2019 Latin American Robotics Symposium (LARS), 2019 Brazilian Symposium on Robotics (SBR) and 2019 Workshop on Robotics in Education (WRE)

Automated Inspection of Pressure Vessels through a Climbing Robot with Sliding Autonomy

Piatan S. Palar [1], Andre S. de Oliveira [2], Vinícius V. Terres [3], Júlio E. Ramos [4]

***Abstract*— AIR is a climbing robot designed for non-destructive testing and inspection of weld seams in tanks and vessels of the oil and gas industry. In this paper a Fuzzy control system is proposed to a optimal selection of Levels of Autonomy (LoA) at each moment, mixing joystick inputs from an operator and sensor information from the environment to ensure that the movement of tracking weld seams is being achieved while allowing the operator to have full control of the robot's movements without having to control each maneuver manually. Experiments were executed in a simulator environment and are presented along with future ideas for research.**

I. INTRODUCTION

In the petrochemical industry, the integrity of structures like pipes and vessels requires strict quality control and proper inspection to prevent hazardous accidents. Monitoring these materials can be a dangerous task because of harsh environments and difficult to access areas. For weld seams inspection, non-destructive testing can be achieved utilizing ultrasonic sensors. In oil refineries, the tanks and vessels that hold the fluids can be as large as an 80 meters diameter cylinder, hindering the inspection task for humans [1]. Climbing robots are a valid substitute for this task, presenting a more reliable and safe method of inspection.

There are multiple ways to supervise and control the robot, its sensors, routines, and movements, ranging from fully autonomous systems to teleoperation. In inspection tasks, usually direct control is needed because the operator has to analyze sensor information while maneuvering the robot. A more intelligent approach is the robot having different Levels of Autonomy (LoA), so the operator can - in moments of stress, high workload or anxiety - assign some tasks to the robot while being concentrated on others [2]. To change the LoA, the operator often needs to select and adjust levels manually, but in many cases, the operator is unable to choose the best mode available, either because he is concentrated on another task or because the best LoA is unknown to him.

This paper presents an option of robot control using Fuzzy Control to automatically select one of four levels of Autonomy to move the robot better, using the concepts of Sliding Autonomy. The primary motivation of this work is that the change in LoA to be invisible to the operator. While the operator maneuvers the robot, the robot corrects where the operator is doing wrong and also let the operator controls the velocity and the path that the robot will follow. An operator gives the inputs in the Human-Robot Interaction via a joystick, and together with sensor information, these are used to select the Autonomy level. An evaluation of the strategy is presented in a simulation environment.

In the following section, a background on Human-Robot Interaction, Autonomy Levels, and some related work are presented. In Section III are presented the robot, the scene, the LoA, the Fuzzy control system developed, and the experiment setup. In the in Section IV, results about the experiments are shown, and in Section V, the conclusions are drawn.

II. HUMAN-ROBOT INTERACTION

Robots are a reality in human life for decades and facilitate our lives in a multitude of repetitive, tedious, and dangerous tasks. Industrial tasks like casting, stacking, welding, painting, and sorting have been made by robots for more than 30 years now all over the world [3]. With the advancement of technology, more and more communication and cooperation between robots and human operators are necessary, through what is called Human-Robot Interaction (HRI). This interaction is no longer made only with buttons and handles [4] and is increasingly resembling human communication, making humans and robots act together and cooperate to accomplish the desired tasks, bringing these agents together and saving the cost needed for more operators and training drills [5].

According to [6], the HRI can be defined as the field of studies that covers, from the very first conception to the final development, robots that interact with humans in a physical, affective or social way. Industrial robots, robot arms, autonomous cars, assistant robots, and rescue robots are examples of robots operating with collaboration, communication, or cooperation with humans [7].

In the industry, HRI is observed in processes like collaboration for handling movements in assembly, automatic orientation for cranes and riveting. Technologies such as human and object detection in 3D environments and gesture recognition can be utilized to help in accomplishing these goals [8].

In rescue operation for disasters, robots can be assigned for dangerous places while being teleoperated by an operator in a safe station. This distance, however, creates challenges for the operation, such as communication delay and struggle to visualize better and analyze the situation [9]. Rules for autonomy levels were defined, for robots to adopt in specific tasks and emergencies or problems in regular operation.

UTFPR - Universidade Tecnologica Federal do Parana
[1]piatan@alunos.utfpr.edu.br
[2]andreoliveira@utfpr.edu.br
[3]viniciusterres@alunos.utfpr.edu.br
[4]julio.ramos@petrobras.com.br

978-1-7281-4268-5/19/$31.00 ©2019 IEEE
DOI 10.1109/LARS-SBR-WRE48964.2019.00057

A. Levels of Autonomy

One definition of autonomy, considering the social feature of an agent, is the notion that an agent is autonomous when it can choose act in a way that contradicts the decisions of other agents [10]. An agent can possess several autonomy levels, determined by how much their decisions are affected by other agents. Another definition of autonomy for robots is for how much time they can be ignored. The more a robot can operate without human interruption, more autonomy that the robot has [6].

In several applications, changing the autonomy level on the fly is needed. A fully autonomous robot could need some help in some situations, and different tasks can require different autonomy levels. While being fully autonomous dismisses the attention of an operator, unwanted situations can occur and also endanger or threaten humans. On the other hand, with no autonomy, more safety is achieved, but with efficiency loss [11]. Varying autonomy is, therefore, a compromise between efficiency and safety. Various levels of autonomy were defined and can be seen in Table I.

TABLE I: Autonomy levels in decisions and action selection [12]

10	The computer decides everything and acts autonomously
9	Informs the human only if it, the computer, decides to
8	Informs the human only if asked
7	Executes automatically then necessarily informs the human
6	Allows the human a restricted time to veto before execution
5	Executes a given suggestion if the human approves
4	Suggests one alternative
3	Narrows the selection down to a few
2	The computer offers a set of decision/action alternatives
1	Human must take all the decisions with no assistance

In Table I, ten autonomy levels are observed, from fully autonomous (level 10) to no autonomy at all (level 1). Within the robotics context, studies [13] usually separate in 4 the autonomy levels. The two ends are fully autonomous, and no autonomy and the intermediate levels are Safe mode, where the operator executes control, but the robot prevents collisions and harmful actions and Shared mode, where the robot usually drives autonomously but allows the operator to jump in and affect movements. Some cases require a scale for autonomy levels relying on parameters that can be changed in online to produce what is often called Sliding Autonomy, Sliding Scale Autonomy, Adjustable Autonomy, or Mixed Initiative.

B. Related Works

A related research [2] tested teleoperation with high and low operator workload and full autonomy with high and low sensor noise. Results showed that a higher workload have a significant impact on speed performance, and sensor noise had a considerable impact on autonomy performance. In [14], Fuzzy control is used for shared autonomy on swarm vehicles, representing drivers in different classes separated by their response times. Other research [15], evaluates the effectiveness of both autonomous and teleoperated levels of autonomy in inspection robots in a laboratory with 21 participants. The participants performed best with assisted autonomy because they felt they had more focus on observing and inspecting than controlling the robot. In another research [13], many autonomy levels were achieved by modifying the values of some navigation parameters, like velocity defined by the user and the robot, speed limit, inflation distance to objects, among others. In another paper, [16], three autonomy levels are defined using destiny points and heuristics, setting general driving information for the robot to follow in predetermined places on the map and places to avoid. The speed of the robot is determined through the details of the map and the robot's current goal. [17] presents research about changing the autonomy level according to the operator experience level. Experiments are carried out first for the system to classify the user in navigation, handling, and cooperation tasks. The results shown indicated less time to accomplish tasks using the adapted autonomy, then using a fixed level.

III. Autonomous Inspection Robot (AIR)

In this section, the Autonomous Inspection Robot (AIR)[18] can be seen in Fig. 1.

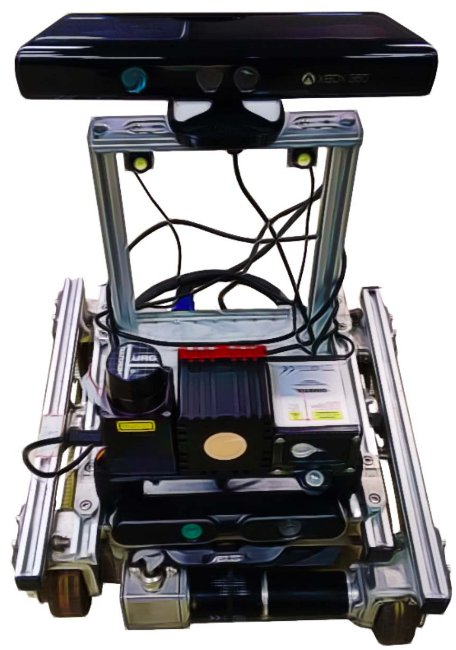

Fig. 1: Autonomous Inspection Robot (AIR) - a robot designed for navigation in cylindrical and spherical tanks.

AIR [19] is a climbing robot with four magnetic wheels, and each pair of wheels features a timing belt moved by a brushless motor. AIR utilizes differential drive for moving and can move from all positions, including upside down. It also has several perception sensors including an LRS 36/6 profile sensor which is capable of sensing the weld seams for navigation purposes only. Algorithms were developed for the robot to follow the weld seams and are part of the autonomous mode.

There is also a laser, shown in Fig. 2, for visual reference only for the operator to better visualize the orientation of the robot. The actual weld seams inspection is accomplished by other sensors, and this process is beyond the scope of this work.

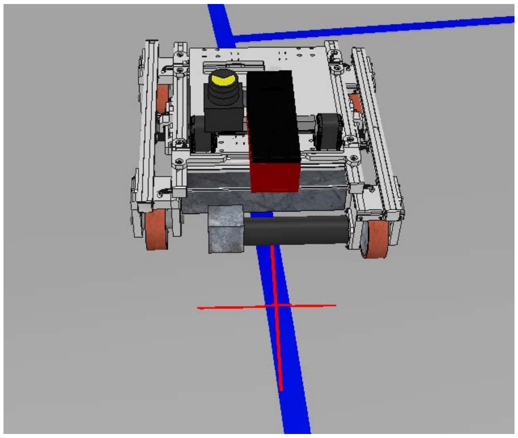

Fig. 2: Two types of lasers are emitted by AIR's sensors. The horizontal one represents the profile sensor that is capable of sensing the weld seams. The vertical one is only a visual reference for orientation issues and do not return to the robot any kind of information.

IV. Sliding Autonomy

The four levels of autonomy organized for selection when operating the robot are summarized in Table II. The first mode is when the operator has full control of robot movements, controlling linear and angular velocities. The only action that the robot can take in this mode is to stop a movement requested by the user that can induce a collision. The second mode is Shared Control, where the robot stays in the weld bead by controlling angular velocities, and the user controls how fast the robot will move forward. The third level of autonomy is Supervisory Control. In this mode, the robot will move at a safe speed staying in the weld bead and waits for the user to choose a direction when an intersection is found. The fourth and final mode is Full Autonomous, where the user defines a set point, and the robot will determine the best route to reach that destination. The setpoint can be global by locating a point in the tank or local, by establishing a distance related to the actual position of the robot. In this work, the Full Autonomous mode setpoint is always defined at the endpoint of the experiment.

A. Fuzzy Control

The Fuzzy system takes in information from the back and front sensors, linear and angular velocities input by the operator on the joystick and the position of the weld seam relative to the center of the robot and outputs the most fitting LoA with the available information.

The membership function for linear and angular velocities input by the operator and the weld position detected by the profile sensor are displayed in Fig. 3. The Fuzzy sets for linear velocities are Negative Low, Negative Medium, Negative High, Zero, Positive Low, Positive Medium, and Positive High. For angular velocities and weld seam position, the sets are both:: Left High, Left Medium, Left Low, Center, Right Low, Right Medium and Right High.

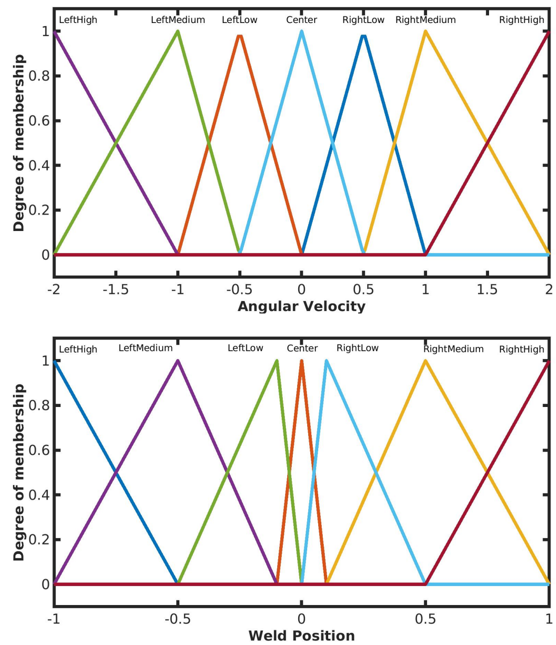

Fig. 3: Membership functions for some of the inputs of the Fuzzy control. Linear and angular velocities are input by the operator via a joystick and the weld seam position is detected by a profile sensor. Front and back proximity sensors were also used but are not displayed in this figure.

A control surface representing Weld Position and Angular Velocity values and the corresponding LoA can be seen in Fig. 4. If the values of Weld Position and Angular Velocity are aligned, e.g., a high value of left angular velocity and the weld position located on the left side of the robot, the Autonomy is set to Manual - lower on the Figure. If however, the joystick is moving the robot to the left and the weld position is on the right, the LoA will be set to either Shared, Supervisory or Autonomous, depending on how wrong the joystick input is.

V. Experimental evaluation

For this paper and optimization of the simulation scene, several sensors were cut off from AIR, mainly sensors that were used for mapping and localization with object detection. The only sensors that were kept were the LIDAR sensor for collision prevention and the profile sensor for weld seam detection. The simulation scene used for the experiments can be seen in Fig. 5 with both AIR and the tank with weld seams represented in blue lines.

The Human-Robot Interaction is accomplished through an industrial joystick, that can be seen in Fig. 6. In the

TABLE II: Description of Autonomy Levels

	Mode	User capabilities	Robot capabilities
1	Full direct control	Linear and angular velocities	Avoid collisions
2	Shared Control	Linear velocity and choosing directions in intersections	Angular velocity to stay in the weld bead
3	Supervisory Control	Choosing directions in intersections	Linear and angular velocities
4	Full autonomous	Defining an end point	Calculating a path and defining linear and angular velocities

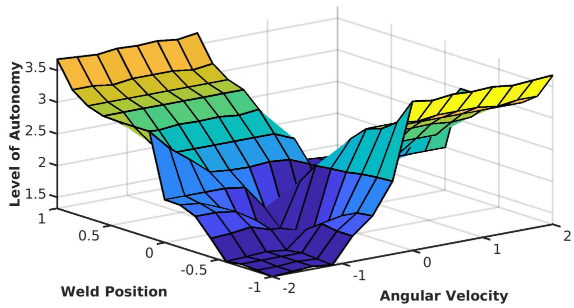

Fig. 4: Control surface showing the impact of both angular velocity and weld position in ascertaining the Level of Autonomy. The higher up the values are in this figure, the more autonomy is given to the robot.

Fig. 6: Joystick for the operator to maneuver the robot, selecting the LoA, angular and linear velocities and initiating routines.

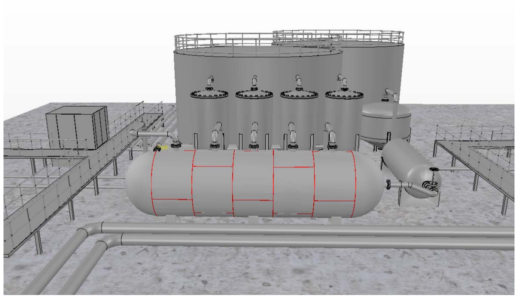

Fig. 5: Simulator scene representing a refinery with tanks for weld seams inspection and AIR, the climbing robot who holds the instruments necessary for the inspection processes to be done.

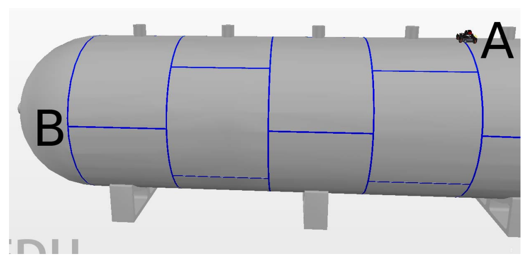

Fig. 7: The experiment setup in the V-REP simulator. The goal is to go from point A to point B while tracking the blue lines - representing weld seams - as much as possible.

upper right, there's a stick that moves the robot forward and backward and also rotates the robot by moving the stick sideways. There are on the left two sliders that select linear and angular velocities maximum values. There is also a 4-position selector for manual selection of autonomy that is not used in this work. There are five subroutine and sensors switches that are not used in this paper and an emergency button on the bottom, for stopping the robot at any time.

The environment simulation was built using the V-REP simulation platform. A model of AIR was already developed. In this project's phase, environment mapping and localization techniques were not used. The simulation environment of the refinery was simplified for optimization and performance gain. In Fig. 7, the practical part of the refinery for this experiment can be seen, containing only AIR and the tank.

The goal of the experiments is to navigate the cylindrical tank from point A - the starting position of the robot - to the intersection in point B, trying to maintain the robot in the weld seam for as long as possible during the route. The camera angle is fixed to simulate the real position in which the operator would control the robot in real scenarios. Four cases were studied. In case A, the robot was set to manual mode and a participant maneuvered the robot. In case B, the fully autonomous mode was set. In case C, a participant could control the LoA manually in the joystick. In case D, the Fuzzy system introduced in this paper was set while a participant controlled the robot. In experiments C and D, it was requested for the participant to maneuver slowly in the vertical weld seams, simulating a more precise inspection on those segments.

VI. Results and Discussion

In this section the results of the experiments will be discussed. First, a performance metric P was calculated from each experiment, as seen in Equation 1:

$$P = \frac{\sqrt{AccumulatedErrorSquared}}{TimeElapsed} \quad (1)$$

The accumulated error is the robot alignment error based on the profile sensor. It is squared because the error can be positive or negative if the robot is more to the left or the right of the weld seam. Since this accumulation will only increase over time, it is divided by the time elapsed since the beginning of the experiment. This performance metric proved to be very useful in measuring how well the weld seams are being tracked by the robot, and the lower it is, the better. Another metric used only for experiments C and D is the number of shifts of LoA during the experiment. The Table III summarizes all the results.

TABLE III: Description of Autonomy Levels

Experiment	Error	Time(s)	P	LoA shifts
Manual	569.96	174.14	0.137	-
Autonomous	81.29	157.39	0.057	-
LoA chosen	273.34	172.02	0.096	11
LoA Fuzzy	65.66	166.92	0.048	55

A. Manual Mode

This experiment exhibited as expected the worst performance, with the highest error accumulated and the highest time to complete. The path covered can be seen in Fig. 8 and it shows how hard it to control a robot in a cylindrical tank.

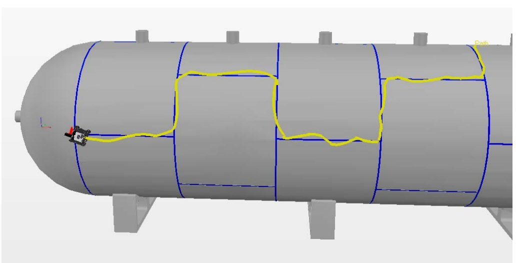

Fig. 8: The path described by the robot in the experiment with Manual mode set.

B. Autonomous Mode

In this mode, whose path can be seen in Fig. 9, the best time and the second-best performance rating were achieved. The excellent performance was expected since, in this mode, there is no human aid. However, the velocities of the robot could not be altered in online, and so the inspection task in this mode is undermined.

C. LoA chosen by the user

This experiment has shown the second-worst time and a lot of error accumulated. The shifts can explain the time in LoA. The errors occurred because there's a critical moment in this path, where the robot has to rotate right and move up in the tank, as can be seen in Fig. 10. This task has proven to be hard while changing the Autonomy Level to control a slower velocity upward.

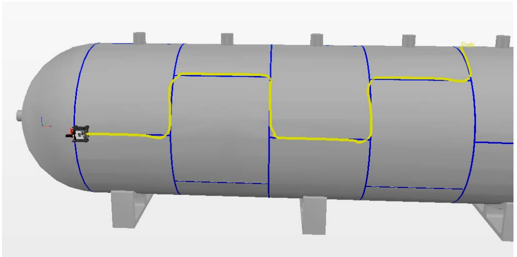

Fig. 9: The path described by the robot in the experiment with Autonomous mode set.

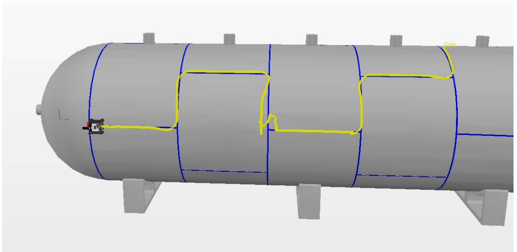

Fig. 10: The path described by the robot in the experiment with LoA chosen by the operator.

D. Fuzzy Approach

The experiment involving the Fuzzy system presented the best results in performance and error. The control that can be applied to move the robot more slowly generates a more fluid and controlled motion, as can be seen in Fig. 11. The path is very similar to the observed in autonomous mode. However, in this mode, the velocity of the robot can be highly controlled. Also noting is that there were five times more shifts in the LoA in this mode, almost one every 3 seconds. This high frequency in shifts is improbable to be accomplished by an operator while maneuvering the robot. A comparison between LoA shifts is shown in Fig. 12.

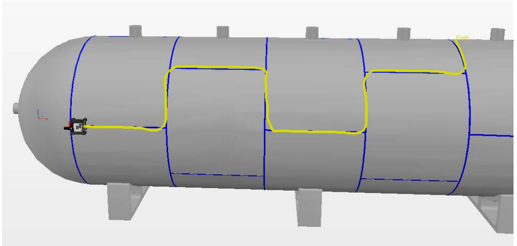

Fig. 11: The path described by the robot in the experiment with LoA chosen by the Fuzzy system.

It can be seen that when the operator changes the autonomy manually, Shared and Supervisory modes were preferred, but that can change according to the level of skill and experience of the operator. When the weld seam was lost, Manual mode was activated and in the last part, Autonomous mode was selected to finish the course. In the fuzzy approach, all the shifts went unnoticed and the operator was under the impression that he was in fully control of the robot.

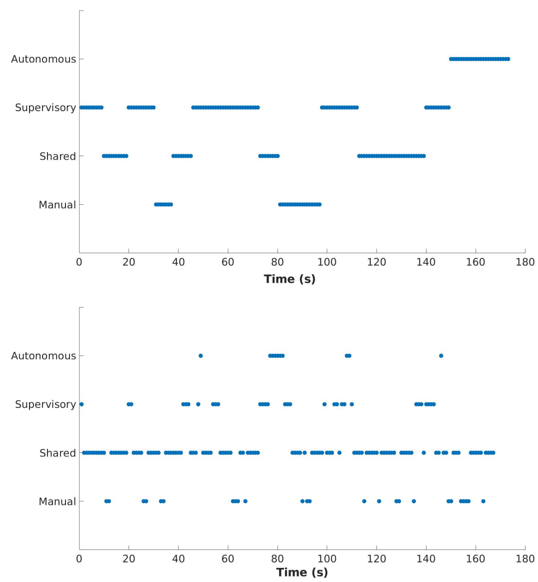

Fig. 12: Changes in LoA in the middle of the experiments C and D. The Fuzzy system helps the user by shifting automatically between Autonomy Levels.

With these experiments and fuzzy architecture, the operator kept the LoA at most in Shared mode, with 4 shifts to Autonomous mode and 13 shifts to Manual mode, which represents an intermediate level user.

VII. Conclusion

In this work a Fuzzy system was presented for better controlling a climbing robot capable of inspecting gas and oil tanks and vessels without jeopardizing the operator's attention while maintaining full control of the robot's movements.

For future work, additional experiments simulating the need for a timed inspection in some areas are required, for better exercise the real-life situations, along with more participants with different levels of skills operating the system. Also, there are plans for incorporating a Myo armband - an armband that receives input from electrical activity in human arms and muscles - in the system. Experiments with the robot in real life tanks and vessels are the ultimate goal.

References

[1] R. A. Gnoatto and A. Bianchi. Reprojeto e construção do protótipo de um robô de inspeção de cordões de solda em superfícies metálicas verticais e esféricas (segunda geração), 2015.

[2] Manolis Chiou, Nick Hawes, Rustam Stolkin, Kimron L. Shapiro, Jess R. Kerlin, and Andrew Clouter. Towards the Principled Study of Variable Autonomy in Mobile Robots. *Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015*, pages 1053–1059, 2016.

[3] Clint Heyer. Human-robot interaction and future industrial robotics applications. *IEEE/RSJ 2010 International Conference on Intelligent Robots and Systems, IROS 2010 - Conference Proceedings*, pages 4749–4754, 2010.

[4] P. Masinga, H. Campbell, and J. A. Trimble. A framework for human collaborative robots, operations in South African automotive industry. *IEEE International Conference on Industrial Engineering and Engineering Management*, 2016-Janua:1494–1497, 2016.

[5] Tytus Wojtara, Masafumi Uchihara, Hideyuki Murayama, Shingo Shimoda, Satoshi Sakai, Hideo Fujimoto, and Hidenori Kimura. Human-robot collaboration in precise positioning of a three-dimensional object. *Automatica*, 45(2):333–342, 2009.

[6] Michael A. Goodrich and Alan C. Schultz. Human-Robot Interaction: A Survey. *Foundations and Trends® in Human-Computer Interaction*, 1(3):203–275, 2007.

[7] Przemyslaw A. Lasota, Terrence Fong, and Julie A. Shah. A Survey of Methods for Safe Human-Robot Interaction. *Foundations and Trends in Robotics*, 5(3):261–349, 2017.

[8] Alberto Tellaeche, Inaki Maurtua, and Aitor Ibarguren. Human robot interaction in industrial robotics. Examples from research centers to industry. *2015 IEEE 20th Conference on Emerging Technologies & Factory Automation (ETFA)*, pages 1–6, 2015.

[9] Shu Jiang and Ronald C. Arkin. Mixed-Initiative Human-Robot Interaction: Definition, Taxonomy, and Survey. *Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015*, pages 954–961, 2016.

[10] Gordon Beavers and Henry Hexmoor. Types and Limits of Agent Autonomy. *Agents and Computational Autonomy. Potential, Risks, and Solutions*, pages 95–102, 2004.

[11] Matthew Ball and Vic Callaghan. Explorations of autonomy: An investigation of adjustable autonomy in intelligent environments. *Proceedings - 8th International Conference on Intelligent Environments, IE 2012*, pages 114–121, 2012.

[12] Raja Parasuraman, Thomas B Sheridan, and Christopher D Wickens. A Model for Types and Levels of Human Interaction. *IEEE Transactions on Systems Man and Cybernetics Part A Systems and Humans*, 30(3):286–297, 2000.

[13] Munjal Desai and Holly A. Yanco. Blending human and robot inputs for sliding scale autonomy. *Proceedings - IEEE International Workshop on Robot and Human Interactive Communication*, 2005:537–542, 2005.

[14] Aaron J. Sengstacken, Daniel A. Delaurentis, and Mohammad R. Akbarzadeh-T. Optimization of shared autonomy vehicle control architectures for swarm operations. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 40(4):1145–1157, 2010.

[15] Øyvind Netland, Gunnar Jenssen, Hilde Marie Schade, and Amund Skavhaug. An experiment on the effectiveness of remote, robotic inspection compared to manned. *Proceedings - 2013 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2013*, pages 2310–2315, 2013.

[16] J.W. Crandall and M.A. Goodrich. Experiments in adjustable autonomy. *2001 IEEE International Conference on Systems, Man and Cybernetics. e-Systems and e-Man for Cybernetics in Cyberspace (Cat.No.01CH37236)*, 3:1624–1629, 2001.

[17] Bennie Lewis, Bulent Tastan, and Gita Sukthankar. An adjustable autonomy paradigm for adapting to expert-novice differences. *IEEE International Conference on Intelligent Robots and Systems*, pages 1656–1662, 2013.

[18] Marco Antonio Simoes Teixeira, Nicolas Dalmedico, Higor Barbosa Santos, Andre Schneider de Oliveira, Lucia Valeria Ramos de Arruda, and Flavio Neves. Enhancing robot capabilities of environmental perception through embedded gpu. In *2017 VII Brazilian Symposium on Computing Systems Engineering (SBESC)*, pages 217–224. IEEE, 2017.

[19] Marco Antonio Simoes Teixeira, Higor Barbosa Santos, Nicolas Dalmedico, Lucia Valeria Ramos de Arruda, Flavio Neves-Jr, and Andre Schneider de Oliveira. Intelligent environment recognition and prediction for ndt inspection through autonomous climbing robot. *Journal of Intelligent & Robotic Systems*, 92(2):323–342, 2018.