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Review of studies on NAO robot

NAO robot üzerindeki çalışmaların incelemesi

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Abstract

Robots are reducing the various workload of humans in numerous fields, shaping many new scientific areas. This review provides an overview of research and developments conducted on the humanoid robot NAO between the years 2020 and 2024. It encompasses a general examination from the robot's physical structure to its hardware and software components. The review categorizes studies related to NAO into three main areas: Human-Robot Interactions, Navigation, and Others. The explanation of recent developments in NAO robot aims to facilitate a deeper understanding of potential advancements in the future of robotics.

Keywords: NAO Robot, Robotics, Human Interaction, Navigation

Öz

Robotlar birçok alanda insanların çeşitli iş yükünü azaltarak birçok yeni bilimsel alanı şekillendirmektedir. Bu inceleme, 2020-2024 yılları arasında insansı robot NAO üzerinde yapılan araştırma ve gelişmelere genel bir bakış sunmaktadır. Robotun fiziksel yapısından donanım ve yazılım bileşenlerine kadar genel bir incelemeyi kapsamaktadır. İnceleme, NAO ile ilgili çalışmaları üç ana alanda kategorize etmektedir: İnsan-Robot Etkileşimleri, Navigasyon ve Diğerleri. NAO robotundaki son gelişmelerin açıklanması, robotiğin geleceğindeki potansiyel ilerlemelerin daha derinlemesine anlaşılmasını kolaylaştırmayı amaçlamaktadır.

Anahtar Kelimeler: NAO Robot, Robotik, İnsan Etkileşimi, Navigasyon

1 Introduction

Increasing need of information in today's world, the tasks undertaken by humans have slowly shifted to robots. These tasks have wide range of examples such as heavy-duty automotive industry, field of health in cases where risky surgeries take place, autism diseases for the purpose of protecting children's mental health and so on. Within these areas, developments have been made with the help of the robotics. Thanks to these developments, easiness is benefited more than realized in small areas of lives. While we are able to access innovations that make our lives easier faster with the systematic progress of these developments. Examples can be given from many robots that prioritize these different developments specific to each need. For instance, Boston Dynamics, which produces humanoid or dog-like robots for use mostly in the defense industry, small robots responsible for cleaning our house, and the humanoid-looking NAO robot by Aldebran Robotics are the main ones. Studies on robots must successfully implement several basic policies for a robot to perform its task. The most important of these policies are undoubtedly to perceive its environment and act within certain rules in this environment. In a general approach, the tasks of the robot vary with the sensors used, and mechanical designs. NAO robot, which has a wide variety of tasks, offers a rich resource for improvements.

This review article was written in order to present a brief summary of how these diversities lead to new developments, how the improvements progress and how their diversity is brought to the literature in some way. The review summarizes the improvements made on the NAO robot under three main topics. These are human-robot interaction (HRI), navigation and other.

2 Technical aspects of NAO robot

NAO robot has a human-like look at height of up to 58 cm. It has head, torso, arms, and legs. The NAO has range of sensors like cameras, microphones, sonars and tactile sensors which enable it to detect and interpret surroundings. It has a lot of actuates and joints provided at the different body parts that make it move smoothly and accurately. A robot offers an onboard computer that is capable of processing sensory data, motor control and the very complicated decision tasks. The existence of the software platform that is used to program NAO's behavior and interactions makes it accessible for the developers to do programming as well. The NAO principal environment is Choregraphe, which is a graphical interface. Also, NAO supports different programming languages like Python and C++ etc. NAO is powered by the speech recognition, natural language processing features which make it to have a conversation with its user. The LED eyes and audio cues make the robot really interactive for users. NAO also has wireless and Bluetooth connections. It can be tapped into for use with the external hardware and software to execute the duties such as web browsing, data retrieval and cloud computing. Technical details of the NAO robot can be found in Table 1. Also, before passing into studies for better understanding, we present the NAO robot in Figure 1.

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Figure 1. NAO robot [1]

3 Studies on NAO robot

In this section, we will examine the various studies and developments conducted on the NAO robot under three main categories: Human Interaction, Navigation, and Others.

3.1 Human Interaction

The purpose of this section is to explore how humans react towards NAO like in the experiments like speech recognition, natural language processing, face recognition, emotion detection and social interactional abilities.

To begin with the research, Trifirò et al. [2] called roboceptions through interacting with human beings. It is about how the robot will grasp the relationship between linguistic and bodily sensations. The robot's language learning activity uses a human interaction to articulate feelings, before a Dual-NMT-based grounding language technicality. The robosceptions are perceived by a synthetic somatosensory system. Using the RoboLang to analyze roboceptions helps the robot express its basic needs. Translation between RoboLang starts from the close resemblance values and bilingual datasets in bid to overcome the obstacle of small training data. This study uses NAO robot equipped with data collection sensors for research set up and data collection.

Yet another investigation of the NAO robot from Softbank Robotics related to HRI Nama et al. [3] find out that effective gesture-based communication and interaction could improve learning outcome for special need students in elementary level. This experiential program deploys Leap Motion together with custom made action-reaction correlations to weave kids' hand gestures with robot reactions. A strategy aimed at motivating learner to enjoy the learning process. The result of the research outlined to transform the very current content and apply close-loop HRI of disadvantages for kids with special needs face while learning. This research is partly attained by incorporating robotics and gesture recognition technology into learning processes of children. By doing so, according to the study, the activities will become stimulating and interactive, leading to improvements of their cognitive development and reducing the boredom of the children during education activities.

Recupero et al. [4] reveal the approach of the NAO to acquire the knowledge and behavior to fulfill the expressed wishes of the users when they speak. This one represents the actor of robot ontology and situates through the natural language processing engine to comprehend the user commands. There are two different kinds of operational modes for the robot: STATELESS and STATEFUL. When it concerns STATELESS mode, every command is implemented separately. However, in the STATEFUL mode, the robot decides which action to perform after it determines its current position. The system resolves the problem of identifying and running the action commands that fall upon a robot status, and it effectively manages the compound expressions. It describes the technical infrastructure including that of the NAO robot, the programming environment and the cloud-based neural network processing (NLP). To this end, the procedure of getting information from user commands, identifying desired actions and performing robot interactions is clearly stated within the study.

In another study of HRI, Romero-García et al. [5] presents Q-CHAT-NAO, an observation-based autism screening system supported by a NAO robot, which adapts six questions from the Q-CHAT-10. Q-CHAT-NAO collects information directly from toddlers. In this way, detecting early indicators of autism spectrum disorder (ASD) is achieved. Machine learning models, including decision trees, random forests, and boosted trees, are employed. Evaluation metrics is crucial for sensitivity to ensure correct classification of ASD cases. Activities involving the robot and the child, monitored by a therapist, provide input for classification. However, not all original questions are adaptable, resulting in a subset of six questions for the Q-CHAT-NAO.

The development of an integrated robotic system named ChildBot, designed to engage in educational and entertainment activities with children, is presented by Efthymiou et al. [6]. ChildBot incorporates sensors and robotic agents. With this incorporation, robust coordination in complex Child-Robot Interaction (CRI) is achieved. To make communication between the channels, sensors and perception modules are integrated into ChildBot. The Sense-Think-Act paradigm is followed by the system, and an indoor-based architecture is employed. Additionally, the development and integration of perception modules such as audio-visual active speaker localization, 6-DoF object tracking are also applied. The system showed that it enables autonomous interaction between children and robots. NAO robot is used as a supervisor in a game in this study.

In another HRI area, Ivani et al. [7] introduces a therapeutic program for children diagnosed with ASDs. The aim of the program is to integrate an algorithm within the framework of IOGIOCO. This algorithm is designed for gesture recognition. Also, the program is operated within the NAO robot. In the recognition part, firstly, 3D coordinates of body key points captured by a Kinect sensor are utilized. Then, the Residual Neural Network automatically identifies and evaluates gestures performed by children. The recognition process occurs in real-time, allowing for immediate feedback from the robot based on the accuracy of the gestures. Aim behind this feedback is to aid therapists to help their engagement with the program and guiding the children.

A system, Handie, is designed to facilitate interactions between autonomous mobile and cyber physical systems by Håkansson and Amberkar [8]. It is designed especially in humanoid robots like Softbank Robotics' NAO robot v6 and users with hand signs and facial mood expressions. These non-verbal cues serve as commands to the robot, enabling actions such as information retrieval, music playback, and physical tasks execution. Handie uses a deep learning recognition to detect hand signs and facial expressions. The system architecture involves the integration of the NAO robot with an external computer system. The NAO follows the steps like capturing images, recognizing hand signs and mood expressions, then executing corresponding actions based on user input, respectively. The layer manages communication between the robot and the hand signs recognition component (HSRC). Behind the HSRC working logic convolutional neural networks are employed for image classification.

Gaze cueing effects in both young and older adults are investigated by Morillo-Mendez et al. [9]. For the gaze cueing task, NAO robot's head is used as the central cue observing from the back. The primary aim was to realize age-related disparities in response to the robot's head orientation. Particular focus is the scenarios where visual eye cues were absent. Also, the analysis was conducted by excluding data from three recruits who in overall seem to be outliers. At the same time the accuracy of the remaining sample was almost zero error. Given the participants' reaction time in the ANOVA tests, age, stimulus synchrony, stimulus onset asynchrony, and gaze congruency main effects showed difference which indicated how gaze-cueing happens in different situations and populations.

Jeon et al.' [10] purpose in this paper is to present an approach to AI interactivity with the NAO robot in the process of balancing tables with time-sensitive training from a human trainer. The system uses Deep Q-Network (DQN) . Then the system integrates sentiment through the training session from trainer speech using an originally designed reward function. The research uses this method on the NAO robot. It detects the current image of the table state and adjusts its joint parameters to adapt the executed actions to the planned ones. The human trainer gives the robot a judgment, i.e. if the robot's movement is good or bad, and the evaluation is involved in the DQN's environment reward. The interactive deep reinforcement learning (DRL) architecture gives full command over the robot learning and doing better as a result of a high rate of task completion success. Hyper parameters of the DQN training can be found in Table 2.

3.2 Navigation

In this section, the findings of study on the navigation of the NAO robot are reviewed. This review involves navigation of NAO autonomously within its environment, including such functions as obstacle avoidance and path planning. Knowing NAO's capacity to navigate its movement through different realistic situations is very significant for the best possible mobility. In addition, the trajectory of studies in this field has been studied to see different top areas of research they are focusing on.

To begin with the core logic of navigation, Kumar et al. [11] introduce a hybrid control system. From the proposed hybrid control system, enhancing of humanoid navigation is expected. For this purpose, regression analysis with fuzzy logic is combined. Inputs coming from NAO's ultrasonic sensors are provided to the regression architecture. Regression is processed these inputs to generate a temporal turning angle. This temporal turning angel is further refined by the fuzzy controller to obtain the ultimate turning angle. This approach provides smooth motion control, obstacle avoidance, and goal-reaching. Petri-Net aids in managing inter-collision risks in the navigation of multiple NAOs.

A novel hybrid navigation system tailored for NAO humanoid robots is presented by Kashyap et al. [12]. This navigation system consists of the Dynamic Window Approach (DWA) and Teaching–Learning-Based Optimization (TLBO) techniques. Optimizing the velocity and turning angles is discussed to prevent obstacles and reach targets effectively. The hybrid approach is evaluated across both static and dynamic terrains. For these environments, it has been noted that there are risks of inter-collision in multi-robot. Those problems are mitigated by the incorporation of Petri-Net controllers. In the simulations and real-world experiments, the proposed technique showed its ability to achieve collision-free paths while reaching designated targets. The article pointed out its potential in tackling more intricate terrains such as stairs or slopes. Block diagram of the DWA- TLBO can be found in Figure 2.

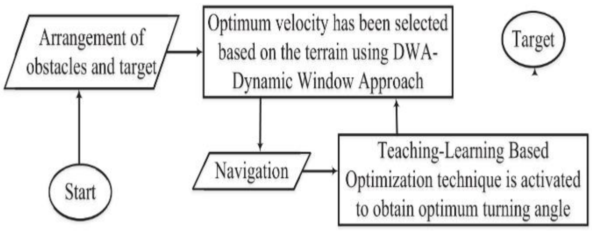

Figure 2. Block diagram of hybrid DWA-TLBO [12]

García and Shafie [13] propose Safe Reinforcement Learning (SRL) to enhance NAO's walking behavior. SRL makes robotwalk faster while reducing falls. Policy Reuse for Safe Reinforcement Learning (PR-SRL) improves walking behavior by combining an increasing risk function. Experimental evaluation on a NAO robot demonstrates PR-SRL's minimizes falls compared to state-of-the-art algorithms.

Gait planning for humanoid robots is discussed for their stability and task execution. In this paper, a hybrid approach using the linear inverted pendulum model and particle swarm optimization (PSO) tuned Proportional Integral Derivative (PID) controller is proposed by Kashyap et al. [14]. The linear inverted pendulum model (LIPM) is coupled with center of mass (COM) and zero moment point (ZMP) criteria. LIPM aids in selecting step length and period. Also, sensory data and desired trajectory help in inverse kinematics for trajectory planning. The PSO tuned PID controller optimizes parameters for obstacle avoidance and stability. Aim behind this approach is to reduce travel time and length. Simulation and real-world experiments show a significant reduction in stabilization time and overshoot.

Kashyap et al. [15] described the implementation of navigation approaches for single and multiple NAO robots. In this approach, collision-free path optimization in static and dynamic terrains are main focus. An Adaptive Network-based Fuzzy Inference System controller is utilized. This controller generates a transitional driving angle based on obstacle distance. Output of this process is optimized by a TLBO approach to produce an optimum driving angle (ODA). Path selection is discussed based on Euclidean distance and ODA. Integration of a dining philosopher controller solves inter-collision issues in multiple NAO navigation. Simulation outcomes showed the controller's importance resulting in optimizing path length and travel time.

For the further implementation again, Kashyap et al. [16] focused on optimizing path length, energy demand, and task completion time problems. The solutions are discussed as development and implementation of a hybrid navigational controller for humanoid robotics. The aim is to improve path planning efficiency and task completion in humanoid robots. The hybrid controller includes Improved Spider Monkey Optimization (ISMO) approach besides Regression Analysis (RA) approach. RA approach takes the obstacle and target locations to determine navigational directions. Afterwards, the ISMO approach refines trajectory by adjusting turning angles. Also, B-Spline path smoother is applied to stabilize trajectory step by step. The effectiveness of the hybrid controller is attributed to the longer decision-making times and higher computational costs. Experiments were done in simulation and real time using NAO robot. The combination of RA and ISMO techniques showed the success in the experiments. Improvement in the path length and task completion of proposed approach percentages are presented in Table 3.

Navigation for humanoid robots and multi-objective problems are discussed by Kashyap et al. [17]. Under these solutions lay down integrating modified multiple adaptive neuro-fuzzy inference system (MANFIS) and multi-objective sunflower optimization (MOSFO) techniques. These generate optimal steering angles for obstacle avoidance. Operation is done with two steps. In the first step MANFIS takes the inputs like obstacle distances and target direction then it is used to determine intermediate steering angles. Then as a second step MOSFO technique provides the final steering angle. In the simulation environment of WEBOT using NAO, experiments' deviations are achieved under 5% compared to real-time experiments. Optimization of trajectory planning is aimed by combining modified MANFIS and MOSFO.

A framework is proposed by Kasaei et al. [18] to provide human-like walking. The framework is created by combining walking approach and DRL. The framework has six modules to reduce complexity and increase flexibility. The core of the framework is a specific two masses for upper and lower body modeling. An adaptive and fully parametric reference trajectory planner and an optimal controller are designed based on this dynamic model. A learning framework is developed using Genetic Algorithm (GA) and Proximal Policy Optimization (PPO) algorithms. Aim behind the GA and PPO is to optimize parameters and improve stability by adjusting arm movements and CoM height.

Kashyap et al. [19] discuss the development and implementation of a hybrid control system for NAO. With this development, emphasizing trajectory planning and obstacle avoidance is achieved. The primary aim is to achieve optimum steering angles for NAO robots to navigate in environments with minimum effort. The approach involves a three-step optimization procedure including regression analysis (RA), cell decomposition (CD), and whale optimization algorithm (WOA). Firstly, initial steering angles based on sensory data are provided by RA, then the configuration space is transformed into cell regions for path planning by CD. Finally the steering angles are optimized based on the characteristics of hunting prey by WOA. With this approach NAO is prevented from getting trapped in local minima. Then, Dining Philosopher Controller (DPC) is integrated to prioritize navigation among multiple NAO robots. With this addition, the DPC integration, inter-collisions are prevented.

A deep learning-based footstep planning method making use of Generative Adversarial Networks (GANs) for indoor navigation is proposed by Mishra et al. [20]. The objective of the program is to achieve efficient and accurate path planning within Robot Operating System (ROS) framework. Traditional path planning algorithms like Rapidly Exploring Random Tree (RRT*) and A* are found to be limited in narrow paths. Experimental results demonstrate the GAN-based approach over traditional algorithms, achieving approximately 93% accuracy. The design combines GAN-based method generation. Feedback techniques through ROS topics for step specific Monte Carlo localization to perform for robust localization in complex indoor environments. Odometry estimation is done by using classical approaches and IMU sensors. The footstep planner node utilizes odometry information and path images to employ weighted A* and probabilistic R* for the planning. The GAN-based approach fits for unlocking vision-based capabilities for humanoid robots. Also, the GAN-based approach facilitates navigation through complex environments and dynamic obstacle avoidance through path replanning. Experiments are done on NAO in simulation.

In the study, Kashyap et al. [21] aim to develop an obstacle-free route for single and multiple humanoid robots. A Firefly Algorithm (FA) strategy is utilized for autonomous motion. The FA agent's response is determined by obstacle positions and distances between robots. The FA approach provides a driving angle to aid the robot in obstacle avoidance. Experiments are conducted on the NAO robot using the WEBOT platform for simulation. Multiple simulation test demonstrates that the effectiveness of the proposed approach in navigating the NAO robot in complex environments.

The navigation of humanoid robots in complex environments was investigated by Muni et al. [22]. Algorithm uses a fuzzy embedded neural network-based controller. Proper target angles were obtained using the Mamdani fuzzy algorithm with obstacle distances. Petri-net controller supplies to help dynamic path analysis. Many single humanoid robots are used for simulation and guidance testing in a variety of challenging environments. Smooth communication is provided by a cascade neural network with a fuzzy system and a Petri net controller. The cascade trains the neural networks to obtain the required target angle, which is fed to the fuzzy controller to determine the effective target angle. The Petri grid controller resolves conflicts when multiple robots try to interact with each other. It is done by prioritizing motion planning. The experiments use V-REP simulation software and are simulated under laboratory conditions. The results for both conditions are compared, showing accuracy within acceptable errors.

Vikas et al. [23] analyzed the optimization of path planning for humanoid robots in rough paths in the article. Combining improved gravitational search algorithm (IGSA) with a differentially perturbed velocity approach was introduced. Aim behind this was to mitigate limitations of the primary IGSA. The algorithm aimed to minimize path length from source to goal, also stability and collision avoidance during locomotion. Humanoid robots' interaction to avoid collisions and environments considering obstacles for decision-making are the main parts of the proposed approach. The NAO robot was used in this study. Additionally, the Petri-net was discussed to handle conflicts during the navigation.

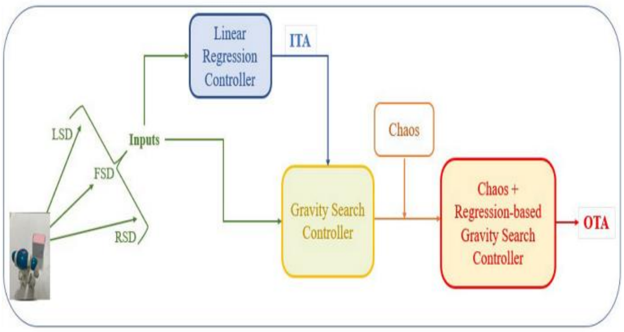

Figure 3. Scheme of proposed controller [24]

To step further, Vikas and Parhi [24] analyze the navigation of humanoid robots in complex terrains. In the analysis, classical approaches with reactive techniques are combined. These are linear regression based approach with gravitational search algorithm (GSA). Product of them is RGSA, supplemented with Chaos for optimizing path planning. To achieve the smooth trajectory planning, numerous chaotic maps are employed. The NAO robot is tested with static and dynamic obstacles during the experiments. The comparative study with other methods ensures cost-effectiveness and simplicity of the approach, and also shows that solutions can be applied in the future in sports, however it has limitations to deal with obstacles of autonomous movement. However, GSA also prevent several obstacles such as early convergence, adequate detection at later stages etc. Proposed controller scheme can be found in Figure 3.

3.3 Others

In this part a variety of studies that focus on several aspects about robotic humanoids rather than only navigation and HRI can be found.

A method for improving 3D object recognition for the NAO robot is studied by Coquin et al. [25]. In the study an IoT multi-camera system is used. Cameras are integrated through an IoT platform. Feature extraction and belief functions are employed to address uncertainties and conflicts in recognition. Both global and local feature-based recognition algorithms are utilized to analyze extracted features, ensuring robust recognition in uncertain environments.

The approach called End-User Development of Model-driven Adaptive Robotics Software (EUD-MARS) was presented by Akiki et al. [26]. EUD-MARS enables end-users to develop robotics software without requiring advanced technical skills. In this approach, software developers prepare robot profiles supporting with code based APIs. EUD-MARS was evaluated technically by controlling various robots, including Lego Mindstorms bots, an iRobot Create vacuum cleaner, a NAO humanoid, and a Parrot Bebop 2 drone. Software developers provided feedback on the XML-based language and visual tool for defining robot profiles and API configurations. In Figure 4, proposed EUD-MARS approach is presented.

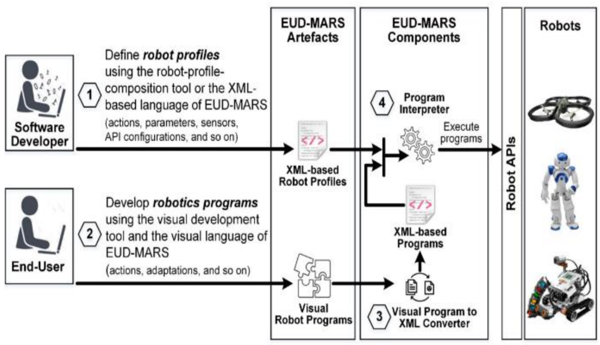

Figure 4. EUD-MARS approach [26]

Riccio et al. [27] introduces an iterative learning algorithm which is called as LoOP. LoOP combines planning and learning techniques to generate action policies. The paper remarked that LoOP combined with Monte-Carlo Search Planning and Q-learning has limitations in the planning and learning methods. It achieves focused exploration during policy refinement on the NAO robot. In multi-robot scenarios, LoOP makes the robot learn competitive policies without the need for joint action modeling.

Table 1. Technical details of NAO robot over the years

Version	Release Year	Dimensions	Sensors	Battery	Processor	Connection	RAM	Software
Version 6	2018	574x311x275 mm 5.48 kg	Microphones x4 2D Camera x2 Gyrometer x1 (3-axis) IMU x1 (3-axis) Sonar x4 FSR x8	Lithium-Ion 62.5 Wh	ATOM E3845	Ethernet (RJ45) WIFI (IEEE 802.11a/b//n) Bluetooth	4 GB DDR3	Gentoo
Version 5	2014	574x311x275 mm 5.48 kg	Microphones x4 2D Camera x2 Gyrometer x1 (2-axis) IMU x1 (2-axis) Sonar x2 FSR x8	Lithium-Ion 48.6 Wh	ATOM Z530	Ethernet (RJ45) WIFI (IEEE 802.11a/b//n) USB	1 GB	Gentoo
Version 4	2011	574x311x275 mm 5.48 kg	Microphones x4 2D Camera x2 Gyrometer x1 (2-axis) IMU x1 (1-axis) Sonar x4 FSR x8	Lithium-Ion 48.6 Wh	ATOM Z530	Ethernet (RJ45) WIFI (IEEE 802.11a/b//n) USB	1 GB	Gentoo

There were two options called as Gaussian Mixture Models and Deep Neural Networks in application of LoOP for the nonlinear data. It is observed that LoOP reduces computational load and presents effective policy generalization, however it faces high simulation calls and reliance.

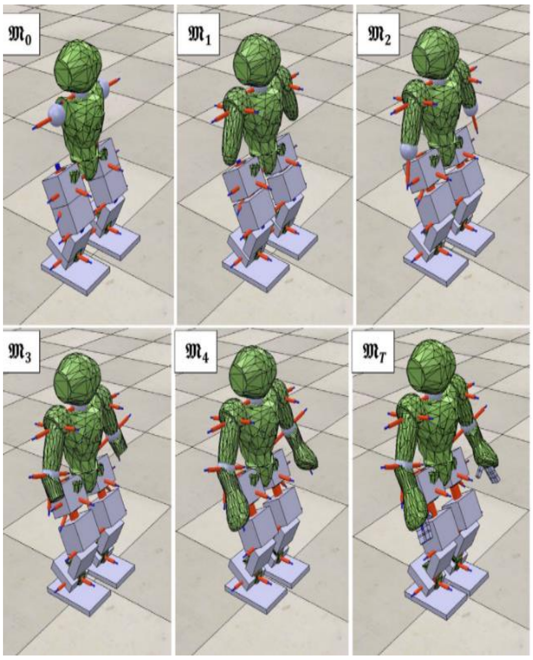

Figure 5. Morphological development stages of the NAO robot [29]

When the communication comes into the topic, Grillo et al. [28] focuses on a Trust Framework for task sharing among robots, in scenarios like robots must cooperate without full knowledge of each other's capabilities. The system architecture, implemented in ROS, enables robots to execute actions, and verify the execution of actions by other robots. Real-world experiments are tested on NAO robot and two Pepper robots. The experiments explore the robots' volume levels and positions, as well as their dispositions towards each other.

Combining navigation with mechanic, Naya-Varela et al. [29] explored the different developmental ways on a NAO robot to learn a bipedal walking. The researchers implemented five developmental ways by varying in speed and order. The NAO robot was controlled by an artificial neural network (ANN) optimized through an algorithm. The ANN's inputs and outputs had purposes of generating periodic signals and controlling the actuation of joints, respectively. Also, morphological parameters were considered focusing on legs. Smooth developmental ways were found to be effective in maintaining stability and learning performance. In Figure 5, development stages of the NAO morphology are described.

Botta et al. [30] explores methods and applied in robots like NAO, Amigobot to protect against attacks. It is demonstrated that protecting robots at the OSs and network levels is more critical than the physical level. However, it is remarked that protecting robots at the physical environment is important to understand their cyber security problems. The cyber security of robots necessitates a parallel study across all levels. General issues from the cyber security is described in Figure 6.

Table 2. Hyperparameters of DQN training

Parameter	Value
Learning rate α	0.001
Discount factor γ	0.9
Epsilon ε	20
Number of episodes	20.000
Number of voice feedbacks	300
Shrinking feedback factor *d*	0.1

An artificial somatosensory system is developed to enable the robot to perceive its embodiment while performing tasks. These perceptions enable the robot to move with its physical needs while the task is also running. On the test-bench, NAO was utilized, compatibility of the NAO fits the study's objectives. Through the incorporation of roboceptions, awareness of robot's physical condition is gained by Augello et al. [31].

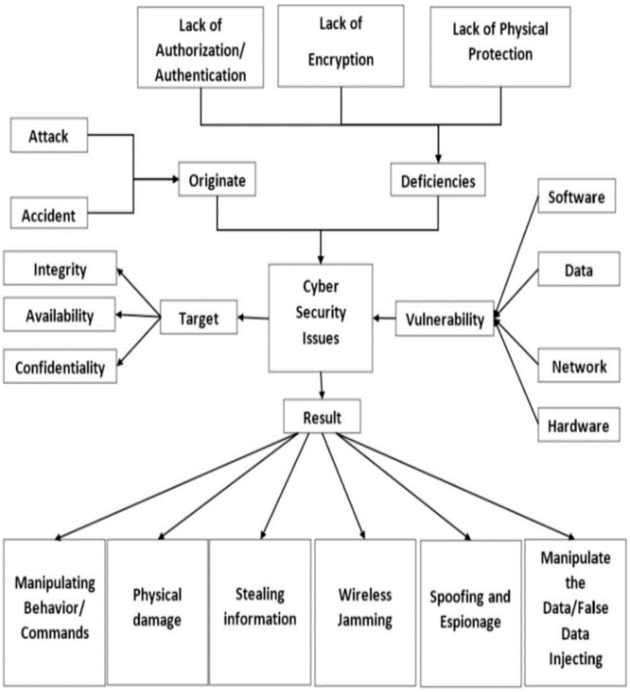

Figure 6. Morphological development stages of the NAO robot [30]

Kuo and Chen [32] explore a way to help robots become more independent. The main idea is teaching a humanoid robot how to pick up and put down objects by itself. This is done through a DRL, combined with fuzzy logic. It is found that the best computer method for this was the artificial bee colony algorithm. Deep learning helps the robot get picking up and putting down things. Fuzzy logic makes it even better by increasing how often the robot succeeds. Method is shown that it works well by testing. The method is used on NAO robot, making it learn how to grab things and put them where they are supposed to go. This learning is broken into two parts: first, the robot learned to grab things, and then it learned to place them in certain spots. Optimization algorithms are used to tweak things and make the robot's learned skills work better. DRL and Fuzzy logic usage example can be found in Figure 7.

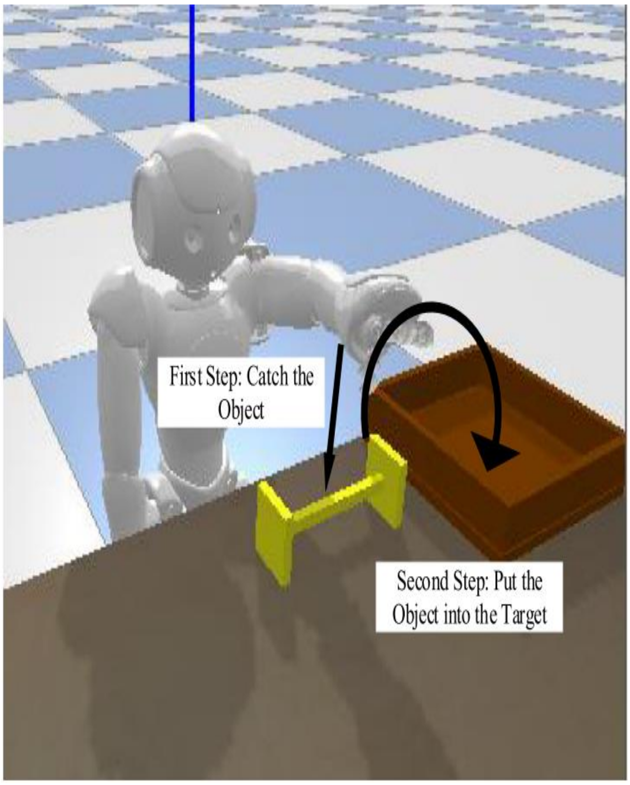

Figure 7. DRL and fuzzy logic usage purpose [32]

Table 3. Improvement percentages of proposed approach referencing IGA technique

Sl. No	IGA technique		RA-ISMO controller		Improvement (%)	
	Length	Time	Length	Time	Length	Time
1.	22.7273	234	24.37	264	-7.23	-12.82
2.	22.7273	234	18.11	173	20.32	26.07
3.	22.7273	234	21.09	207	7.2	11.54
4.	22.7273	234	19.52	195	14.11	16.67
Avg.	22.7273	234	20.7725	209.75	8.6	10.365

4 Findings and Discussion

We can see the contributions over the year with respect to search areas in Table 4.

Table 4. Number of contributions over the year

Year	Human-Robot Interaction	Navigation	Others
2020	3	4	2
2021	1	4	1
2022	3	4	1
2023	2	2	4
2024	-	-	1

5 Conclusion

NAO is a humanoid robot. Its humanoid appearance, coupled with its ease of adaptation to developments, enables it to be utilized in various fields for collaboration with humans. This review presents advancements in the NAO robot from 2020 to 2024, focusing on navigation, HRI, and other enhancement and development types. The current developments on NAO robot can perform many tasks; however, more development needs to reach perfection such as improving processor-based algorithms to decrease the need for external computers, prediction of battery percentage, etc. Undoubtedly, although navigation is not a new development area, realizing it in humanoid robotics is a new area that can be considered, so it is a fact that the improvements that have been made and will be made here will continue. In addition, the HRI field comes across as a much newer field and allows the interaction between people who are not interested in technology and robots to be more mellifluous. Combining the increasing artificial intelligence activities in the field of navigation with navigation algorithms and creating more understandable and easily usable interfaces developed for HRI can be achieved with a review article that can be a source for new developments and ideas.

Conflict of interest

The authors declare that they have no conflict of interest.

Smilarity Rate (iThenticate): %16

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