possible actions to take in case the human operator requires assistance. In (Reina et al., 2016), a multisensory perception system is presented, whose objective is to increase the ambient awareness of agricultural vehicles that operate in the fields. For this purpose, various sensor technologies such as LiDAR, 6 radar, stereovision and thermography, are analysed. Combinations of them are used to detect obstacles and estimate transversable areas.

A localisation system for a precision agricultural vehicle is tested in tree fruit production processes presented in (Freitas, Zhang, Hamner, Bergerman, & Kantor, 2012), and the corresponding interface and operation concept for effective HRI is described in (Bergerman et al., 2015). In this approach, vehicle position is computed without the use of expensive differential GPS. The localisation algorithm depends only on the wheel steering encoders (odometry) and LiDAR sensors for row following. An extended Kalman Filter is used to fuse the sensors information. The resulting pose estimation tells the vehicle where it is within a crop row, allowing it to autonomously track desired positions in terms of distance along the row and offset from the centreline of the row. This capability forms the basis for three autonomy modes that are used for different types of collaboration between the robot and humans working around it: Mule Mode, Pace Mode, and Scaffold Mode. In all three modes, a simple interface is provided that allows a user to control the vehicle speed, offset from the centreline, and desired stopping intervals. In Mule Mode, a user walking near the robot controls its position in the row through a web-based interface on a hand-held device such as a smart phone. This setup allows the user to easily stop and start the robot so that it follows a team of workers through the field, assisting with tasks such as harvesting. In Pace Mode, a user specifies a speed, row offset, and a set of rows to cover using a web-based graphical interface. Then, the robot autonomously covers the desired area while accomplishing a task such as spraying or crop load scouting. In Scaffold Mode, users standing in the robot control the speed and distance from trees with a simple control panel (Fig. 3) as the robot drives down the row. In Scaffold Mode, a HRI concept is clearly observed because both (human and robot) work as a unified collaborative system, where the vehicle navigates autonomously along the rows of structured trees while humans on the vehicle can focus on performing activities such as thinning, pruning, harvesting, tying trees to wires,

Fig. 1 – Agricultural robot sprayer (Adamides, 2016).

Fig. 2 – Selecting targets using a mouse (left), a Wiimote (up), and a digital pen on a smart interactive whiteboard (right) (Adamides, 2016).

Fig. 3 – Precision agricultural vehicle system: (Left) An operator panel used to intuitively control the speed, row offset, and stopping intervals of an autonomous vehicle as it drives down a row in Scaffold Mode, (Right) Workers performing tree training while standing in an autonomously moving platform. This work was supported by the US Department of Agriculture under the Speciality Crop Research Initiative, award number 2008-51180-04876 (Bergerman et al., 2015; Freitas et al., 2012).

and placing pheromone dispensers. For example, the authors report trials for a tree trimming tasks where humans working on the robot in Scaffold Mode were able to trim trees more than twice as fast as humans using the traditional ladder-based approach.

The design and training of complex systems, such as HRI in agriculture, requires an understanding of the task demands and cognitive factors of the operators. In this context, a qualitative research method developed to inform technology design and training is presented in (Cullen et al., 2012). In such work, knowledge engineering approach is used to evaluate the mowing task in a citrus grove, by creating a work model based on system information and obtaining knowledge from operators, among others. Then, all the information is categorised using diagrams to present the information efficiently. Other works on HRI in agricultural fields use sensors aimed at detecting or estimating the cognitive state of the human operator (Gomez-Gil, San-Jose-Gonzalez, Nicolas-Alonso, & Alonso-Garcia, 2011). In this case, analysis and implementation of non-invasive sensors such as EMG (electromyography) and its performance in the handling of a tractor in the agricultural field are studied. Presented in (Szczepaniak, Tanas, Pawlowski, & Kromulski, 2014) is a driver working in a tractor with a model for a better understanding of the driver-vehicle control system. This work shows that it is possible to adapt the agricultural construction to the psychophysical characteristics of the driver, in order to improve the active safety of the agricultural process.

As shown in (Bechar & Edan, 2003), on average, the use of HRI strategies increased melon detection by 4% compared with manual detection, and by 14% compared with a fully autonomous approach. This means higher detection rates, which are on average, between 94% and 100%. Such results represent a considerable improvement in the limitations of fully autonomous systems, where detection success was on average less than 75%–85%. Additionally, the HRI strategies can achieve detection times 20% shorter than those achieved manually.

Two concepts for human–robot collaboration for spraying applications are presented in (Berenstein & Edan, 2012): human–robot collaboration levels and a spray coverage optimisation function. The human–robot collaboration levels are as follows: fully manual, robot suggests and human approves, robot sprays and human supervises, and finally fully autonomous robot spraying. On the other hand, the spraying efficiency (over grapes and foliage) depends on parameters such as the human operator, the robotic sprayer, the HRI method and the optimisation function. The optimisation function evaluates the profit of the spraying process given the spraying parameters (flowrate and geometry), robot parameters (target detection and navigation), human parameters (fatigue, workload, and awareness), and human–robot collaboration parameters (target marking method and collaboration interface).

Finally, (Tkach, Bechar, & Edan, 2011) presents algorithms designed for real-time dynamic switching (a closed loop is required) for several collaboration levels in an HRI target recognition system. In this particular case, the experiments were performed for melon harvesting. The system performance was evaluated using simulations for different target probability distributions.

Robotic service units that share the workspace and tasks with human workers in agricultural applications are presented in (Cheein et al., 2015). The HRI approach used is flexible automation, which is based on the coexistence of automated and manual operational modes. In such work, robotic service units can navigate, build a map, sense the environment and accomplish a certain task. It is emphasised that the service unit should be capable of interpreting the human intention in order to approach or follow the human and perform a task efficiently. In addition, obtaining and studying human perception is another key factor to achieve a successful flexible automation process.

5. Health and safety

Health and safety are two of the main concerns in industries, especially in places where a person works by manipulating machinery or sharing space with it and thus may endanger his/her physical integrity. The risk of an accident exists when working in agricultural environments. The influence of HRI strategies could significantly contribute to enhancing safety.

5.1. *Safety in human–robot interaction*

HRI techniques can be used to understand the influence of human behaviour and the cognitive factors involved in the occurrence of work accidents. The influence of robots on accidents is also important, as they can perform a series of movements that can be dangerous for nearby humans. To prevent accidents, it is necessary to analyse dangerous situations in which humans suffer injuries (Vasic & Billard, 2013). There are norms to manage safety, such as the International Organisation for Standardisation (ISO) and American National Standards Institute (ANSI). In particular, ISO 10218 and ANSI/RIA R.15.06–2012 provide useful safety guidelines for collaborative robot applications (ISO, 2011). Among the most relevant techniques to manage safety in cooperative applications, the following are found: force-torque sensors with the respective control algorithm, tactile and pressure sensors, the safe maximum allowed speed for the robot (limited to $0.25\ m\ s^{-1}$), proximity sensors, area detectors and cameras to detect a human nearby, and the need for a stop emergency button, among others (ISO, 2011; Vasic & Billard, 2013). In the agricultural context, these norms could be partially applied, but there are still no standards focused on flexible automation environments.

5.2. *Analysis of occupational accidents with agricultural machinery*

Agriculture is the second field (after mining) in which the most work accidents occur in the USA, even much higher than in other areas such as construction or manufacturing (Smith, 2002). The situation is similar in Europe, where in agriculture and forestry in countries such as Austria there is a higher number of accidents than in any other industrial sector (Robert, Elisabeth, & Josef, 2015). The variety of agricultural accident environments and circumstances in which a human can be injured is broad. Accidents such as slipping, falling and losing control of the machine often occur in agricultural applications. The most common workplaces in which accidents occur are farmyards and fields. Moreover, agricultural tillage and harvesting operations have higher accident rates, followed by maintenance and repair work.

The most common accident cause is a collision with a machine or machine part. Finally, the most common cause of accidents with agricultural machinery is related to human factors, followed by machine and environmental factors. Figure 4 summarises the most common accident courses, and Fig. 5 summarises the causes of occupational accidents with agricultural machinery (Robert et al., 2015). These statistical

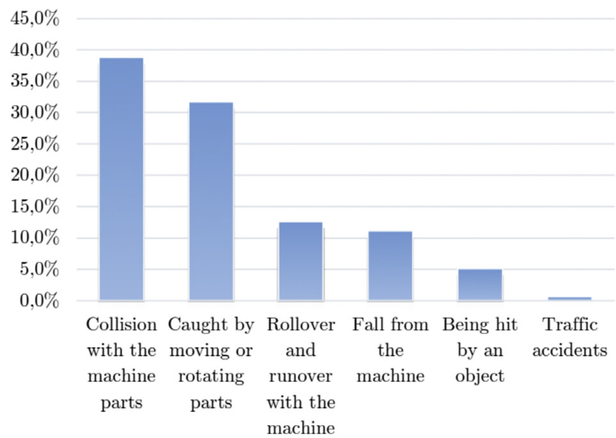

Fig. 4 – Accident causes using machinery in agricultural environments (Robert et al., 2015).

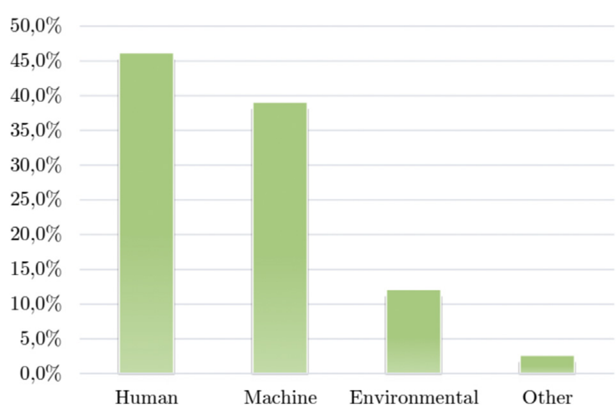

Fig. 5 – Accident causes in agricultural environments (Robert et al., 2015).

results suggest that safety should be a key design consideration in agricultural robotic systems, especially if humans and robots work cooperatively sharing space (Cheein et al., 2015). Additionally, HRI cognitive ergonomics can contribute to understanding human factors such as attention, mental workload, stress, and sleepiness, which can provide valuable information to support humans and improve their cognitive capabilities (Bouargane & Cherkaoui, 2015), which can help to significantly reduce the number of accidents in agricultural environments.

6. Productivity, profitability and management

The need to improve agricultural production in a sustainable manner is urgent in many countries. Even in the most developed, there is a concern about being able to respond to future food demands. For this reason, the main objective of sustainable agriculture is to increase production, to make food accessible and affordable to all people, and to try to minimise as much as possible the environmental impact (Garnett et al., 2013). In this context, robotics in agriculture has been widely used as an efficient tool to increase productivity and reduce operational times and heavy workloads. However, these technological advances should be based on well-founded economic and feasibility studies so that they can be successfully implemented.

6.1. *Autonomous systems perspective*

Economic feasibility studies of autonomous robotic vehicles compared to conventional systems have been realised for various agricultural applications (Pedersen, Fountas, Have, & Blackmore, 2006). The results obtained showed that autonomous machines are more economically feasible (in the medium term) than conventional systems since the former perform tasks more efficiently, improve productivity by working more hours, and reduce the amount of herbicides needed, among other benefits. In (Have, 2004), the effects of automation costs for soil tillage and crop establishment indicated that the initial investment is greater for an automated tractor than for a manual one. Moreover, the labour that is required could be 80% lower, and the robot should be capable of working as long during the day. The analysis also indicates that a shift to automatic control could decrease the tractor's size, whereby the investment could be reduced. However, the final cost of the autonomous equipment will depend on its application, work capacity, and design features, among others. As shown in (Pedersen, Fountas, & Blackmore, 2007), robotic tractors during initial ploughing and ridging can reduce the human labour required by 5 times compared that of a conventional tractor. However, large-scale autonomous robots are not always the best choice, as they are only viable if they work in large agricultural fields. Small and medium-sized farms usually cannot use this technology because of economic and environmental limitations (Pedersen, Fountas, & Blackmore, 2008). Another key factor to analyse is safety criteria, which are usually more demanding for autonomous robots. Such robots need to be sufficiently reliable to operate by itself, which could mean additional development costs. One of the main limitations of autonomous robots for agricultural environments is that they adapt well only to specific and repetitive tasks, and can be very sophisticated; thus, their maintenance and operation might require people with specialised skills and infrastructure for power supply according to the facility, among others (Belforte et al., 2007).

6.2. *Human–robot interaction from an agriculture systems perspective*

Although it is possible to substitute repetitive processes with autonomous systems in large-scale farms, various processes are extremely difficult to fully automate in medium and small farms due to environmental constrains or economic limitations, or simply because the task is too difficult to be automated completely (Pedersen et al., 2008). For example, in the case of harvesting from fruit trees, some of the robots tested are slow and still need sensors and algorithmic improvement to pick fruit properly, and an HRI approach could be feasible for this application (Aloisio, Kumar Mishra, & English, 2012). HRI approaches can also be useful in cases where workers need to handle heavy loads of vegetables and fertilizer bags

(Yaghoubi et al., 2013). In this context, to be a viable solution, HRI strategies must provide a significant improvement in productivity and quality with an overall reduction in costs that justifies their use with respect to manual and automated modes. As an advantage, HRI strategies include a human within the system, which provides additional benefits, such as decision-making corrections and the use of creativity to solve problems efficiently. Another aspect to consider is that in agriculture, many tasks are usually performed during certain seasons of the year, and it may be not affordable to have one particular autonomous robot for a single task. Therefore, HRI strategies could be a viable and economical solution due to their flexibility and adaptability. Such benefits might help to reach multiple task modes, which means making that method profitable versus autonomous solutions for complex applications. HRI approaches should help to reduce the workload needed and the amount of inputs required (energy, fertiliser, and herbicide) in small and medium field activities such as harvesting, planting, fertilising, spraying, and weed control, among others (see (Adamides, 2016; Adamides et al., 2014; Toyama & Yamamoto, 2009)). Moreover, based on specific human behaviours or cognitive measures, the robot should be capable to complement or even replace human labour in risky or complex tasks if the operator is not capable to perform it correctly (Gomez-Gil et al., 2011).

Another area that can benefit from the technologies with HRI is farm management (Fountas et al., 2015). By combining information and communication technologies (ICT) with HRI in agriculture, a management information system capable to obtain and analyse information from humans, machines and their environments could be implemented. The management system should help to identify humans, machines, crops status and even estimate actual and future requirements.

7. Discussion

In this section, the main features of current HRI approaches in agriculture are discussed. It is to be noted that due to the wide range of applications, concepts involved and taxonomy, a comparison among the different HRI architecture becomes critical without proper metrics. Therefore, Table 1 presents the scientific articles published in the last decade and their HRI-related topics. To compare them, five main aspects were considered: general concepts, metrics, design concepts, taxonomy, and human factors. These aspects are the basis of every HRI. Related to agriculture, the works listed in Table 1 cover the following tasks: spraying, harvesting, mowing, and transportation.

As can be observed in Table 1, several works are focused on the interface design with emphasis on the HRI concepts and metrics for teleoperation tasks (Adamides et al., 2014, 2015; Adamides, 2016; Berenstein & Edan, 2017; Adamides et al., 2017b,a). Such works depend on some level of human intervention using an interface to cooperative target-marking for spraying tasks. Concepts such as mission effectiveness, human behaviour efficiency, robot behaviour efficiency, and collaborative metrics are also considered.

These approaches are aimed at improving the agricultural process in tasks that could affect human health.

In (Bergerman et al., 2015; Freitas et al., 2012), humans and robots worked cooperatively in a natural manner and shared the workspace for harvesting applications. In these approaches, the level of autonomy, interaction roles, structure of the team, situation awareness and level of shared interaction concepts are reviewed for each mode configuration. Although such approaches tend to be on the dynamic side in terms of the level of autonomy, which covers collaborative control methods and peer-to-peer collaboration, they still use some type of interface that allow humans to command the robot. Those systems are capable of reducing the human workload and increasing process efficiency.

Models for human–robot collaboration are presented in (Oren, 2008; Tkach et al., 2011; Berenstein & Edan, 2012; Szczepaniak et al., 2014). In particular, in (Szczepaniak et al., 2014), metrics such as mission effectiveness, human and robot behaviour efficiency, and collaborative metrics are reviewed. Although the level of autonomy may vary, these methods depend at some level on an interface for an effective interaction.

In (Cheein et al., 2015), several HRI concepts are analysed for robots that share the workspace with humans, such as social acceptance, human comfort and naturalness. The importance of robot situation awareness and the interpretation of human intentions in order to increase productivity of agricultural tasks is also studied. Additionally, human and robot safety concepts and HRI criteria design are reviewed. However, such considerations should be addressed in future works considering environmental limitations. Situation awareness is also extensively studied in (Reina et al., 2016) using several multi-sensory perception systems and their combinations for autonomous agricultural tasks. Although such approaches can help to detect environment characteristics, in future works, agriculture applications may require extracting more information such as human detection and crop characterisation. In this context, it is important to achieve fast processing times to handle rapid decision-making and avoid accidents.

There are some HRI aspects that are barely analysed or have not been considered yet in the literature, such as human cognitive and physiological indicators, structures of teams, adaptation, task criticality, the ratio of people to robots, the composition of robot teams, the level of shared interaction, decision support, interaction roles, time-space taxonomy, trust automation and mental models. Such considerations could provide meaningful information for future works regarding HRI in agriculture tasks. Moreover, there are many applications that have not been considered yet from an HRI point of view such as land preparation, pruning, monitoring and inspection, greenhouse applications, transplanting and transportation. However, since each environment is complex and has different requirements, it may be necessarily to develop HRI strategies and improve taxonomies for each agricultural process and task. Additionally, HRI concepts should provide guidelines to increase efficiency of agricultural activities. Productivity and profitability studies about how an economic investment are also required for small or medium-sized farms, which may be critical because there are activities that can be done only in certain seasons, and the robotic equipment should not be

Table 1 – Summary of Human–Robot interaction (HRI) in agriculture.

	General concepts					Metrics						Design concepts					Taxonomy										Human factors			
Author	Interface designs	Collaboration models and schemes	HRI concepts	Health and safety	Productivity, profitability and management	Mission effectiveness	Human behaviour efficiency	Human cognitive indicators	Human physiological indicators	Robot behaviour efficiency	Collaborative Metrics	Level of autonomy (LOA)	Nature of information exchange	Structure of team	Adaptation	Task Shaping	Task type	Task criticality	Robot morphology	Ratio of people to robots	Composition of robot teams	Level of shared interaction	Interaction roles	Type of human-robot physical proximity	Decision support	Time-space taxonomy	Human workload	Situation awareness	Trust automation	Mental models
Adamides et al. (2014)	X			X		X	X			X	X		X				S							T	X			X		
Adamides, Christou, Katsanos, Xenos, and Hadzilacos (2015)	X					X	X			X	X		X			X	S							T	X		X	X		
Adamides (2016)	X		X	X		X	X			X	X	X	X				S		X					T			X	X		
Berenstein and Edan (2017)	X					X	X			X	X						S		X					T						
Adamides et al. (2017b)	X					X	X			X	X						S							T				X		
Adamides et al. (2017a)	X						X			X	X	X					S		X					T				X		
Bergerman et al. (2015)	X			X								X		X		X	H		X			X	X	W			X	X		
Freitas et al. (2012)	X				X							X		X		X	H		X			X	X	W			X	X		
Oren (2008)		X				X	X			X	X	X					D							T						
Tkach et al. (2011)		X				X	X			X	X	X					D							T						
Berenstein and Edan (2012)		X	X		X	X	X			X	X	X					S							T			X	X		
Szczepaniak et al. (2014)		X		X			X	X			X						N							W						
Cheein et al. (2015)			X	X	X											X	N						X	W				X		
Reina et al. (2016)				X													N	X						W				X		
Gomez-Gil et al. (2011)	X					X	X	X	X								N							W						
Cullen et al. (2012)			X	X	X								X				M							W						
Bechar and Vigneault (2016)			X	X								X				X	N		X					W			X	X		

X = related information, T = Teleoperation, W = Sharing workspace, S = Spraying, H = harvesting, D = Detection, N = navigation and transport, M = Mowing.

unoccupied the rest of the time. To solve this particular problem, the HRI designs may need to be focused on developing multi-task robots. This can be an opportunity for companies that want to provide agricultural robot services, which could be more profitable than acquiring a group of robots for each farm. However, this will also depend on production costs, which may not be excessive if the assembly becomes serial in the future.

8. Conclusions

A survey of HRI in agricultural applications has been presented, motivated by the need to find a sustainable solution to the lack of labour workforce due to its migration to other productive sectors. HRI strategies can contribute to solve the lack of labour workforce problem to increase productivity and to facilitate heavy work in agricultural activities, such as fruit harvesting, handling heavy crops and fertilizer load bags, and delivering and transporting in shared environments.

In terms of health and safety in agriculture, it was shown that most accidents in which humans and machines interact in agriculture are caused by collisions and human errors. In this context, HRI strategies can be used to mitigate the accident causes. This approach especially useful in situations where humans and robots work cooperatively sharing work space, and thus where it is necessary to avoid collisions, and when it is possible to detect human cognitive factors, which would enable taking preventive actions if humans were not capable to perform a risky task correctly.

In agricultural environments, several HRI approaches have already been implemented. However, the path to take advantage of all of the capabilities of HRI strategies in agriculture is still long. In particular, the flexibility and adaptability of these techniques give them potential to increase productivity and generate a positive economic impact in the near future. Additionally, HRI approaches can contribute to farm management processes by obtaining information from humans, machines and their environment. Such factors might generate opportunities for new technology development companies, which means more solutions to contribute the creation of new market chains ranging from the designer of HRI technologies to the farmer.

A series of considerations based on ISO and ANSI standards for cooperative applications has been analysed, which can be applied partially in HRI agricultural tasks. However, there are still no standards for dynamic interaction in agricultural environments, which can be a challenge for future work.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biosystemseng.2018.12.005.

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