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A Review on Human–Robot Interaction Control Systems

Geku, Diton
Department of Electrical and Electronic Engineering, Federal university otuok, **Nigeria**

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***Correspondence**
Geku Diton

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Abstract

Human-Robot Interaction (HRI) is an evolving field where robots are increasingly integrated into environments requiring close cooperation with humans, such as manufacturing, healthcare, and service industries. The efficiency and safety of these systems are critical, and this paper explores two essential factors: control and safety. Effective control in HRI ensures that robots adapt to human actions and environmental changes, while safety mechanisms prevent harm to human operators. The Virtual Admittance (VA) control system is discussed in the context of enhancing robot responsiveness, where both virtual damping and inertia are adjusted to achieve smoother, more efficient collaboration between humans and robots. The paper also examines collision detection methods, emphasizing model-based and data-driven approaches, to ensure safe interaction between robots and humans. Performance metrics such as task completion time, human effort, accuracy, and system stability are compared across various VA control systems used in co-manipulation tasks. Additionally, the paper reviews safety measures through collision detection, highlighting methods that integrate sensors and neural networks to detect and prevent harmful interactions. By providing a comprehensive analysis of VA control systems and safety mechanisms, this paper offers insights into the advancements and challenges of human-robot collaboration. The goal is to guide future developments in HRI, emphasizing the importance of robust control systems and safety protocols for improving the performance, efficiency, and reliability of these interactions in diverse applications.

Keywords

Human, Robot, Interaction, Control System

Introduction

Human–Robot Interaction (HRI) is an area of growing importance as robots are increasingly being integrated into environments that require close cooperation with humans. This integration is particularly vital in settings like manufacturing, healthcare, and service industries, where robots and humans must work together to complete tasks efficiently and safely. Achieving efficient HRI relies on addressing two critical factors: safety and control. Both factors are not only fundamental to ensuring the performance of these systems but also essential to preventing potential harm to human operators [12,45,25].

The first essential factor in HRI is safety. The introduction of robots into environments where they work alongside humans presents a significant challenge, especially when considering the proximity of humans to robots [23]. Robots are designed to assist in various tasks, yet they also present risks such as collisions, mechanical failures, or unintended movements that could potentially cause injury [12]. Hence, safety mechanisms such as collision detection and avoidance systems must be integrated into the robot's control architecture to safeguard human collaborators. These systems must be robust, reliable, and capable of adapting to dynamic and unpredictable human movements and environmental changes. The second key factor in effective HRI is control [18]. The control systems of robots must be advanced and capable of adapting to human intentions and changes in the surrounding environment. A robot should be able to interpret the operator's actions and adjust its behavior accordingly. This adaptability is crucial in co-manipulation tasks, where both the robot and the human are involved in performing a specific task, such as lifting or assembling parts [25]. To achieve smooth, efficient, and natural interaction, robots must be equipped with control systems that not only follow predefined commands but also learn and adapt to real-time interactions. Advanced control systems like Virtual Admittance (VA) controllers play an essential role in ensuring that robots respond in real-time to the varying forces and motions imposed by human interaction [1].

This paper aims to explore these two vital aspects of HRI: control and safety. The study is presented in two main parts. The first part delves into VA control systems, where the virtual damping, inertia, or both are adjusted to create a safer and more responsive interaction between the robot and its human counterpart [23]. This section reviews the different developed methods, co-manipulation tasks, applications, and performance evaluation criteria. By examining these approaches, the study highlights the role of VA control in improving the overall efficiency and safety of HRI systems. It also provides guidelines for researchers interested in designing and evaluating their own VA-based control systems [19].

The second part of this paper focuses on the safety aspect of HRI. The safety of the robot-human interaction is explored through the lens of collision detection, with an emphasis on model-based and data-driven methods. Collision thresholds and their determination play a crucial role in ensuring that robots can detect and prevent any harmful interaction with humans. The effectiveness of these safety systems is analyzed, compared, and discussed with respect to their applications and performance measures [15]. Through these two parts, the paper offers a comprehensive overview of the advancements in control and safety mechanisms in HRI systems, as well as the challenges and opportunities in improving the performance and reliability of these systems. The goal is to present a clear path for future enhancements in the field, guiding both researchers and practitioners toward achieving safer and more efficient human-robot collaboration.

The content of the methodology followed in this paper is presented in Figure 1.

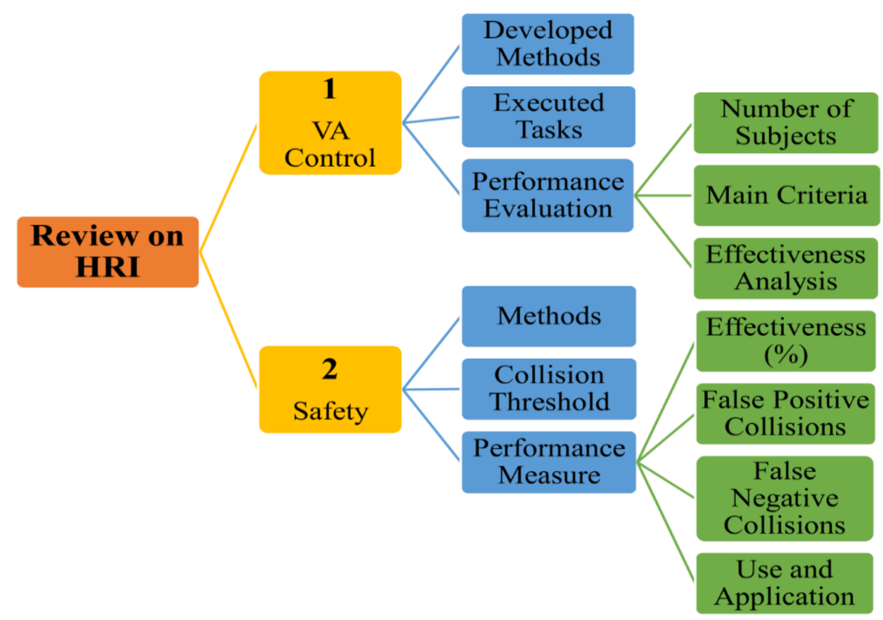

Figure 1. The content of the presented survey on HRI.

2. Control Methods for HRI

The collaboration between the machine and the individual in manufacturing, assistance, joint handling, and healthcare scenarios could improve the efficiency of both the person and the automated system. Cooperative machines are utilized for aiding individuals, resulting in an enhancement of their abilities in three areas: accuracy, rapidity, and strength. Additionally, the machines have the ability to alleviate the strain or fatigue experienced by the human worker, thus enhancing the environment in which they operate. Within the collaboration, the human participant adds value in several areas: their expertise, the understanding necessary for performing tasks, their instinct, flexibility in adapting and acquiring new skills, and their ability to grasp control strategies easily [25,26]. A multitude of robotic applications and diverse tasks create the need for the creation of adaptable parameter controllers to achieve the robotic objective. The regulators ought to be modified based on the goals of the human partner and the variations in the surroundings (for instance, the load of the machine). As a result, amicable machines engage with people. This part focuses on regulatory oversight, especially access management. The upcoming sections examine and analyze thoroughly the VA controller within HRI.

2.1. Compliance Control (Impedance/Admittance)

Grasping the obedient actions is an age-old challenge in the field of robotics. This holds significance when the machine engages with its surroundings, especially if those surroundings are entirely or partially understood. This section presents and discusses the robot's impedance control and admittance control. Regulatory oversight (resistance or receptance) [27–29] is consistently employed as a management framework to establish a fluid connection between the machine and individual. In access regulation [30], an effective location or speed regulator (path following regulator) and an outside force detector must be identified. The pressure detector is unnecessary for the resistance regulator when the mass is not configured. The robot's lively actions are modified by calibrating the simulated damping, mass, and rigidity rather than separately managing the position or the force.

Furthermore, the concept and the implementation of both controllers is shown in Figure 2.

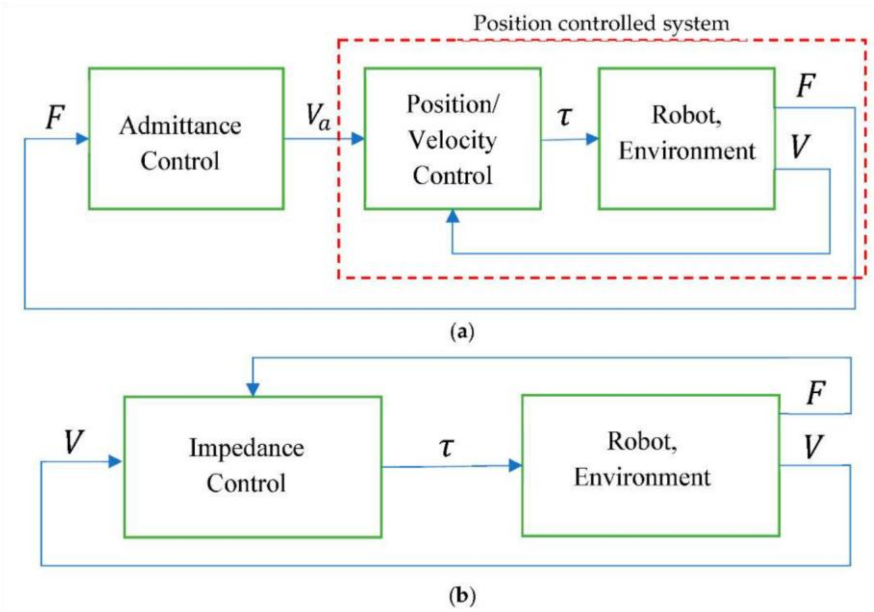

Figure 2. The concept or the implementation of the admittance and impedance controller (a) Admittance Control and (b) Impedance Control.

The advantages and properties of impedance and admittance control can be shown in a better way by comparing them with other modes of control such as force control, position control, and hybrid control. Table 2 presents this comparison depending on the work presented by Song et al. [31].

2.2. Methods for VA Control System in Co-Manipulation Tasks

This section outlines the techniques created for the VA controller, detailing instances where either the virtual damping parameter, the virtual inertia parameter, or both are modified at the same time.

The settings of VA controllers are modified using various methods, including human intent, strategies that maintain passivity, the power relayed from humans to robots, and data-driven techniques like fuzzy logic, neural networks, trajectory forecasting, and real-time fast Fourier transform (FFT) of recorded forces [6,37–50].

These classifications are presented in Figure 4.

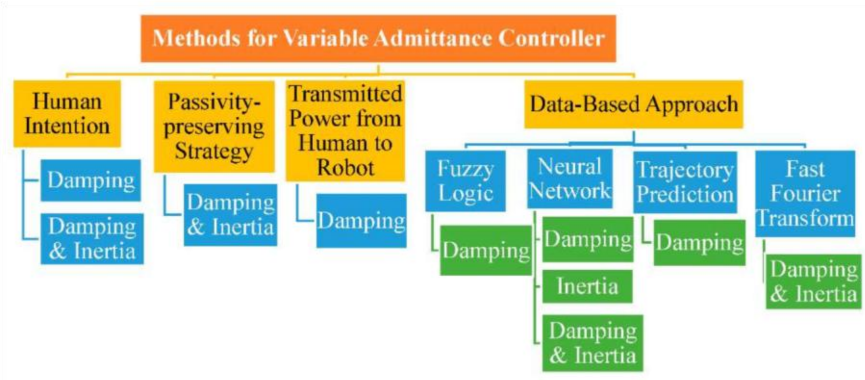

Figure 4. The classifications of the used techniques for developing VA control whether adjusting the damping only, the inertia only, or both the damping and inertia.

The understanding of human purpose formed the foundation of the subsequent creations. Duchaine and Gosselin [37] enhanced the understanding of individuals by focusing solely on the modification of the virtual damping. Their VA regulation was created by utilizing the time rate of change of the exerted force, and subsequently, it was employed to deduce the intentions of the individual. Lecours and colleagues [46] created a VA regulation where both the virtual damping and the virtual inertia were modified. Their regulator was established utilizing the interpretation of human intentions while taking into account the preferred operator's speed and acceleration. The limitations of the previously mentioned methods involve the need for numerical differentiation, which introduces noise into the signals, subsequently necessitating filtering that results in delays. In [41], Topini et al. executed a VA regulation where both the simulated inertia and the simulated damping were adjusted in real-time to align with the user's movement intent. Their framework adhered to the identical methodology outlined by Lecours et al. [46]. Nonetheless, the area of usage varied. Furthermore, the sought-after reference strength or the origin of such a strength reference measurement was not supplied by Lecours et al. [46].

The approach of maintaining passivity was employed to adjust the parameters of robotic admittance regulation. TSUMUGIWA and colleagues [45] introduced a technique to modify both virtual resistance and mass while taking into account the stability measure and a maximum threshold of the force exerted by an individual. Within their approach, the inactivity metric was employed to distinguish the operation of functioning from alternative processes, specifically the energy exchange occurring between human and machine throughout the partnership. When the passivity index registered a favorable figure that surpassed a specified limit, the individual supplied the machine with the power necessary to carry out the task of collaboration. This inactivity metric was likewise employed to identify the entire human labor procedure. Subsequently, the final exerted force measurement was utilized to segment the entire operational procedure into four sections. Subsequently, suitable traits of acceptance regulation were implemented to every component. An approach that maintains passivity was additionally suggested by C. T. Landi and colleagues in [48], wherein they modified the virtual inertia parameter of the admittance control to eliminate high-frequency oscillations and revert to the intended interaction model. Additionally, the virtual damping factor was modified according to a fixed ratio of damping to inertia to maintain comparable system dynamics post-adjustment, which is more intuitive for individuals [46].

Based on the conveyed energy from person to machine, Sidiropoulos et al. [40] suggested a VA regulation for adjusting the virtual resistance while considering the reduction of the energy supplied by the individual, enabling the participant to manage the activity.

Techniques reliant on information such as fuzzy reasoning and artificial neural systems were likewise created. Methods grounded in fuzzy reasoning were suggested by the subsequent studies. Z. Du and colleagues [43] created a combined VA model utilizing a fuzzy Sarsa (λ) learning approach, focusing on rotational motion around a single axis, to achieve seamless and natural engagement during the pose modification of minimally invasive surgical manipulators. Dimeas and Aspragathos [44] introduced a technique that integrated human-like decision-making with an adaptive fuzzy inference algorithm. The assessed speed of the robot and the exerted force by the human served as the inputs for their approach, while the dynamically modified virtual damping coefficient was the result. Their soft reasoning framework was modified employing the soft model reference training regulator. The foundational framework for this understanding was the minimum jerk trajectory model, and it is essential to uncover the expert insights for seamless collaboration.

Artificial intelligence models were likewise employed for modifying the settings of robotic compliance management systems. In [6,49,50], Sharkawy et al. introduced a multi-layer feedforward neural network (MLFFNN) that is trained online to modify either the virtual damping parameter or the virtual inertia parameter of the admittance control. The instruction took place based on the mistake correction method and taking into account a discrepancy that illustrates the gap between the real speed of the robot and the intended smooth motion speed. In [38], the online and simultaneous adjustments of both the virtual damping and inertia were achieved through the application of Jordan recurrent neural networks. The system was indirectly educated through real-time recurrent learning, taking into account the discrepancy between the robot's actual speed and the preferred minimum jerk path speed. In these methods, the requirement for specialized understanding for the instinctive teamwork was absent, and this is favorable. A technique was created in [39] to enable the robot to engage with unfamiliar surroundings. A watcher in the robotic joint realm was utilized for assessing the engagement torque. The acceptance management was implemented to oversee the fluctuating actions at the interaction juncture while the robot engages with the unfamiliar surroundings. An RBF-based controller was developed to ensure accurate trajectory following. The expense formula was established to attain the effectiveness of the torque control interaction and the path following. Furthermore, it was reduced by the acceptance framework’s adjustment.

Drawing from an analysis of the predicted path of human hand movement, Wang et al. [42]

suggested a VA regulation in HRI. The trajectory of the robot's end-effector, directed by the human operator, was utilized to train a long- and short-term memory neural network (LSTMNN) offline. Subsequently, the path estimators were employed in VA management to forecast in real-time the path along with the motion orientation of the robot’s end-effector. The advanced VA regulator modified the simulated resistance to lessen its magnitude in the direction of movement.

A different approach grounded in data was created in [47]. In [47], Okunev and colleagues employed a digital rapid Fourier transform (FFT) of the forces, which were recorded using a fixed sensor at the robot's terminal component. Their approach was employed for identifying the fluctuations and for flexibly adjusting the virtual resistance and mass to mitigate the fluctuations and enhance the sensation of tactile engagement of the collaborating individual. Furthermore, they created an algorithmic approach to incorporate human inclinations into the control framework. The approach relied on analyzing individuals and their assessments.

The automated functions employed by these investigators throughout the creation and assessment of their VA controller are examined in the following subsection.

2.3. Accomplished Co-Manipulation Tasks with VA Control

During the development and the evaluation of the VA control, different tasks were proposed and accomplished by the researchers. These tasks are classified into two main categories as follows:

1) The collaborative co-manipulation tasks in which the human effort and oscillations should be reduced. These types of tasks are the main interest of this paper and are discussed in this subsection.
2) The rehabilitations tasks in which the robot should apply high force and assist the human, or in other cases the robot should leave the patient to act alone. These types of tasks are out of scope of this paper.

The classifications of the collaborative co-manipulation tasks are presented in Figure 5.

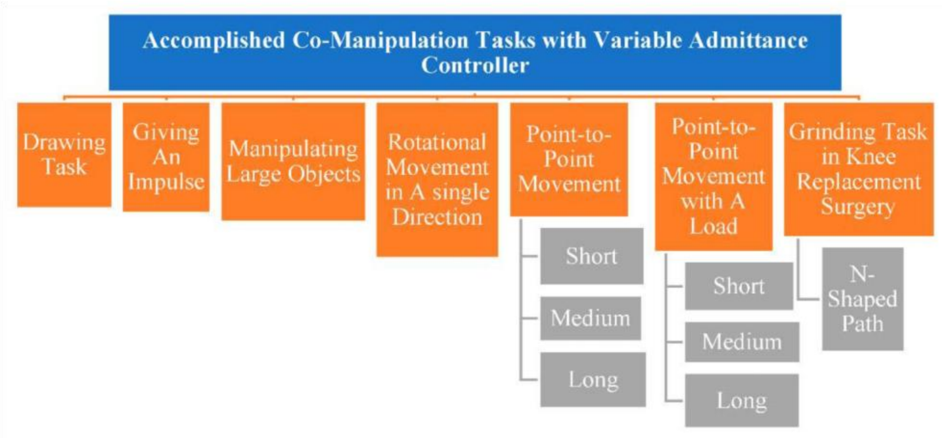

Figure 5. The robotic tasks accomplished during the development and the evaluation of the VA control that appeared in the literature.

Joint manipulation activities, including the pick-and-place activity, point-to-point motion, drawing activity, and handling of sizable items, were suggested alongside the subsequent research efforts. Duchaine and Gosselin [37] developed their VA control system for both the cooperative pick and place activity and the drawing activity. Lecours et al. [46] successfully completed the drawing task and provided an impetus for the support apparatus in their efforts to create and assess the adjustable controller. In [45], TSUMUGIWA et al. performed the direct movement as the intended objective for creating and assessing their VA controller. The objective accomplished by Sidiropoulos and colleagues [40] in creating and assessing their VA control system involved the handling of substantial items with significant inertia.

The spinning action of a joint in a minimally invasive surgical device aimed at two objectives in one direction was utilized as the suggested task with Z. Du and colleagues [43]. In [44], Dimeas and Aspragathos created their VA control mechanism for a linear motion along a singular axis of the Cartesian robot environment. Their VA regulation was assessed through various actions; brief, moderate, and extended ranges. Sharkawy and colleagues [6,38,49,50] created and engineered their VA control system for a linear motion in one direction within the Cartesian robot environment. Furthermore, their VA regulation was assessed through various motions; brief, moderate, and extended ranges. In [50], the VA regulation was assessed by attaching a weight or an item of 1 kg to the robot's end-effector to mimic the process of moving an object from one location to another under human guidance. The movement occurred in a linear path (brief, moderate, and extended ranges). Additionally, the VA regulation was examined and explored across various directions of movement and along a linear path. Wang and colleagues [42] created their VA control to replicate a test where the robot was utilized for polishing the prosthesis insertion surface. The chosen route was a zigzag trajectory spanning the area. A recovery assignment was suggested by Topini et al. [41]. A hand exoskeleton system was created to connect with the VA control for performing rehabilitation tasks based on virtual reality. The activities involved in their job included unrestricted movement and handling a virtual round object. Nonetheless, restorative activities fall beyond the boundaries of this document.

While various assignments were employed with the investigators, additional practical tasks and implementations are suggested for exploration and utilization, including intricate and curved movements. Additionally, the activities in actual (commercial, healthcare, farming, etc.) settings can be accomplished.

2.4. Performance's Comparison of VA Controllers in Co-Manipulation Tasks

In this section, the achieved performance of the developed VA controllers is compared. For this purpose, we concentrate on the number of subjects and the criteria used to evaluate the developed VA control system as well as the effectiveness and the improvements that were obtained by the VA control. The main used criteria for evaluation of the developed VA control included the following terms:

1) The required effort for performing the task.
2) The needed time for executing the task.
3) The oscillations and the number of overshoots.
4) The achieved accuracy.
5) The accumulated jerk.
6) The opposition of the robot to human forces.

The control system for VA created by Duchaine and Gosselin [37] was assessed regarding the time required to complete the drawing task and the frequency of overshoots. Their VA management framework was evaluated against a steady admittance regulation with the assistance of six participants. Through their VA management, the objective was accomplished swiftly with fewer instances of overshooting. Furthermore, the duration was enhanced/decreased by 18.23% in comparison to the steady admittance regulator. The necessary exertion for executing the assignment and the precision were not evaluated, and the findings from a supplied survey were not incorporated. The VA management by Lecours et al. [46] was evaluated against a low fixed admittance controller and a high fixed admittance controller, utilizing task completion duration and maze overshoots as the primary metrics, with the assistance of six participants. When executing a sketching assignment, utilizing their VA controller made it simple to achieve swift and precise motions. The time required to complete the task was similar to that of the low constant admittance controller, and 20% less than that of the high constant admittance controller. The excess distance given by their VA controller matched that achieved by the high constant admittance controller. Furthermore, it was five times less than what was achieved through the low constant admittance regulation. Through the impulse assessment, their velocity and acceleration controller achieved elevated target speed and acceleration, akin to those reached by the low steady admittance controller. Nonetheless, their VA regulation exhibited reduced capacity for executing delicate actions.

Moreover, the speed diminished at a faster rate. This occurred due to the increased speed outcome of the VA regulation principle. In both activities (sketching and motivation), the assessment of the necessary human input was overlooked, and subjective outcomes through a survey provided to the participants were absent. In [41], Topini and colleagues assessed their created VA control using a solitary trained healthy participant. The findings indicated that the created VA control exhibited encouraging effectiveness in tracking the user's unrestricted movements. Furthermore, it was particularly appropriate for recovery uses due to its gentle performance at reduced operating frequencies. Data regarding precision, necessary exertion, and duration for completion were absent. Furthermore, relying on a single subject to assess the system is neither just nor sufficient. The VA regulation created by TSUMUGIWA et al. [45] was evaluated against a standard VA regulation and a fixed admittance regulation involving 10 participants. The systems were evaluated based on the surges and the subsequent increase of the exerted force throughout the positioning phase. The investigation revealed that with the advanced VA controller, there was no resurgence in the exerted force, no overshoot during the positioning phase, and the collaboration proceeded seamlessly. A surplus of the exerted human effort was observed at the conclusion of the positioning segment when the constant admittance regulation was implemented. Restoring the exerted pressure was essential at the outset of the alignment phase when the traditional VA regulation was implemented. The overall capability and efficiency of their VA controller were not examined or assessed through various actions. Furthermore, the evaluation omitted the precision of every controller and the duration taken to complete the tasks. The ratio of the enhancement of their created VA control was not determined. The provided survey for the participants focused solely on the aspect of manipulability. Nonetheless, the assessment of the sensation of necessary human exertion and the perception of the fluctuation was omitted. The VA management created by C. T. Landi and colleagues, as referenced in [48], was assessed solely through a survey. A survey was administered to 26 participants split into two categories, the initial category consisting of 12 individuals and the latter comprising 14 individuals, to assess the usability of the system utilizing the system usability scale (SUS) [51]. The score for the first group was 81.66%, while the second group achieved a score of 82.88%. Overall, this rating was elevated.

Sidiropoulos and colleagues in [40] assessed their VA control using 10 participants, focusing solely on two primary factors: the energy transferred from the human to the robot, indicating the necessary human exertion, and the energy conveyed by the robot to the human, reflecting the robot's resistance to the human's forces. Their findings demonstrated that their VA management decreased the human labor by roughly 33% to 46% in comparison to a high constant admittance controller. Furthermore, their VA regulator was evaluated against the VA regulation shown in [52], where the virtual damping was adjusted based on the velocity norm. The findings demonstrated that their VA controller exhibits superior efficiency in comparison to the VA control reliant on velocity norm [52]. Moreover, the subsequent VA management diminished the human workload by 32%. Details regarding the attained precision and duration for task fulfillment were absent. In addition, the personal findings from a survey were omitted.

In [43], the VA regulator introduced by Z. Du et al. was evaluated against three distinct systems: a low constant admittance regulator, a high constant admittance regulator, and a VA regulator grounded in torque/force, involving the participation of 8 individuals. The evaluation focused on precision, the exertion involved, and the total disturbance experienced.

Their VA regulator attained superior precision compared to the steady low admittance regulator. Furthermore, the average of the greatest distance following the elimination of the interaction torque was reduced by 90.3%. The utilized human input was decreased and enhanced by 44.3% compared to the elevated steady admittance regulation. The fluidity of the collaboration was notably enhanced by their adjustable regulator in contrast to the VA regulator reliant on the torque. In addition, the average of the total jerk during the event was decreased and enhanced by 31.4% compared to the VA controller based on the torque. Nonetheless, the required duration for performing the intended action was not evaluated. The feedback collected from the participants indicated that their VA control system achieved the desired outcomes based on key comparison factors; the feeling of control and the fluidity of movement. The survey failed to provide any insight regarding the effort experienced by individuals during the motion, the vibrations and oscillations, as well as the system favored by the participants. In [44], Dimeas and Aspragathos created a fuzzy reasoning framework (FRF) for VA regulator. Their developed FIS was evaluated against the untaught, manually adjusted FIS across various motions (short, medium, and long ranges) with the assistance of 12 participants. The evaluation encompassed the necessary human input and the time needed to finish the task. In brief, it was observed that a 1% enhancement/decrease in the effort was achieved with the trained FIS, and this enhancement/decrease rises to 7% for the medium range and ultimately to 13% for the extended range. The average time to complete in the scenario of the trained FIS is reduced by 12% when compared to the untrained system. Nonetheless, the fluctuations and the precision were omitted from the evaluation. Furthermore, it is not a sensible method to evaluate a developed system against an undeveloped one, as it stands to reason that the developed one will demonstrate superior performance. The evaluation of a steady admittance controller was likewise omitted. The outcomes from the distributed survey to the participants demonstrated that the trained FIS was favored over the untrained FIS. The sensation of human exertion throughout the motion, the precision, and the fluctuations were overlooked in the given survey.

In [49], Sharkawy and colleagues created a VA controller utilizing the trained neural network system. Their VA regulator was part of a comparison alongside three additional constant admittance regulators (low, medium, and high). The evaluation was conducted utilizing various actions (brief, moderate, and extended ranges) and with the assistance of 13 participants. The primary factors for this evaluation included the necessary human input to operate the robot, the time required for the task, and the achieved precision at the designated location. Through their VA regulation, it was discovered that, over a brief range, the necessary exertion and the time needed for the task were enhanced and diminished by 65.22% and 6.65%, in comparison to the elevated constant admittance regulator. The precision was enhanced and elevated by 5.30% compared to the minimal steady admittance regulator. In the intermediate range, the necessary human exertion and the required duration for the task were enhanced and minimized, respectively, by 58.83% and 16.89% compared to the elevated steady admittance regulation. The precision was enhanced and elevated by 4.031% in relation to the minimal steady admittance regulation. Over the extended range, the human input and the required duration were enhanced and diminished by 63.63% and 15.184% compared to the high constant admittance control, while the precision saw an increase of 3.86% in relation to the low constant admittance controller. Based on the personal feedback from the survey administered to the participants, their visual attention management demonstrated excellent results, requiring minimal effort while achieving peak accuracy. Additionally, it was the favored method among the participants. The created VA controller was assessed with the assistance of 10 participants. Their virtual assistant controller enhanced and minimized the necessary human input and the required duration for tasks, achieving reductions of 58.58% and 23.86% compared to the high constant admittance control during the brief linear motion segment. Additionally, the precision was enhanced by 5.12% compared to the minimal steady admittance regulation.

During the average linear movement, the VA controller enhanced and minimized the necessary human exertion and the time needed for the task, respectively, by 51.474% and 24.30% compared to the elevated constant admittance control. The precision was enhanced and elevated by 5.00% in relation to the minimal steady admittance regulation. During the extended linear movement, the VA controller enhanced and minimized the human input and the required duration, respectively, by 57.154% and 26.57% compared to the elevated steady admittance regulation. The precision was enhanced and elevated by 4.456% in relation to the minimal steady admittance regulation. The capability of their VA control was evaluated by attaching a load or an item to the robot's end-effector to replicate a co-manipulation task. In this scenario, the VA controller enhanced and minimized the human effort and the required task duration, specifically, by 43.235% and 19.76% during short straight-line segment movement, and by 51.856% and 22.35% with medium straight-line segment movement, as well as by 58.658% and 22.892% when long straight-line segment movement was executed, in comparison to the high constant admittance control. The attained precision with their VA controller saw enhancements of 9.678%, 8.576%, and 8.653% for short, medium, and long distances, respectively, compared to the low constant admittance control. In [38], the VA regulation, where both the virtual damping coefficient and inertia coefficient were modified, exhibits superior performance in comparison to the VA regulation that involved only the adjustment of the virtual damping or the VA regulation that focused solely on the virtual inertia coefficient. The evaluation was conducted with a group of 10 participants.

In [42], Wang and colleagues assessed their created VA regulation by contrasting it with a fixed admittance regulation, taking into account the operational force, jerk, and trajectory error (precision) as the primary benchmarks, aided by two participants. Their VA controllers minimized the trajectory inaccuracies by 51%, lessened the operating force by 23%, and decreased the operating jerk by 21%. The personal outcomes from a survey were absent. Furthermore, relying on merely a pair of participants was insufficient and unjust.

In [47], the VA controller introduced by Okunev et al. was evaluated with the involvement of 10 participants alongside four steady admittance controllers; the initial one exhibits elevated values, the subsequent one shows moderate values, the third one displays reduced values, and the final one presents the least values. The evaluation was carried out with a mobile robot equipped with two 7-DoF human-like arms, which grasp an aluminum rod. The personal outcomes were shared solely from a supplied survey to the individuals involved. The outcomes pertained to the weight and the fluctuations associated with each regulator. Upon evaluating their adjustable regulator against the initial fixed admittance regulator, it was found that their adjustable regulator was lighter and exhibited greater oscillation. In relation to the second controller, the adjustable controller was roughly at a similar weight as the second controller, which exhibited reduced oscillation. When contrasted with the third fixed acceptance regulator, their adjustable regulator was lighter and less prone to oscillation. In contrast to the fourth constant admittance regulator, the fourth regulator failed during the trials, where failure indicates that the frequency of the integrated robot safety mechanism deactivated and the adaptive regulator exhibited reduced oscillation. Nonetheless, the assessed outcomes from these evaluations were omitted, which hold greater significance than the personal ones.

The quantity of participants employed to assess the VA regulation by investigators can be contrasted. The illustration of this comparison can be found in Figure 6. Figure 6 illustrates that the quantity of participants utilized by investigators varies from 1 to 13, with the exception of one study that employed 26 participants to assess their VA control system. Nonetheless, we suggest utilizing a greater number of subjects (for instance, over 30) to assess VA control for more accurate statistics and outcomes.

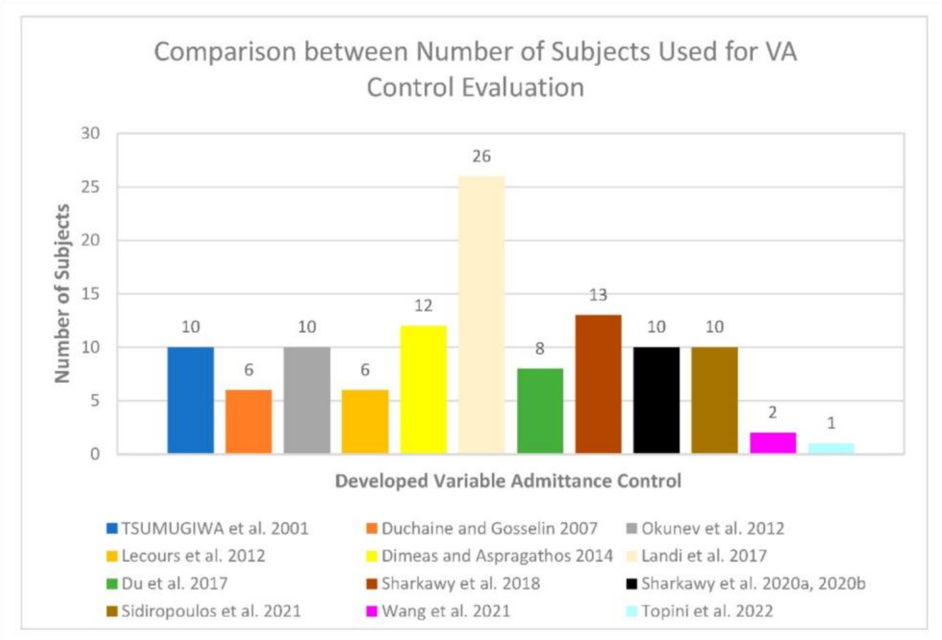

Figure 6. The comparison between the number of subjects used to evaluate the developed VA control, according to the literature presented in this subsection.

From this discussion, it is difficult to compare the performance of all VA control systems quantitatively because the used criteria and the accomplished tasks with each system are different from the others. In addition, the obtained results with some VA control systems in form of values are missing. However, we present a figure that can compare the performance of the closest VA systems to help the reader to see the difference easily. These systems are as follows:

1) The VA control system based on inference of human intention [37],
2) The VA control system depending on transmitted power by human to robot [40],
3) The VA control system based on the velocity norm [52],
4) The neural network-based system to adjust the damping only [49],
5) The neural network-based system to adjust the inertia only [50], and
6) The VA control system depending on the trajectory’s prediction of the motion of a human hand [42].

This comparison is presented in Figure 7. The percentage of the improvement in the required human effort and time of all systems is relative to high constant admittance control. The percentage of the improvement in the achieved accuracy is relative to low constant admittance control.

The good results obtained from these previous works need further investigation by developing new methods for variable admittance control. In addition, as is clear from Figure 7, using a neural network-based approach is promising in improving the performance of the VA control system in a better way. This needs further investigation by applying different types of neural networks as well as deep learning-based techniques.

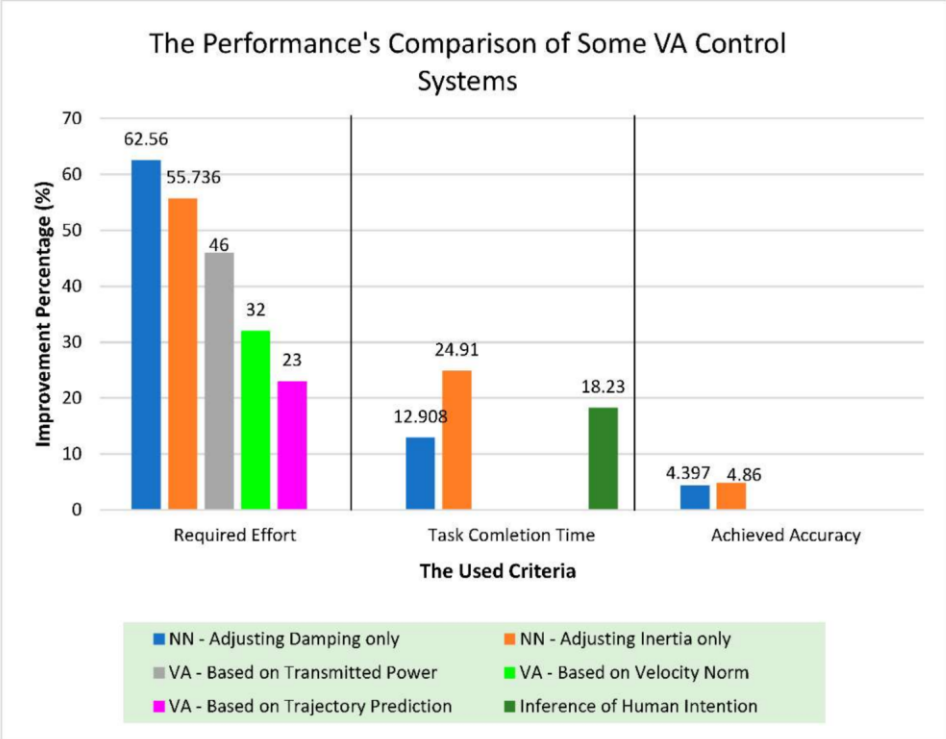

Figure 7. The performance's comparison between some developed VA control systems. The main criteria used are the required human effort, needed task time, and the obtained accuracy.

3. Safety of HRI

Ensuring protection is essential and vital when humans and robots work together in the same environment or space. The proximity of humans to robots can lead to potential harm. Consequently, a secure approach or strategy needs to be identified for the automated system. Safety is viewed as a comprehensive and vital area of study. Gualtieri and colleagues in [53] categorized the latest studies and topics that are closely associated with the security of HRI. These categories were established following a thorough examination of all pertinent studies and subsequently organizing them. The classifications are illustrated in Figure 8.

Safety protocols and stipulations should be adhered to throughout the HRI. The criteria for incorporating the industrial robotic systems are outlined in ISO standards as detailed in references [54,55]. In ISO, the scenarios of dangers are depicted, and the criteria for removing or minimizing the related threats posed by these dangers are also outlined. In [56], ISO/TS 15,066 outlines the safety criteria for collaboration between humans and industrial robotic systems. Furthermore, it provides direction on the functioning of the cooperative industrial robot as referenced in [54,55]. The limits for both quasi-static and transient contact are also provided. Yamada and colleagues [57] examined safety and established the threshold for discomfort. When crafting the control system in human-robot interaction, it is essential to prioritize safety. Created frameworks for ensuring the protection of robotic interactions with people were categorized as methods for preventing collisions and techniques for detecting collisions. Methods for preventing collisions relied on detectors to effectively observe the surroundings. The techniques employed utilized depth detectors and visual systems as shown in references [58–60] and chromatic sensors as indicated in references [61,62]. These techniques work well in the absence of blockages or issues while identifying the individual or the barrier and the machine. When the detector is extremely distant or extremely near to the operational area, several detectors need to be positioned to oversee the area from various angles. The quantity of detectors was examined by scholars in two scenarios: the initial scenario utilized individual-sensor options as shown in references [63,64], while the subsequent scenario employed multi-sensor methodologies as suggested by references [65,66]. These methods require adjustments in the structure of the machine due to the placement of the detectors. Neural networks were additionally employed for the prevention of collisions as referenced in [67]. The examination of collision prevention methods is beyond the boundaries of this document. This document primarily focuses on examining the techniques for detecting collisions, as categorized in Figure 9. The subsequent sections provide a thorough examination of these categories.

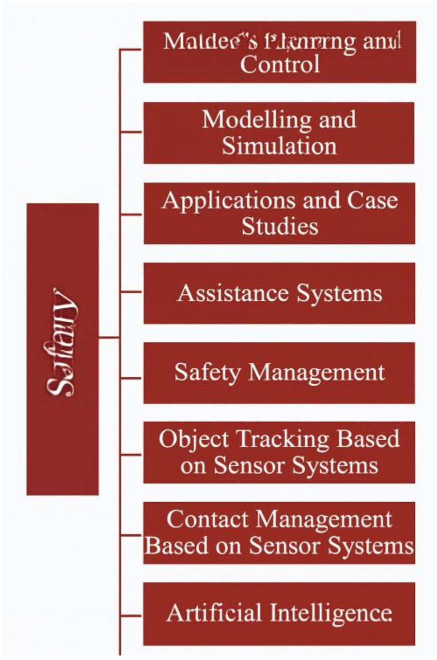

Figure 8. The research contents and themes related to safety and investigated in recent years by Gualtieri et al. [53].

3.1. Collision Detection Techniques

For the improvement of system of safety in HRI, the collision detection and reaction approaches are necessary and required in case the collision avoidance level fails. Various techniques for detecting and identifying the collisions were developed by researchers. The classifications of these techniques are either model-based or data-based. These methods are presented in the following two subsections.

3.1.1. Model-Based Methods

Researchers considered disturbance observers, impedance and admittance control, along with the application of force/torque sensors in the model-driven methodologies. The disturbance observer was introduced through the subsequent research. In the method proposed by Haddadin and colleagues [68], two systems for detecting collisions and five strategies for responding were utilized with the LWR robot for collaborative and interactive tasks. The initial impact identification mechanism required the overall momentum, while the subsequent mechanism contrasted the observed joint torque with the predicted torque derived from the robot's model. In the work by Cho and colleagues [69], a method for detecting collisions was created along with three strategies for responding. The approaches to these responses included (1) the oscillation pattern, (2) the torque-free movement, and (3) the forced halt, each applied in various collision situations. Their impact recognition mechanism relied on the overall momentum and the inputs from joint torque detectors. A 7-DOF service robotic manipulator was created, utilized for carrying out the experiments. Jung and his team [70] introduced a set of band-width filters within a disturbance observer to identify the collisions happening between humans and robots. The features of the oscillation of every section of the manipulator and interferences were examined and utilized for identifying the impacts. Pengfei Cao and colleagues [71] introduced the model-driven approach for sensorless collision detection in human-robot interaction. Their approach relied on the leftover torque, characterized as the gap between the standard torque and the real one, utilizing data from the motor side.

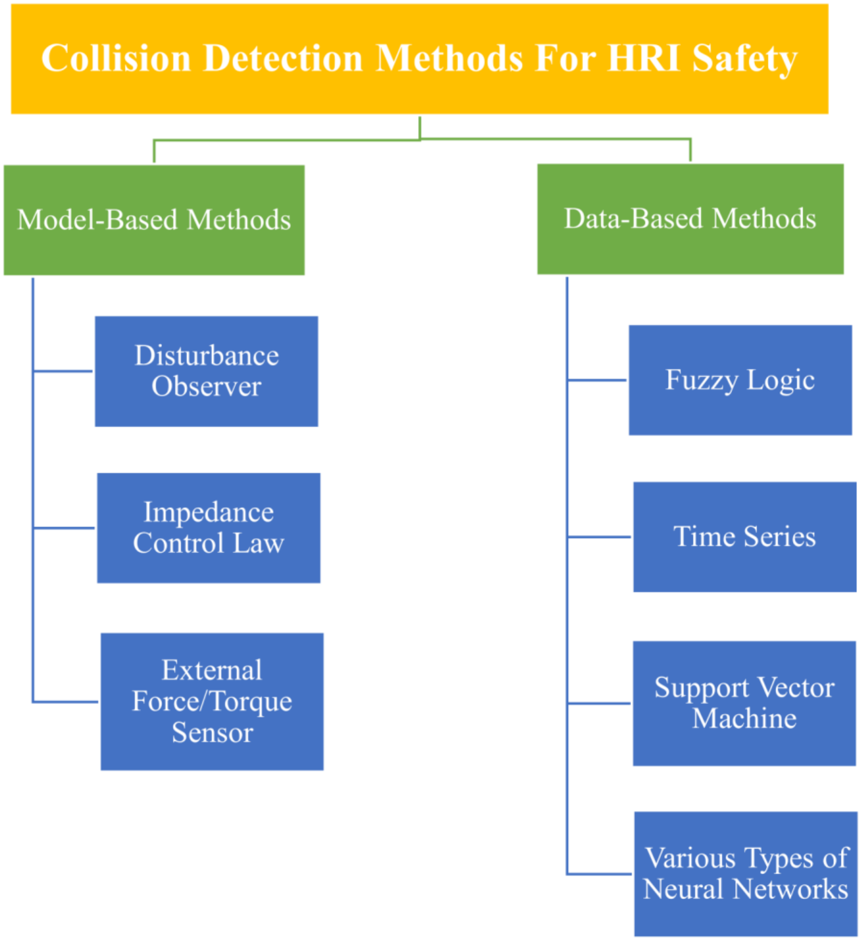

Figure 9. The classifications of the collision detection techniques used for the safety of HRI's systems.

Resistance and conductance regulation were additionally employed for impact identification. Morinaga and Kosuge devised a nonlinear impedance controller that operates independently of any external sensors. Their method relied on the discrepancy in rotational force, which was characterized as the variation between the real input manipulator force and the benchmark input force established from the dynamic manipulator characteristics. In [73], Kim introduced a method for detecting and responding to collisions in collaborative robots, utilizing a sensorless admittance control approach. The impact monitor relied on the compelled reaction of a mechanical setup. To accurately identify the impact, a low-frequency filter was integrated with a high-frequency filter in a cohesive manner.

The application of an external force/torque sensor for collision detection was introduced by Shujun Lu and colleagues [74]. In their method, a pair of six-axis force and torque detectors were utilized. The initial one was located on the foundation and the subsequent one was positioned on the arm. Their approach was examined and evaluated with 1-DOF and 2-DOF manipulators.

The primary challenges of these model-driven methods are that they require a clear dynamic robot representation, which may occasionally be missing or unattainable. Furthermore, there exist ambiguities in the identification of the dynamic parameters.

3.1.2. Data-Based Methods

Methods grounded in data are introduced and advanced for the detection and identification of collisions between humans and robots. These techniques utilize information to educate an advanced framework, and subsequently, the educated framework is employed to assess and identify the impacts. Frameworks relying on imprecise reasoning, sequential data analysis, classification algorithms, and neural networks were evaluated. In the research by Dimeas and colleagues [75,76], two approaches were created. The initial relied on vague recognition, while the latter was based on chronological sequences. Both approaches were examined utilizing a single-degree-of-freedom manipulator and a two-degree-of-freedom planar manipulator. Their soft frameworks were created for approximating the impacts before identifying them, with the inputs being the joint position discrepancies, the recorded joint forces, and the real joint speeds. A distinct fuzzy framework was created and educated for every joint. Their method, grounded in fuzziness, successfully and swiftly identified the collisions by employing reduced threshold values. For their approach utilizing time series, the impact torque was assessed solely through the data from the recorded joint speed. Moreover, the necessary duration for identifying the impact was minimal; nonetheless, its established limit was elevated in comparison to the fuzzy framework. Their frameworks were created without considering the dynamic interaction happening during the movement of the joints. Additionally, the capacity for generalization and the efficacy of their approaches were not explored beyond the training range of motion and under varying circumstances.

Franzel and colleagues in [77] developed a method that utilizes the understanding of the performed task along with the resulting deviation from human engagement to differentiate between contact occurrences and standard execution through a contact event detection system. To achieve this goal, a classifier for contact types was developed utilizing SVM, which underwent training with the designated events. In [78], Cioff et al. employed SVM to categorize the interactions occurring between humans and robots by analyzing time series data of joint load torque signals. The scenarios of interaction were divided into two categories: the first involved deliberate engagements, while the second pertained to unintentional encounters. The rough positioning was additionally performed to determine whether the connection was on the top or the bottom robotic arm.

In [74], Shujun Lu and his team created a technique for detecting collisions based on the training of the neural network. Their approach required a foundation along with wrist strength and a torque detector, and it was explored utilizing 1-DOF and 2-DOF manipulators. The elements of the crafted neural network included the brief record of joint angles and the measurements from the wrist and base force/torque sensors, while the results consisted of the impact forces and the locations of contact. The outcomes from their approach were encouraging and demonstrated its credibility; nonetheless, two additional sensors were required, and exploring its applicability and efficiency was lacking beyond the training range movement and under varying circumstances. BriquetKerestedjian and colleagues [79] executed a guided learning method for a neural network-driven strategy to distinguish between instances of accidental contact (marked as collisions) and anticipated ones (marked as interactions). Furthermore, their method aimed to deduce which of the upper or lower robotic appendages made contact. The issue with the classifications lies in overlooking the strength of external influences (collisions), rendering the classifier impractical and ineffective for estimating this force. In [80–83], Sharkawy and his team introduced and crafted the multilayer feedforward neural network (MLFFNN) to identify collisions involving robots and humans, along with determining which link was involved in the collision. The broad application and the efficiency of their approach were examined and showcased under various circumstances. Their approach achieved remarkable success with an impressive rate, and the outcomes looked encouraging. The MLFFNN discussed in [80,81,83] is applicable solely to collaborative robots that have access to the signals from the joints' position and torque sensors. The MLFFNN described in [82] is suitable for any robotic system as it relies solely on the signals from the position sensors of the joints in the manipulator. In [84], three varieties of neural networks were examined and contrasted for detecting collisions between humans and robots. The categories included: (1) multilayer feedforward, (2) cascaded forward, and (3) recurrent neural networks. The developed neural network took into account the dynamics of the manipulator joints and aimed to utilize solely the signals from the intrinsic position sensors of the robotic manipulator, ensuring that it could be validated and implemented by any robot. The evaluation of the three constructed neural networks was both numerical and descriptive.

3.2. Collision Threshold

As previously mentioned, security is an essential element in human-robot interaction; thus, any collisions must be accurately recognized, and the involved connection should be pinpointed to ensure a secure partnership between robots and humans. In the realm of HRI literature, the impact limit was established by taking into account the subsequent elements. The primary consideration was the protection of individuals, while the secondary consideration involved reducing erroneous collision detections to ensure seamless and uninterrupted human-robot interaction. The interaction force and the rotational force at the joint served as the foundation for establishing the impact limit. The interaction force was examined by Shujun Lu and colleagues [74]. In [74], the impact limit was characterized as a figure that fell beneath the contact force defining the combined pain endurance threshold of humans, which was examined and explored in [57]. The combined force was taken into account alongside Haddadin and colleagues [68]. In [68], the limit was established as 10% of the peak nominal robot torque. A dynamic limit was suggested in [73]. The impact limit relied on the simulation inaccuracy, and it was revised solely when the collision status was OFF to observe the unadulterated simulation error, such as movement without impacts. Alternatively, the impact limit was rising alongside the produced external joint force due to the impacts. This explanation was derived from the work shown in [85].

In the research conducted by Dimeas and colleagues [76], the limit was established as the highest value of the estimation error. The discrepancy in this estimation was the variance between the external joint torque measured by the external force and torque sensor and the predicted torque by their created fuzzy system, in a scenario of movement without any impact. Morinaga and Kosuge [72] established their impact limit based on the traits of the normal distribution. In [80,81], the impact limit was established as the peak of the magnitude of the estimation inaccuracy. The discrepancy in this estimation was the variance between the external joint torque acquired from KRC and the projected external torque by the developed neural network, in a scenario of movement free from any collisions.

In light of this conversation, the assessment of the impact limit requires further exploration and thorough examination.

3.3. Performance Measure and Effectiveness Comparison of the Safety Methods

This section examines and contrasts the efficacy and performance metrics of the collision detection techniques.

The approaches grounded in models, such as those outlined in [68–73,86], necessitate a clear dynamic model of the robot. This design is absent and inaccessible in the majority of the machines. Moreover, ambiguities are present in this framework. The majority of these methods are created based on the feedback from the torque sensors in the joints, which are absent in many industrial robotic manipulators. As a result, these techniques work solely with the cooperative machine. The researchers have not supplied the efficacy and performance metric (%) of these approaches.

The primary focus in this section is to evaluate the efficiency and performance metrics of data-driven methods. A method for identifying collisions was introduced in [76], utilizing fuzzy reasoning and implemented with a two-degree-of-freedom robotic arm. The total effectiveness of this imprecise framework in identifying impacts was 72%. The rate of incorrect negative interactions with the fuzzy system was 28%, while the count of incorrect positive interactions stood at zero. A method grounded in time series analysis was suggested in [76] for identifying instances of the robot colliding with a human. The total effectiveness of this method for identifying the collisions stood at 70%. The incorrect negative encounters were 30% and the incorrect positive encounters were 11%.

In [77], the contact classifier utilizing SVM reached an effectiveness of 92.5% with the trained individuals, while this effectiveness dropped to 84.4% with the new (untrained) individuals.

In [82], two neural network architectures were created and trained to identify collisions between humans and robots. These structures were utilized for a two-degree-of-freedom manipulator. The initial design (MLFFNN-1) (MLFFNN-1 denotes the multilayer feedforward neural network structure that was developed based on the data from both the inherent joint locations and joint torque sensors of the robotic manipulator. MLFFNN-2 denotes the multilayer feedforward neural network structure that was developed solely based on the inherent joint position sensors of the robotic manipulator. was created utilizing the data from both inherent joint locations and joint torque detectors. This structure demonstrated an efficiency of 82.52%. The rate of incorrect negative interactions stood at 1.136%, while the rate of incorrect positive interactions was 16%. The subsequent design (MLFFNN-2) relied solely on the inherent positions of the joints' sensors within the robotic manipulator. Therefore, this approach may be utilized for any traditional and industrial robot. This structure demonstrated an efficiency of 85.73%. The rate of incorrect negative encounters stood at 7.95%, while the rate of incorrect positive encounters was recorded at 6.82%. In [83], a layered neural network (NN-1) was developed and trained for detecting collisions between humans and robots. The approach was utilized on a three-degree-of-freedom manipulator, relying on the positions of the inherent joints as well as the torque sensors associated with the joints of the robotic manipulator. The performance of the trained neural network was 86.6%. The count of incorrect negative collisions stood at 4.7%, while the count of incorrect positive collisions reached 8.7%. In [84], a comparison was made among three varieties of trained neural networks for detecting collisions between humans and robots. The categories included: (1) the multilayer feedforward networks (MLFFNN-1 and

MLFFNN-2), (2) the cascaded forward networks (CFNN), and (3) the recurrent networks (RNN). Such varieties of neural networks were utilized for a single degree of freedom manipulator. The performance of the MLFFNN-1 stood at 76%, with false negative collisions accounting for 16%, and false positive collisions making up 8%. The performance of the MLFFNN-2 reached 80%, with false negative collisions accounting for 16%, and false positive collisions at 4%. The trained CFNN demonstrated an efficacy of 84%, with false negative collisions occurring at a rate of 16%, while false positive collisions were absent. The trained RNN achieved an effectiveness rate of 80%, with false negative collisions accounting for 20%, while false positive collisions were nonexistent.

In the method proposed by Lu et al. [74], a neural network was created to identify the collisions that occurred with humans. The primary issue regarding their method was the requirement for the two outside force detectors: one positioned at the foundation and another at the wrist. Consequently, this raised the expense. The broad application of their trained neural network and its performance metric (%) were absent/not provided.

A classifier utilizing neural networks was introduced in [79] to distinguish between instances of unexpected contact and anticipated ones. Through this method, the participants needed to adapt to the sensitivity of the categorization in order to achieve improved outcomes. As a result, the outcomes (total success percentage) increased from (70–72)% for individuals lacking previous familiarity with the classifier to (85–87)% following adjustment to the classifier.

In light of the preceding conversation, Figure 10 is provided to contrast various databased techniques for collision detection, focusing on effectiveness, as well as the counts of false positives and false negatives as the primary benchmarks. Based on the analysis provided in this section, it is evident that methods reliant on data hold great potential for enhancing the safety of human-robot interaction. Additionally, the neural networks are regarded as outstanding techniques that demonstrate significant efficiency and performance metrics in identifying the incidents that occur between humans and robots during cooperative tasks, taking into account the characteristics outlined in reference [87]. Nonetheless, additional inquiries ought to be contemplated for these techniques employing 7-DOF machines. Furthermore, various forms of neural networks and advanced learning techniques ought to be explored as well. Models utilizing support vector machines or neural networks demonstrate significant efficiency and performance metrics with familiar users, while this efficiency diminishes when applied to unfamiliar or new users. This aspect may also be taken into account regarding upcoming projects involving classifiers.

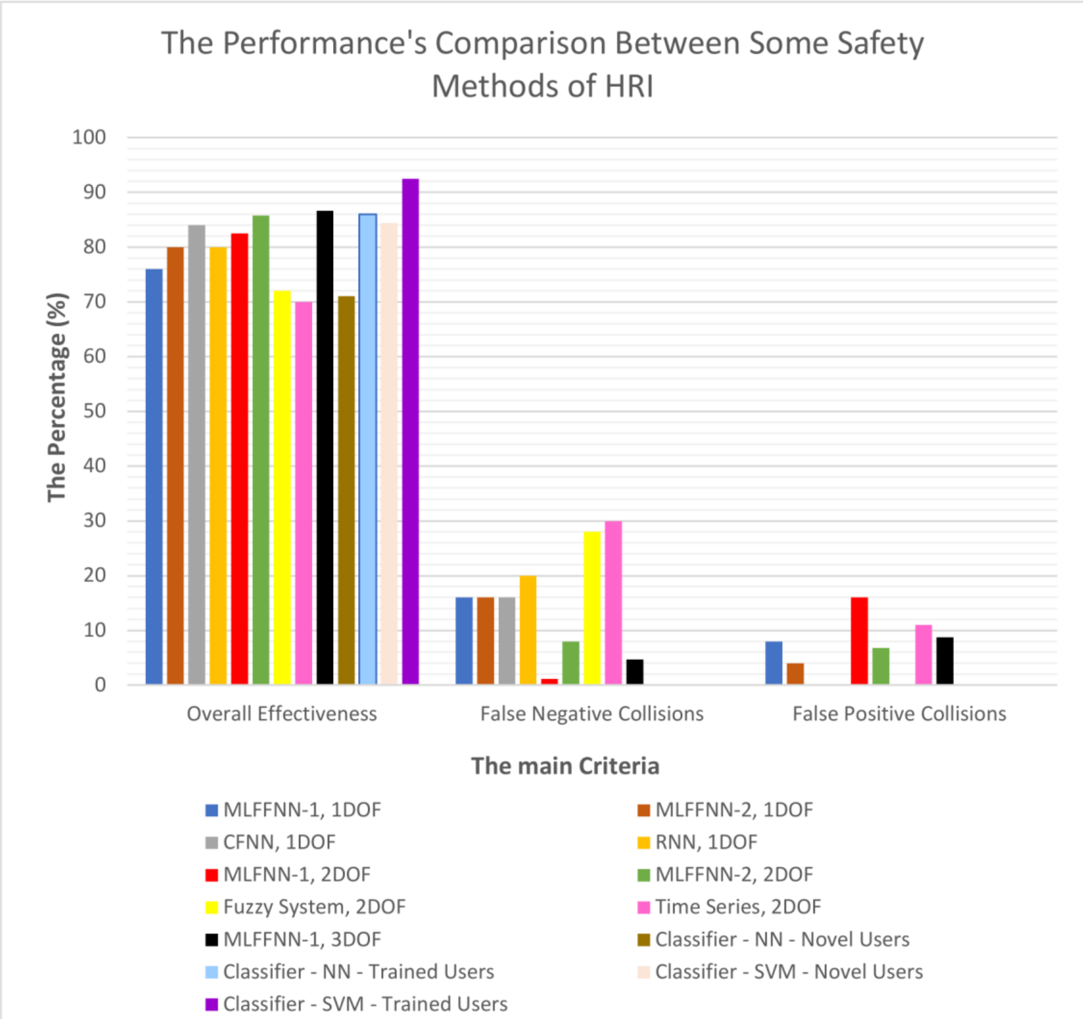

Figure 10. The comparison between the performance of collision detection methods for HRI in terms of the effectiveness, the false negative collisions, and the false positive collisions.

4. Perspectives

This part outlines various viewpoints, requirements, impacts, and anticipations regarding the security and regulation of human-robot interaction for upcoming robotic technologies. The conversation outlined in the earlier two segments indicates that the HRI research efforts are extensive and thorough. Nonetheless, certain elements require thorough examination and connection with the divided research efforts shown.

In the realm of HRI management, certain factors must be acknowledged. The initial concern, as highlighted by the findings in Section 2.4, is that creating VA controllers for robotic manipulators utilizing soft computing methods is both promising and essential for enhancing the performance of HRI. It is advisable to conduct additional exploration using various forms of neural networks and techniques rooted in deep learning. The subsequent concern is that, as highlighted in the existing research, merely a single study focused on modifying solely the virtual inertia factor of the admittance regulation. The findings from this study demonstrated that modifying the inertia solely enhanced the system's stability, reduced the oscillations, and overall elevated the performance of HRI. Consequently, additional exploration for modifying solely the virtual inertia is essential and necessary. The third concern is that creating new VA controllers ought to minimize extensive calculations and intricacy. Moreover, these frameworks ought to bypass specialized insight for instinctive collaboration. The fourth point is that the criteria presented in the existing document for assessing the VA controllers must be considered when creating new variable controllers. Additionally, fresh standards may be evaluated that examine the fluctuations throughout the robot's movement. The final concern is that additional practical assignments need to be explored throughout the creation and assessment of the new VA controllers. These activities may involve intricate and curved movements as well as operations in actual settings such as industry, healthcare, agriculture, and more. Additionally, the quantity of participants involved in assessing the VA controller ought to exceed 30 individuals for more accurate and valid data.

Within the realm of HRI safety, certain concerns must be taken into account and thoroughly examined. The initial concern revolves around the efficiency and evaluation metrics of existing methods for detecting collisions (including their intensities, trajectories, locations, etc.) involving robots. Individuals can engage in countless distinct and diverse scenarios of impacts with the robotic handler; accurate assessment of these impacts is a crucial aspect in human-robot interaction and warrants comprehensive exploration. This may assist in broadening the existing studies from the uses of automated production facilities to additional robotic domains, which is essential for the robotics community. This concern pertains to the adaptability of the approach across various scenarios and situations. The assessment of the impacted connection should likewise be taken into account. The subsequent concern involves establishing the impact limit, which requires further exploration and thorough examination in light of the literature provided in this paper. The third concern is that the majority of existing methods are developed with a focus on joint torque signals, while fewer methods utilize other traditional signals like joint position or current signals. As a result, numerous advanced human-robot interaction systems are utilized exclusively with collaborative robots, which tend to be pricier, while fewer systems are implemented for traditional and industrial robots. The fourth concern is that a single established system is favored and suggested for all joints of the robot rather than having a separate system for each joint. This can reduce the work, the duration, the intricacy, and the calculations. The fifth concern is that the categorizer, regardless of being founded on SVM or NN, demonstrates significant efficiency with the familiar users, yet its efficiency diminishes with the unfamiliar or new users. Consequently, this matter requires additional examination and analysis. The final point is that, as highlighted by the results shown in Section 3.3, employing approaches based on machine learning, especially neural networks, shows great potential in enhancing human-robot interaction and is efficient in identifying collisions. Consequently, additional inquiries are suggested for these methods regarding 7-DOF machines. Additionally, various other forms of neural networks and advanced learning techniques can be explored.

When it comes to approaches that merge elements of security and regulation, an opportunity emerges where innovative studies can be utilized. Sophisticated human-robot interaction frameworks can be achieved when this integration is executed based on artificial intelligence and machine-learning algorithms. The efficiency and performance evaluation of these systems across a wide range of conditions, along with the applications and utilizations of these techniques for various robots, can be a crucial element of the anticipated research efforts.

5. Conclusions

This document offers an overview of VA control mechanisms in collaborative tasks, safety strategies, and viewpoints for human-robot interaction. The various methods for developing VA control, the robotic tasks accomplished, and the comparison of performance are thoroughly examined. The findings from this assessment suggest the adoption of gentle computational approaches, as they show potential in enhancing the effectiveness of HRI. Furthermore, it is essential to incorporate more practical assignments and expand the participant pool for assessing the VA controllers. This review examines the safety of human-robot interaction, focusing on methods for detecting collisions (both model-based and data-driven), establishing collision thresholds, and evaluating the effectiveness of each approach. This assessment led us to conclude that the efficiency of the impact identification techniques under various circumstances must be evaluated alongside the novel strategies. The assessment of the impact limit requires further exploration. Furthermore, the updated method ought to be implemented and utilized with any robotic system, focusing solely on traditional indicators like joint positions or current readings.

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