International Journal for Innovative Engineering and Management Research
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IMPLEMENTATION OF REAL TIME DYNAMIC NAVIGATION FOR MOBILE

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ABSTRACT- Real-time operation systems (RTOS) have become very important to the development of autonomous mobile robots. The choice of RTOS has tremendous sway with processor utilization, response time, and real-time jitter. In this paper, we present experimental trials and analyze the feasibility of RTOS on a single-board computer for image recognition and vision-based navigation of small autonomous robot. Several real-time (RT) patches Linux frequently used not only in robotics are implemented and tested on the Raspberry Pi2 equipped with a native camera board. To study the speed of image recognition (classification) OpenCV library was used. Test results show that the RT Patch Linux can produce higher throughput compared to Xenomai, but it can be seen that RT systems almost did not affect the speed of static images recognition systems almost did not affect the speed of image recognition

INTRODUCTION

Single-board computers are gaining increasing popularity due to their size, with the result that they are widely used in robotics. But for the short form factor, you have to pay weak technical characteristics. Vision-based navigation is one of the crucial tasks that robotics address. Many factors are imposing practical limitations on a robot's ability to see, learn and explore the environment. For this reason, navigation in unknown or partially unknown environments remains one of the biggest challenges in today's autonomous mobile robots implemented on single board computers [1]. This task requires a sufficiently large number of capacities, and to solve it in a single-board computer we should use all possible potential. To date, there are various ways of improving computer performance for a particular task. One of the possible solutions is to utilize of real-time (RT) systems, where compliance with specific time limits is very important, but, along with this, the overall system performance may decrease. Thus, the developer is faced with the hard choices of using real-time systems to dealing with performance or accuracy in image recognition and vision-based navigation. Objectives of this research are to study and use a real-time operating system (RTOS), Linux and their patches on a Raspberry Pi single board computer and to perform its further implementation in a small autonomous mobile robot equipped with the camera module and IR sensor. The purpose of the article is to investigate the feasibility of using real-time operating systems (RTOS) on a single-board computer for image recognition and vision-based navigation of small autonomous robot. Achieving this goal requires the following tasks: • testing and estimating the delay of real-time systems to improve recognition efficiency during cyclic (continuous) operation; • assessment of the quality and speed of classification of images.

The main contribution of this work is adding knowledge, experience, and insight about RT-patched Linux as an RTOS for vision-based navigation of small autonomous robots, implemented on Raspberry Pi single board computer, comparing time-delays in RT-systems, their influence on image recognition and further usage raw sensory data for dynamic robot navigation; to develop, implement and producing a small autonomous system based on RTOS.

LITERATURE SURVEY

The current task joins three areas related to the realtime systems; they are dynamic navigation for mobile robots, machine vision and real-time image recognition, and real-time operating systems evaluation

Dynamic navigation for mobile robots is explored in a large number of publications. Thus, Habib [1] presented a state-of-the-art in map building and localization for mobile robots navigating within an unknown environment. The deep reinforcement learning technique for robot navigation in unknown rough terrain is proposed in [2]. They used elevation maps and high dimensional sensory data from depth images to perform robot navigation through rough terrain. They are also categorized existing work on dynamic navigation into two groups that focus on classification technique and learning technique

Paper [3] includes a comprehensive classification of vision systems for ground mobile robots. The modern sensing systems of intelligent robots are discussed in [4]. A real-time image recognition system for tiny autonomous mobile robots is discussed in [5]. Mahlknecht et al. proposed an object recognition algorithm based on a combination of edge and color detection and used a fixed model for each recognizing object. Objects classification technique for mobile robots is presented in [6]. Mobile robot navigation using a neural network for image classification is also discussed in [7, 8, 9]. Visual image processing technique based on OpenCV for a mobile robot is presented in [10]. A framework for image processing on a Raspberry Pi platform is proposed in [11]. As it mentioned in [12], evolutionary adaptation is one of the most important functions for the mobile robot navigating in the unknown, unstructured environment. At the same time, one of the most challenging tasks in navigation is real-time communication and control. In this context, researchers turn to the subject of measuring and evaluating real-time performance in robotic applications. Thus, the real-time performance of UDP based communications in Linux on multicore embedded devices is evaluated in [13]. Results of analysis and benchmarking performance of real-time patch Linux and Xenomai are presented in [14]. Marieska et al. compare both RTOS based on three performance metrics: processing time, jitter, and throughput. The performance of RTOS on a single board computer for a wheeled mobile robot with the ultrasonic sensor is analyzed in [15]. Achieved results showed that RTOS with Qt-based program enables the robot to respond less than 1 second. In this paper, we try to extend the awareness of RTOS performance on a single board computer for classification tasks and vision-based navigation of small autonomous mobile robots.

M. K. Habib. "Real Time Mapping and Dynamic Navigation for Mobile Robots," International Journal of Advanced Robotic Systems, (September 2007). doi:10.5772/5681

This paper discusses the importance, the complexity and the challenges of mapping mobile robot's unknown and dynamic environment, besides the role of sensors and the problems inherited in map building. These issues remain largely an open research problems in developing dynamic navigation systems for mobile robots. The paper presenst the state of the art in map building and localization for mobile robots navigating within unknown environment, and then introduces a solution for the complex problem of autonomous map building and maintenance method with focus on developing an incremental grid based mapping technique that is suitable for real-time obstacle detection and avoidance. In this case, the navigation of mobile robots can be treated as a problem of tracking geometric features that occur naturally in the environment of the robot. The robot maps its environment incrementally using the concept of occupancy grids and the fusion of multiple ultrasonic sensory information while wandering in it and stay away from all obstacles. To ensure real-time operation with limited resources, as well as to promote extensibility, the mapping and obstacle avoidance modules are deployed in parallel and distributed framework. Simulation based experiments has been conducted and illustrated to show the validity of the developed mapping and obstacle avoidance approach An autonomous mobile robot is required to wander around and explore its environment without colliding with any obstacles for the purpose to fill its mission by executing successfully an assigned task, and to survive by affording the possibility of finding energy sources and avoid dangerous hazards. To efficiently carry out complex missions, autonomous robots need to learn and maintain a model of their environment. The acquired knowledge through learning is used to build an internal representation. Knowledge differs from information in that it is structured in long-term memory and it is the outcome of learning. In order to enable an autonomous mobile robot to navigate in unknown or changing environment and to update in real-time the existing knowledge of robot's surroundings, it is important to have an adaptable representation of such knowledge and maintain a dynamic model of its environment. Navigation in unknown or partially unknown environments remains one of the biggest challenges in today's autonomous mobile robots. Mobile robot dynamic navigation, perception, modeling, localization, and mapping robot's environment have been central research topics in the field of developing robust and reliable navigation approach for autonomous mobile robots. To efficiently carry out complex missions in indoor environments, autonomous mobile robots must be able to acquire and maintain models of their environments. Robotic mapping addresses the problem of acquiring spatial models of physical environments through mobile robots and it is generally regarded as one of the most important problems in the pursuit of building truly autonomous mobile robots. Acquiring and mapping unstructured, dynamic, or large-scale environments remains largely an open research problem. (Kuipers & Byun, 1991; Thrun & Bucken, 1996; Murphy, 2000; Thrun, 2002). Building maps of unknown and dynamic environment is an essential probem in robotics and requires taking care of connected problems other than mapping itself, such as localization, sensor uncertainty, obstacle avoidance and real-time navigation. There are many factors imposing practical limitations on a robot's ability to learn and use accurate models. The availability of efficient mapping systems to produce accurate representations of initially unknown environments is undoubtedly one of the main requirements for autonomous mobile robots. A key component of this task is the robot's ability to ascertain its location in the partially explored map or to determine that it has entered new territory. Accurate localization is a prerequisite for building a good map, and having an accurate map is essential for good localization (Se et al., 2002; Choset, 2001). All robots, which do not use pre-placed landmarks or GPS, must employ a localization algorithm while mapping an unknown space. Therefore, accurate simultaneous localization and mapping (SLAM) represents a critical factor for successful mobile robot dynamic navigation in a large and complex environment because it enables the robot to function autonomously, intelligently, purposefully, and robustly. The term SLAM was first coined by Leonard and Durrant-Whyte (Leonard & Durrant-Whyte, 1991) to describe a technique used by robots and autonomous vehicles to build up a map within unknown environment while at the same time keeping track of its current position. This technique has attracted immense attention in the mobile robotics literature and has been applied successfully by many researchers (Leonard & Durrant-Whyte, 1991; Se et al., 2002; Choset & Nagatani, 2001). SLAM has not yet been fully perfected, but it is starting to be employed in unmanned aerial vehicles, autonomous underwater vehicles, planetary rovers, and newly emerging domestic robots. All the numerous methods proposed in literature are based on some sort of incremental integration: a newly acquired partial map is integrated with the old maps. To integrate the partial map obtained at each sensing step into the global map of the environment, the localization of the robot is fundamental. To perform localization, it needs to estimate both robot's pose and obstacles positions are needed. Map building in an unknown and dynamic environment has been under study for a long time and many different approaches have been developed and evaluated (Borenstien & Koren, 1991a; Thrun & Bucken, 1996; Singhal, 1997; Borenstien & Ulrich, 1998; Murphy, 2000; Ellore, 2002). Other important issues related to navigation of an autonomous mobile robot are the need to deal with moving obstacles/objects, and fusing sensory information from multiple heterogeneous and/or homogeneous sensors. These issues usually cannot be resolved through the use of conventional navigation techniques. During real time simultaneous map building and localization, the robot is incrementally conducting distance measurements. At any iteration of map building the measured

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distance and direction traveled will have a slight inaccuracy, and then any features being added to the map will contain corresponding errors. If unchecked, these positional errors build cumulatively, grossly distorting the map and therefore affect the robot's ability to know its precise location. One of the greatest difficulties of map building arises from the nature of the inaccuracies and uncertainties in terms of noise in sensor measurements, which often lead to inaccurate maps. If the noise in different measurements is statistically independent, a robot can simply take multiple measurements to cancel out the effects of the noise. But, the measurement errors are statistically dependent due to odometry errors that accumulate over time and affect the way that future sensor measurements are interpreted. Small odometry errors can have large effects on later position estimates. There are various techniques to compensate for this such as recognizing features that the robot has come across previously and re-skewing recent parts of the map to make sure the two instances of that feature become one. For the last decade the field of robot mapping has been dominated by probabilistic techniques for simultaneously solving the mapping problem and the induced problem of localizing the robot relative to its growing map and accordingly different approaches have been evolved. The first category includes approaches that employ Kalman filter to estimate the map and the robot location (Lu & Milios, 1997; Castellanos & Tardos, 1999; Thrun, 2002). Another approach is based on Dempster's expectation maximization algorithm (Thrun, 2001; Thrun, 2002). This category specifically addresses the correspondence problem in mapping, which is the problem of determining whether sensor measurement recorded at different points in time correspond to the same physical entity in the real world. The Extended Kalman Filter (EKF) has been the de facto approach to the SLAM problem. However, the EKF has two serious deficiencies that prevent it from being applied to large, real-world environments: quadratic complexity and sensitivity to failures in data association. An alternative approach called Fast-SLAM is based on the RaoBlackwellized Particle Filter, and can scale logarithmically with the number of landmarks in the map (Montemerlo & Thrun, 2003). The other category of approaches seeks to identify objects and landmarks in th environment, which may correspond to ceilings, walls, doors, furniture and other objects that move. For the last two decades, there has been made tremendous progress in the development of efficient and highly accurate map building techniques. Most of these techniques focus either on capturing the metric layout of an environment with high accuracy (Moravec & Elfes, 1985; Moravec, 1988; Elfes, 1989a; Elfes, 1989b; Borenstien & Koren, 1991a and b; Borenstien & Koren, 1998; Ribo & Pinz, 2001; Ellore, 2002), or on representing the topological structure of an environment (Habib & Yuta, 1988; Kuipers & Byun, 1991; Habib & Yuta, 1993; Kuipers, 2000; Choset & Nagatani, 2001). To acquire a map and achieve efficient simultaneous localization, robots must possess sensors that enable them to perceive the outside world. There are different types of sensor modalities commonly brought to bear for this task such as ultrasonic, laser range finders, radar, compasses, vision, infrared, tactile sensors, etc. However, while most robot sensors are subjected to strict range limitations, all these sensors are subject to errors, often referred to as measurement noise. Laser scanning system is active, accurate but slow. Vision systems are passive and of high resolution but it demands high computation Ultrasonic range finders are common in mobile robot navigation due to their simplicity of operation, high working speed and cheap but usually they are very crude. These sensors provide relative distances between them and surrounding obstacles/objects located within their radiation cone. However, these devices are prone to several measuring errors due to various phenomena, such as, multiple reflections, wide radiation cone, and low angular resolution. Robot motion is also subject to errors, and the controls alone are therefore insufficient to determine a robot's pose relative to its environment. Hence, one of the main problems in SLAM is coming from the uncertainty in the estimated robot pose. This uncertainty creates correlation between the robot pose and the estimated map. Maintaining such a correlation increases computational complexity. This characteristic of SLAM makes the algorithm hard to apply to estimate very dense maps due to the computational burden. This paper discusses the importance, the complexity and the challenges of mapping robot's unknown and dynamic environment, besides the role of sensors and the problems inherited in map building. These issues remain largely an open research problem in developing an autonomous navigation system for mobile robots. The paper introduces an autonomous map building and maintenance method with focus on having an incremental grid based mapping technique that is suitable for real-time obstacle detection and avoidance. The robot maps its environment incrementally while wandering in it and staying away from all obstacles. In this case, the navigation of mobile robots can be treated as a problem of tracking geometric features that occur naturally in the environment. This implementation uses the concept of occupancy grids and a modified Histogrammic In-Motion Mapping (HIMM) algorithm to build and maintain the environment of the robot by enabling the robot to recognize and track the elements of the occupancy grid in real-time. In parallel to this, the incrementally built and maintained map model is integrated directly to support dynamic navigation and obstacle avoidance in real time. Simulation based experiments has been conducted and illustrated to show the validity of the developed mapping and obstacle avoidance approach

K. Zhang, F. Niroui, M. Ficocelli, and G. Nejat. "Robot Navigation of Environments with Unknown Rough Terrain Using Deep Reinforcement Learning" Available: http://asblab.mie.utoronto.ca/sites/default/files/SSRR18_0040_FI

In Urban Search and Rescue (USAR) missions, mobile rescue robots need to search cluttered disaster environments in order to find victims. However, these environments can be very challenging due to the unknown rough terrain that the robots must be able to navigate. In this paper, we uniquely explore the first use of deep reinforcement learning (DRL) to address the robot navigation problem in such cluttered environments with

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unknown rough terrain. We have developed and trained a DRL network that uses raw sensory data from the robot's onboard sensors to determine a series of local navigation actions for a mobile robot to execute. The performance of our approach was successfully tested in several unique 3D simulated environments with varying sizes and levels of traversability Mobile rescue robots deployed in Urban Search and Rescue (USAR) missions must navigate unknown rough terrain in order to explore cluttered environments to search for potential victims [1]. However, the traversability of the rough terrain can vary greatly, consisting of different rubble piles with various shapes and sizes. In order to be able to perform semi-autonomously or fully autonomously, these robots need to find navigation paths to safely navigate in these cluttered environments with unknown terrain with no a priori map of the environment. Previous work in robot navigation of rough terrain has mainly focused on known terrain [2]. A feasible path to a goal location in the environment can be determined using such techniques as graph search [3], rapidly exploring random trees [4] and potential field methods [5], [6]. In cases when the terrain is unknown, the robot can navigate to multiple local target locations using a defined utility function [7]–[11]. By navigating to these local locations, the robot can therefore progress towards the final goal location. For a number of these approaches, the robot also obtains a model of the environment, e.g. [7]–[10]. The challenge with such approaches is that they can require substantial expert input for parameter tuning [12] In order to address this issue, learning techniques have been proposed for robot navigation in rough terrain [12]–[18]. These techniques focus on learning to classify the traversability of terrain from environment features. In particular, learning is used to 1) classify the surrounding terrain which is then represented as a costmap [13], [16]–[18] or 2) to learn the overall cost function [12], [14], [15], in order to plan optimal paths to goal locations. Our own previous research has focused on utilizing traditional learning methods (e.g. MAXQ hierarchical reinforcement learning, support vector machines) and utility function based approaches to address such tasks as exploration, rough terrain navigation, and victim identification [19]–[22]. However, to effectively train learning techniques, usually a large number of labeled data is required, which can be time consuming to obtain [23]. A handful of techniques [13], [18] have automated the process of data collection and labeling by having the robot directly interact with the environment in order to assign a class to a set of online captured data. In this research, we investigate the use of deep reinforcement learning (DRL) to address the robot navigation problem in environments with unknown rough terrain, in particular in USAR scenarios. DRL can directly use raw sensory data to determine robot navigation actions without the need of pre-labeled data [24]. A handful of papers have applied DRL approaches for robot navigation using onboard sensory information in environments with known [25]–[27] and unknown [28] flat terrain. However, DRL has yet to be implemented for cluttered environments with unknown rough terrain. In USAR missions, we have areas of interest with high likelihoods of victims being present. A rescue robot needs to navigate to these regions, in order to search for victims. For the robot navigation problem addressed in this paper, these areas are defined as goal target locations for the robot. Namely, we are addressing the local navigation problem, where the goal target locations can be given by a global exploration planner such as in [29], and the robot needs to locally navigate to these locations without previous knowledge of the unknown rough terrain. Such a scenario would be after a natural disaster such as an earthquake, when a building has collapsed and the terrain at this site is unknown a priori, however, a rescue robot needs to navigate the environment to help search for victims In this paper we present the first use of DRL to address the mobile robot navigation problem in unknown rough terrain such as in USAR environments. The main contribution of this work is in the design of a DRL network which uses raw sensory data from the robot's onboard sensors to determine a series of primitive navigation actions for the robot to execute in order to traverse to a goal location in an environment with unknown rough terrain.

J. Martinez-Gomez, A. Fernandez-Caballero, I. Garcia-Varea, L. Rodriguez, and C. Romero-Gonzalez. "A Taxonomy of Vision Systems for Ground Mobile Robots."International Journal of Advanced Robotic Systems, (July 2014). doi:10.5772/58900

This paper introduces a taxonomy of vision systems for ground mobile robots. In the last five years, a significant number of relevant papers have contributed to this subject. Firstly, a thorough review of the papers is proposed to discuss and classify both past and the most current approaches in the field. As a result, a global picture of the state of the art of the last five years is obtained. Moreover, the study of the articles is used to put forward a comprehensive taxonomy based on the most up-to-date research in ground mobile robotics. In this sense, the paper aims at being especially helpful to both budding and experienced researchers in the areas of vision systems and mobile ground robots. The taxonomy described is devised from a novel perspective, namely in order to respond to the main questions posed when designing robotic vision systems: why?, what for?, what with?, how?, and where? The answers are derived from the most relevant techniques described in the recent literature, leading in a natural way to a series of classifications that are discussed and contextualized. The article offers a global picture of the state of the art in the area and discovers some promising research lines A mobile robot is an automatic machine that is capable of movement in any given environment. Unlike industrial robots, which usually consist of a jointed arm (multi-linked manipulator) and a gripper assembly (or end-effector) that is attached to a fixed surface, mobile robots are able to move around in their environment. Therefore, they are not fixed to one physical location. Specifically, a ground mobile robot (GMR) is a robotic platform that operates while being in contact with the ground and which does not rely upon on-board human presence. GMRs are used in many applications where the presence of a human operator may be inconvenient, dangerous or even impossible. Generally, the robot incorporates a set of sensors to perceive the environment and

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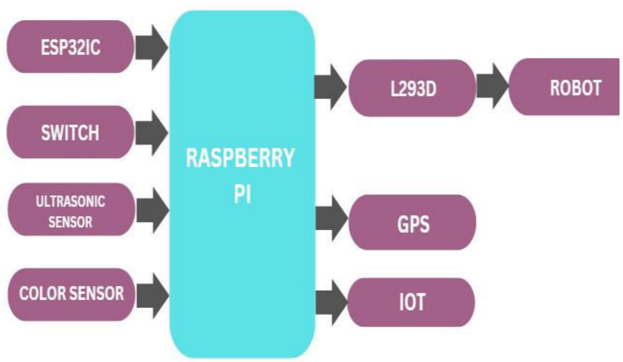
either makes decisions autonomously or pass the information on to a remote human operator who controls the robot via teleoperation. In both cases (autonomous and teleoperated GMRs), the more information that is provided, the better the decisions that are made. While a teleoperated GMR relies on humans for decision-making, autonomous robots need to incorporate artificial intelligence (AI) capabilities to perform this process. In this sense, AI has been roughly divided into two schools of thought since its beginnings: symbolic and sub-symbolic. These two approaches have also had a strong influence on the robotics field [1]. For robotic systems to navigate through an environment, autonomous planning and deliberation offer a number of examples. In these kinds of tasks, an accurate environmental representation is needed. The representation can be adequately obtained using a computer or machine vision system, which provides the robot with the relevant information about the environment and its current state. Visual perception plays a fundamental role in the behaviour of human beings. Unfortunately, robots still do not ’see’ as humans do. To date, no robot has been able to replicate any of the fundamental human abilities. For example, jointly coordinating ’eyes’ and ’hands’, which provides flexibility, dexterity and strength in movement, is not yet possible in robotics at present. Moreover, humans usually rely upon their sense of sight to locate, identify (both static and moving) and follow objects (or even track extremity movements). Vision is also crucial in grabbing and manipulating objects, allowing these tasks to be performed quickly and reliably. As a consequence, these capabilities are especially helpful when developing robotic systems able to successfully address the types of tasks mentioned above. In general, vision in robotics primarily refers to the ability of a robot to visually perceive the environment. Compared to the classical definition of computer visions, robotic vision has to go further in order to accomplish tasks entrusted to robotic platforms. These tasks typically involve: navigating to a specific location while avoiding obstacles; finding agents (either humans or other robots) while interacting with them; locating, classifying and manipulating objects in the scene, and so on. Thus, the goal of robot vision is to exploit the power of visual perception to adequately perceive the environment aimed at while being able to properly react to it. In contrast to computer vision, where sensing is an isolated task and most efforts focus on the scene comprehension and object recognition, robot vision involves dealing with all the internal components/modules available in the platform. In other words, in robot vision, sensing is driven by global tasks where all the system modules play their part [2]. This allows the robot to perceive the environment in order to interact with it appropriately. Vision has been used in robotics applications for more than 30 years. Some examples include applications in industrial settings, services, medicine and underwater robotics, to name a few. In this paper, the proposals for robot vision from the last five years for GMRs are reviewed. Moreover, a taxonomy of vision systems for GMRs is proposed in studying the most recent journal articles. In this sense, the following main questions addressed in this paper have led to the proposed taxonomy (see Fig. 1): (a) ’why’ is a vision system incorporated into a GMR?, (b) 'what' physical components are needed in such a vision system?, (c) 'for what purpose' are vision systems used in GMRs?, (d) 'how' is a vision system for GMRs to be developed?, and (e) 'where' should a vision system for GMRs be exploited? All these questions are answered by discussing some of the most influential examples from the last few years.

IMPLEMENTATION

BLOCK DIAGRAM



POWER SUPPLY

A **regulated power supply** transforms unregulated AC (Alternating Current) into a stable DC (Direct Current). It guarantees consistent output despite variations in input. A regulated DC power supply is also known as a linear power supply, it is an embedded circuit and consists of various blocks

- **Regulated Power Supply Definition**: A regulated power supply ensures a consistent DC output by converting fluctuating AC input.
- **Component Overview**: The primary components of a regulated power supply include a transformer, rectifier, filter, and regulator, each crucial for maintaining steady DC output.
- **Rectification Explained**: The process involves diodes converting AC to DC, typically using full wave rectification to enhance efficiency.
- **Filter Function**: Filters, such as capacitor and LC types, smooth the DC output to reduce ripple and provide a stable voltage.
- **Regulation Mechanism**: Regulators adjust and stabilize output voltage to protect against input changes or load variations, essential for reliable power supply

SENSORS

Sensors are used for sensing things and devices etc. A device that provides a usable output in response to a specified measurement. The sensor attains a physical parameter and converts it into a signal suitable for processing (e.g. electrical, mechanical, optical) the characteristics of any device or material to detect the presence of a particular physical quantity. The output of the sensor is a signal which is converted to a human-readable form like changes in characteristics, changes in resistance, capacitance, impedance, etc.

What is HC-SR04 Ultrasonic Sensor:

The HC-SR04 ultrasonic sensor includes a transmitter & a receiver. This sensor is used to find out the distance from the objective. Here the amount of time taken to transmit and receive the waves will decide the distance between the sensor and an object. This sensor uses sound waves by using non-contact technology. By using this sensor the distance

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which is required for the target can be measured without damage and provides accurate details. The range of this sensor available between 2cms to 400cms.

What is the HC-SR04 Ultrasonic Sensor?

The HC-SR04 is a type of ultrasonic sensor which uses sonar to find out the distance of the object from the sensor. It provides an outstanding range of non-contact detection with high accuracy & stable readings. It includes two modules like ultrasonic transmitter & receiver. This sensor is used in a variety of applications like measurement of direction and speed, burglar alarms, medical, sonar, humidifiers, wireless charging, non-destructive testing, and ultrasonography.

Fig: HCSR04-ultrasonic-sensor

Color Sensor

White light is a mixture of three basic colors known as primary colors. They are red, blue and green. These colors have different wavelengths. Combinations of these colors at different proportions create different types of colors. When the white light falls on any surface, some of the wavelengths of the light are absorbed by the surface while some are reflected back based on the properties of the surface material. Colour of the material is detected when these reflected wavelengths fall on the human eye. A material reflecting wavelengths of red light appears as red. The component used to detect colors is the Color sensor.

What is a Color Sensor?

A color sensor detects the color of the material. This sensor usually detects color in RBG scale. This sensor can categorize the color as red, blue or green. These sensors are also equipped with filters to reject the unwanted IR light and UV light.

Fig: Color-Sensor

RPI –PICO

A Raspberry Pi Pico is a low-cost microcontroller device. Microcontrollers are tiny computers, but they tend to lack large volume storage and peripheral devices that you can plug in (for example, keyboards or monitors).

A Raspberry Pi Pico has GPIO pins, much like a Raspberry Pi computer, which means it can be used to control and receive input from a variety of electronic devices

Raspberry Pi Foundation is well known for its series of single-board computers (Raspberry Pi series). But in **January 2021**

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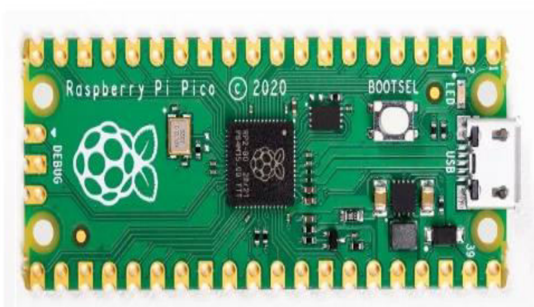
they launched their first micro-controller board known as Raspberry Pi Pico.

It is built around **the RP2040 Soc, a very fast yet cost-effective microcontroller chip packed with a dual-core ARM Cortex-M0+ processor.** M0+ is one of the most power-efficient ARM processorRaspberry Pi PICO board



Raspberry Pi PICO board

Fig: Raspberry Pi Pico Board

Raspberry **Pi Pico is a small, fast, and versatile board that at its heart consists of RP2040**, a brand-new product launched by Raspberry Foundation in the UK. It can be programmed
using MicroPython or C language.

CONCLUSION As a result of the study, it can be seen that RT systems almost did not affect the speed of image recognition. Slight fluctuations in performance are due to the peculiarity of core patches and the displacement of secondary processes, but, as a rule, in the robotics system, the system is not limited to static recognition, but is used for cyclic work. Judging by the histograms, real-time systems have low cycles of delay, indicating a sufficient level of resource planning, so these systems can be used in downloaded cyclic processes, including in cyclic image recognition. The kernel delay using the Xenomai framework turned out to be less good than expected, possibly due to the kernel configuration or a defect in the testing process. Therefore, in order to increase the cyclic accuracy of the recognition task on single-board computers, it is possible to recommend the use of the PREEMPT_RT patch, which has the lowest cyclic delay and gives little advantage over the recognition speed. Regarding the quality of the classification, we can assume that the OpenCV library and the prepared neural network managed to do well. On the first sample, the neural network really found the castle (probability 89%) and the rock (4%), and the second white wolf (63%).

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