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Institute of Industrial Automation and
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Analyzing the Impact of Uncertainty Models on the Occurrence of Risks in Robot Applications

Master Thesis

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Submitted at the University of Stuttgart by
Nikita Majalikar

MSc. Electrical Engineering

Examiner:	Jun.-Prof. Dr.Ing. Andrey Morozov
Supervisor:	Philipp Grimmeisen
External Supervisor:	-

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ROS	**R**obot **O**perating **S**ystem
DOF	**D**egree **O**f **F**reedom
CNN	**C**onvolutional **N**eural **N**etwork
JSON	**J**avascript **O**bject **N**otation
LiDAR	**L**ight **D**etection **A**nd **R**anging
RADAR	**R**adio **D**etection **A**nd **R**anging

Abstract

Robotic manipulation in uncertain environments presents a critical challenge in modern automation, particularly in tasks such as grasping and object handling, where variations in key parameters like object position, gripper width, velocity, and acceleration can substantially affect task success. This thesis focuses on the development of a comprehensive framework to evaluate and improve the grasp success rate of the Franka Emika Panda robotic arm under varying levels of uncertainty, with an emphasis on practical applications in real-world scenarios.

The research is structured into two primary phases: simulation and real-world experimentation. In the simulation phase, the Gazebo environment was employed to model the robot's interactions, allowing for the development and fine-tuning of control algorithms. This phase offered critical insights into the flow of data between the robot's sensors, actuators, and software components, laying the groundwork for refining the robot's behaviour in a virtual, controlled setting. The simulation also allowed for a focused investigation into the effects of uncertainties in object position and gripper width on the robot's grasp performance.

Following the simulation phase, real-world experiments were conducted to validate the results and test the Franka Emika Panda robot under controlled conditions, with uncertainties introduced in object positioning, gripper width, velocity, and acceleration. These experiments were designed to assess the compounding effects of multiple uncertainty factors on grasp success. The results showed that uncertainties in object position and gripper width had the most significant impact on grasp outcomes, whereas variations in velocity and acceleration had a minimal effect, underscoring the stability and robustness of the control algorithms in managing these variables.

Through a detailed analysis of both simulation and real-world experiments, the study demonstrates that object position and gripper width are critical factors that must be prioritized in robotic grasp planning. This work provides key insights into the integration of virtual simulations with real-world testing, highlighting how a dual-phase approach can be leveraged to enhance the robustness and reliability of robotic systems in uncertain environments. The research contributes to the growing body of knowledge on autonomous robotic manipulation and offers practical guidelines for managing uncertainty in dynamic, real-world applications.

Key Words: Robotic manipulation, uncertainty, grasp success rate, Franka Emika Panda, Gazebo simulation, ROS framework

1 INTRODUCTION

In the last decade, advancements in robotics and artificial intelligence have led to rapid progress in automation, transforming industries such as manufacturing, logistics, healthcare, and even everyday household tasks. However, despite the increasing sophistication of robots, one fundamental challenge persists: uncertainty. Robots must operate in dynamic environments where unpredictability can arise from sensor noise, actuator inaccuracies, or even unforeseen obstacles. These uncertainties affect the robot’s ability to make precise decisions and interact safely and efficiently with the world.

In the following section, the motivation for addressing uncertainty in robotic systems is presented, emphasizing its critical importance in achieving reliable and robust automation in dynamic environments. This discussion lays the foundation for exploring the challenges posed by uncertainty and the approaches adopted to mitigate its effects in robotic applications

1.1 Motivation

In the rapidly evolving landscape of modern industrial automation, robots play a pivotal role in optimizing manufacturing processes by handling tasks that demand high precision, consistency, and efficiency. Industrial robots as shown in Figure 1.1: Robotic arm in industry are now integral to sectors ranging from automotive assembly lines to electronics manufacturing, pharmaceuticals, and even food processing. These robots are designed to handle repetitive tasks at speeds and accuracies that far exceed human capabilities, thus minimizing human labour and improving overall productivity [1].

Figure 1.1: Robotic arm in industry [2]

However, as industrial applications become more complex, the need for robots to perform tasks with greater autonomy and flexibility under diverse and uncertain conditions has grown significantly. Traditional industrial robots typically operate in highly controlled, structured environments, where each variable such as object placement, grip precision, and motion trajectory is meticulously predetermined. In these environments, robots can execute their tasks with remarkable accuracy. However, when robots are deployed in dynamic, real-world environments, they encounter a wide range of uncertainties and variations that can disrupt their performance [3] [4].

These uncertainties arise from multiple sources: sensor noise, variations in object positioning, mechanical wear and tear, and fluctuations in motion parameters like speed and acceleration. Such variability can lead to operational inefficiencies, grasp failures, and, in extreme cases, costly interruptions in production lines [5]. For example, a robotic arm designed to pick up fragile objects may not always know the exact position or physical properties of an object, or environmental conditions may change unexpectedly. Thus, understanding and modelling uncertainty in robotics has become crucial for developing systems that are robust, adaptable, and reliable [6]. This has motivated significant research into probabilistic approaches for modelling uncertainty in robotics, as probabilistic distributions provide a mathematical framework for dealing with the unknown [7].

The ability of robots to function effectively in uncertain conditions is increasingly important in safety critical domains like healthcare robotics and autonomous driving [8]. For instance, in robotic surgery, an imprecise movement caused by uncertainty could have life-threatening consequences. Similarly, in autonomous driving, incorrect sensor readings due to environmental uncertainty (e.g., rain, fog) could lead to accidents. Therefore, addressing uncertainty in robotic systems is not merely a technical challenge but also a practical necessity to ensure the safe deployment of robots in human environments [9].

To fully harness the potential of robotic systems in real-world environments, it is essential to develop robust algorithms and models that allow robots to anticipate, adapt to, and mitigate the impact of these uncertainties. Robots need to be equipped not only with precision but also with the intelligence to handle unpredictable conditions. This thesis explores the critical role that uncertainties play in robotic pick-and-place operations, focusing specifically on the Franka Emika robot, a widely-used collaborative robotic arm known for its sensitivity, adaptability, and high degree of control [10].

1.2 Goal

The aim of this research is to understand how various types of uncertainties specifically in object position, gripper width, velocity, and acceleration affect the robot's performance in pick-and-place tasks. By applying probabilistic distribution models to simulate these uncertainties, this research seeks to identify patterns and develop solutions to enhance the overall reliability and performance of robotic systems in uncertain environments.

The integration of robots into industrial processes has revolutionized manufacturing by delivering unparalleled precision and repeatability, especially in tasks like pick-and-place operations. These operations involve identifying an object's position, grasping it securely, and placing it at a predetermined location seemingly straightforward but prone to errors when uncertainties are introduced [11].

The real-world environment introduces challenges that cannot always be accounted for in the robot's programming. Variations in object positioning, mechanical tolerances, or environmental factors such as temperature and lighting can lead to performance degradation. Small inaccuracies can escalate into significant operational failures [12]. For instance, a slight miscalculation in object positioning may result in a failed grasp, or a deviation in gripper width might cause an object to slip, disrupting the entire process.

Uncertainty, in the context of robotics, refers to any deviation or variation that affects the robot's ability to complete its task with high accuracy. This could be caused by inaccuracies in sensor data, variations in mechanical components, or unpredictable external influences [13]. Uncertainty becomes especially critical in tasks requiring fine control, such as manipulating objects of varying shapes and sizes or handling delicate materials. Thus, managing and mitigating these uncertainties is essential to maintaining the high reliability expected from industrial robots [14].

As robots become more common place in diverse industrial sectors, ensuring they can operate safely and effectively in environments filled with uncertainties will be key to expanding their utility. This thesis aims to address the challenge of uncertainties by analysing their impact on robotic performance and proposing strategies for improving system robustness.

1.3 Problem Statement

Despite rapid advancements in industrial robotics, managing uncertainties in key operational parameters such as object positioning, gripper precision, velocity, and acceleration remains a significant challenge, particularly in dynamic, unstructured environments. These uncertainties can lead to frequent task failures in critical operations like pick-and-place tasks, where even slight deviations can result in missed grasps, incorrect placements, or mechanical errors. As a result, efficiency decreases, error rates increase, and production lines face costly interruptions.

Existing control algorithms often lack the capacity to effectively anticipate or compensate for such variability, limiting the overall reliability and precision of robotic systems in real-world applications. Addressing these limitations is crucial to enabling robots to operate consistently and autonomously in environments where uncertainty is inevitable. The Franka Emika Panda robot, known for its advanced manipulation capabilities, offers an ideal platform to investigate how such uncertainties influence performance and to develop strategies that enhance the robustness and reliability of robotic operations. This research aims to close the gap by creating solutions that improve the robot’s adaptability and success rate in uncertain conditions, thus pushing the boundaries of automation in unpredictable environments.

1.4 Objectives

The primary objective of this thesis is to improve the performance and reliability of robotic pick-and-place tasks under uncertain conditions by addressing key uncertainties. The specific objectives are as follows:

1. Analyse the impact of uncertainties on pick-and-place success rate

This objective aims to explore how different types of uncertainties, such as variations in object position, gripper configuration, and robot motion parameters (like velocity and acceleration), influence the success rate of robotic pick-and-place tasks. By systematically analysing these uncertainties, this research seeks to understand their role in task performance and failure rates. This analysis is crucial because uncertainties often lead to unpredictable outcomes in robotic operations, and addressing them can significantly enhance the reliability and efficiency of automation systems.

2. Compare different probabilistic models for uncertainty modelling

Robotic systems inherently face various uncertainties that cannot be easily addressed with deterministic approaches. To manage this, probabilistic models are used to simulate and estimate uncertainties in parameters such as object positioning and movement dynamics. This objective focuses on comparing different probabilistic models such as normal and uniform distributions and evaluating how well they capture the real-world uncertainties affecting robotic pick-and-place tasks. By doing so, the study aims to determine which models are best suited for anticipating and mitigating failures in these tasks.

3. Validate findings through real-world tests with Franka Emika robot

Once the uncertainties have been analysed and modelled through simulations, the next step is to validate these findings in a real-world environment using the Franka Emika robot. The goal of this objective is to translate simulated scenarios into actual robotic operations, observing how the uncertainties manifest in real physical setups. This validation step ensures that the theoretical models developed in the simulation phase hold true in practical applications and offers valuable insights into the challenges of handling uncertainties in industrial settings.

4. Offer insights to improve robotic design and operations under uncertainty

The ultimate goal of the research is to provide actionable recommendations that can improve the design and operation of robotic systems under uncertain conditions.

Based on the analysis of uncertainties and the results from both simulated and real-world tests, this objective focuses on proposing solutions for mitigating the negative impact of uncertainties on robotic performance. This may involve suggesting improvements in hardware (such as gripper design), software (such as better control algorithms), or operational strategies (such as motion planning under uncertainty). The findings from this research will contribute to the broader field of robotic system design, particularly in contexts where robustness and reliability are critical.

1.5 Scope of work

The scope of this thesis encompasses both the theoretical and practical aspects of uncertainty modelling in robotics, specifically focusing on robotic pick-and-place operations using the Franka Emika collaborative robot. The research will involve:

1) Literature Review: A comprehensive review of existing work related to uncertainty in robotics, probabilistic distribution modelling, and current approaches to managing uncertainties in robotic tasks.

2) Uncertainty Modelling: Identification and mathematical modelling of key uncertainties such as object position, gripper width, velocity, and acceleration. Probabilistic distribution methods will be used to simulate these uncertainties and analyse their effects on robotic performance.

3) Simulation and Real-World Testing: Experimental testing will be conducted in real-world scenarios using the Franka Emika robot. Various uncertainty models will be applied to assess their impact on robotic pick-and-place tasks under different conditions.

4) Analysis and Insights: An in-depth analysis of the collected data will be conducted to identify patterns and trends in robotic performance under uncertain conditions. The results will provide insights into how uncertainties can be mitigated or managed through improved control strategies.

5) Recommendations: Based on the analysis, the research will propose strategies to enhance the robustness of robotic systems in uncertain environments and recommend potential areas for future research.

2 FUNDAMENTALS

In the rapidly advancing field of robotics, the ability to perform complex tasks in dynamic and unpredictable environments has become increasingly important. As robotic systems are deployed beyond the structured confines of factories and laboratories, they encounter a wide array of uncertainties that can significantly impact their performance [15]. These uncertainties range from sensor inaccuracies to unmodeled environmental disturbances, making it essential for robotics engineers to account for them in both design and operation.

In this chapter, the fundamental tools and components utilized in this research are discussed in detail. Each element, including the Franka Emika Panda Robot, Framos D400e camera, Robot Operating System (ROS), MoveIt, and Gazebo, plays a critical role in addressing the challenges posed by uncertainty in robotic tasks, particularly in pick-and-place operations. The goal of this chapter is to provide a comprehensive understanding of how these components work together to handle the uncertainties that naturally arise in real-world environments.

Each of these component Franka Emika Panda, Framos D400e Camera, ROS, Gazebo, and MoveIt works in concert to address the challenges posed by uncertainty in robotic tasks. The robot depends on the camera for object detection, ROS for real-time control and communication, Gazebo for simulating various uncertainty scenarios, and MoveIt for accurate motion planning and execution. Together, they form a robust system capable of adapting to dynamic conditions, making the robotic system more reliable and efficient in real-world applications.

2.1 Robotic Manipulator

A robotic manipulator is a mechanical arm that is designed to move and position objects in a specific manner. It is made up of a series of interconnected links that are controlled by motors and sensors. They are employed in a variety of tasks like assembling, welding, painting, and construction. The research makes use of this to do manipulation tasks with objects.

The Franka Emika robot is a 7-degrees-of-freedom (DOF) collaborative robotic arm designed for high-precision tasks. It was chosen for this research due to its flexibility, ease of programming, and widespread use in both industrial and academic environments [16]. Some key features of the robot include:

- **High Precision:** The Franka Emika is equipped with torque sensors at each joint, providing fine control over its movement. This sensitivity makes it particularly well-suited for tasks requiring careful manipulation, such as pick-and-place operations.

- **Adaptive Control Mechanisms:** Its advanced control algorithms allow it to adapt to changes in its environment in real time. This is important when dealing with uncertainties in object position or motion parameters.
- **User-friendly Interface:** The robot offers ease of programming through its software stack and is compatible with the Robot Operating System (ROS). This allows for seamless integration of uncertainty models into its operations, as well as efficient communication with external simulation tools like Gazebo.
- **Collaborative Design:** Franka Emika is designed to work alongside humans safely, making it ideal for experimental environments where safety is a priority.

Figure 2.1: Franka Emika Panda Robot [17]

The Franka Emika Panda Robot as shown in Figure 2.1 is a highly precise, flexible robotic manipulator that is particularly suited for collaborative robotics tasks such as pick-and-place. Its torque sensing and high degree of control allow it to perform precise movements even when faced with variations in object positions or dynamic environments. This robot's adaptability makes it an ideal platform for experiments involving uncertainty, as it can adjust its actions based on real-time sensor feedback [16].

In this research, the Franka Emika robot was tasked with performing pick-and-place operations while accounting for different uncertainties. Its high-precision actuation and real-time feedback capabilities made it a suitable platform for studying how uncertainties affect grasp success rates.

2.2 Camera

Although there are other devices that can be employed for object detection, cameras collect visual data from the environment, which computer vision algorithms can then process and analyze to locate and identify objects. High-resolution images taken by cameras can contain a wealth of data, such as colour, texture, and shape. This information can be used by Computer vision algorithms to analyze the images in real time. Cameras can also capture information from different perspectives, allowing them to identify objects regardless of their orientation or position. Modern cameras are lightweight, compact and cost-effective making them the best choice for robotics applications.

The Framos D400e series camera as shown is Figure 2.2 is a depth camera that is designed for use in 3D vision applications. It is based on Intel RealSense technology and utilizes structured light to instantly capture depth information in real-time. The camera features a compact and lightweight design, making it ideal for use in applications where space is limited. It is also highly configurable and can be adapted to suit a wide range of applications, from industrial inspection and robotics to augmented reality and gaming. The D400e series camera is compatible with a variety of programming interfaces, including ROS, and can be easily integrated into existing systems.

Figure 2.2 Framos D400e series Camera [18]

The Framos D400e series camera is used to gather high-quality depth and visual data from the environment. The role of this camera is crucial in handling uncertainties related to object detection and positioning. In a pick-and-place task, slight deviations in object position can lead to a failed grasp, so the camera provides depth information and visual feedback that enables the robot to accurately locate and manipulate objects, even when their positions are uncertain or vary dynamically [18].

2.3 ROS

ROS (Robot Operating System): ROS is a flexible framework for writing robot software, and it serves as the core communication system for controlling the Franka Emika robot [19]. In this project, ROS enabled various packages such as MoveIt (for motion planning), Gazebo (for simulation), and custom scripts to simulate the effect of uncertainties. It also handled data communication between the control systems and the robot's sensors [20]. ROS provided the following capabilities:

- Real-time control of the Franka Emika robot through custom Python scripts and ROS nodes.
- Integration of motion planning algorithms to simulate pick-and-place operations.
- Logging and recording of experiment data, such as grasp success rates, task completion times, and error margins.

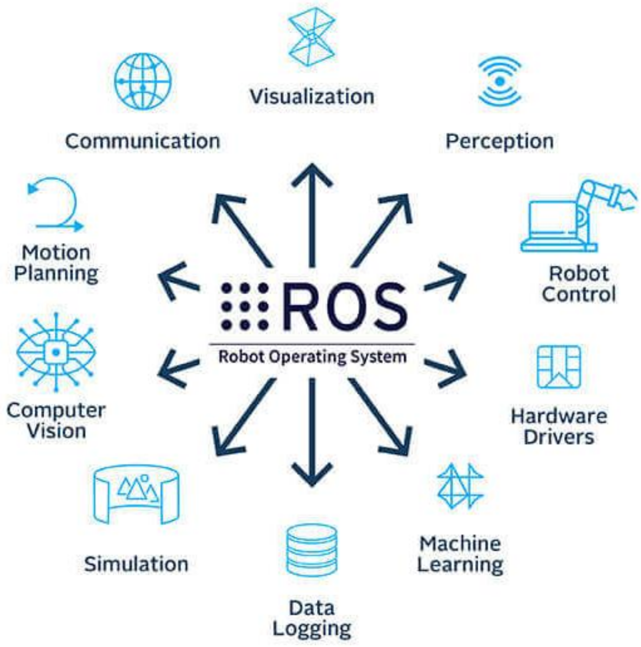

Figure 2.3: Features of ROS [21]

ROS supports a wide range of programming languages, including C++, Python, and Java. Its architecture is divided into three levels of concepts: the Filesystem level, the Computation Graph level, and the Community level as shown in Figure 2.3. The Filesystem level defines the
folder structure and minimum files needed for ROS to function. The Computation Graph level is responsible for communication between processes and systems. It handles the setup of systems, process management, and communication between multiple computers [19].

The Community level provides tools and concepts to share knowledge, algorithms, and code between developers, making it an essential part of the ROS ecosystem. It has a sizable and vibrant community that produces and distributes tools and packages for use in a range of robotics applications. Due to its adaptability, modularity, and community support, ROS has grown to be a popular choice for robotics research and development [20].

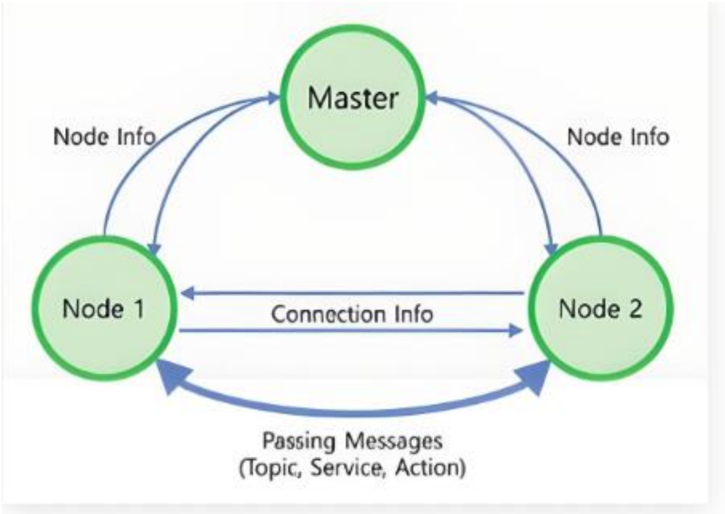

Figure 2.4:Concept of Master and Node [22]

2.3.1 Master

A master is a centralized management system that facilitates communication between nodes. The master is responsible for registering nodes, managing their connections, and coordinating message passing between them. The master maintains a registry of all active nodes in the ROS network and provides a means for nodes to discover each other and exchange messages as shown in Figure 2.4. It acts as a central communication hub and enables nodes to publish and subscribe to topics [23].

2.3.2 Node

A node is a modular and distributed software unit that performs a specific task. It is an executable file within a ROS package. It is the fundamental building block of ROS and allows for a highly modular and flexible software architecture. A node can be thought of as a single process that carries out a single function, such as sending or receiving messages, computing, or performing computations [24].

2.3.3 Topic

A topic is a named bus over which nodes exchange messages. Topics enable communication between nodes by allowing one node to publish messages on a particular topic while another node subscribes to the same topic to receive those messages as shown in Figure 2.5. A message can be published on a topic by one node and then received by any number of other nodes subscribed to the same topic.

ROS provides two types of transport mechanisms to transmit topics: TCP/IP and UDP. TCPROS is a transport mechanism that uses persistent TCP/IP connections to transmit topics and is the default transport used in ROS. UDPROS, on the other hand, is a lowlatency and lossy transport mechanism that uses UDP-based connections to transmit topics [24].

2.3.4 Service

Services provide a way for nodes to send a request and receive a response from another node. A node can offer a service, and other nodes can make requests to that service. The requesting node sends a request message to the offering node, which processes the request and sends a response message back. Services are useful when a node needs a specific action to be performed by another node, or when a node requires some information from another node [24].

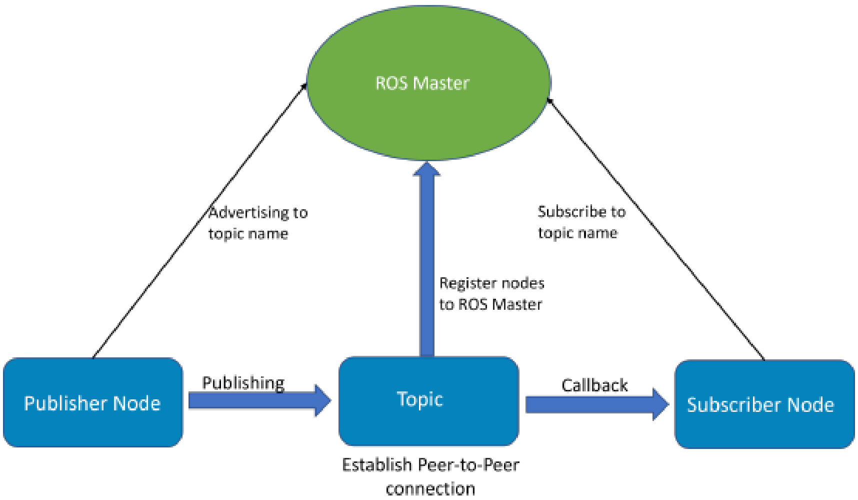

Figure 2.5:ROS communication Architecture [17]

2.3.5 Rviz

RViz (ROS Visualization) is a crucial tool in this research for real-time monitoring, planning, and visualizing the robot’s operations. RViz allowed the researchers to view and interact with the robot's state and sensor data in a 3D environment, making it possible to track how uncertainties affect the robot's behaviour during pick-and-place tasks [25].

Key features of RViz for this research included:

- Real-time visualization of the Franka Emika robot's position, joint angles, and environmental interactions during simulations and experiments.
- Motion planning integration with MoveIt, allowing for visualization of planned paths and their execution in a 3D workspace. This provided insight into the feasibility of robot movements under different uncertainty models.
- Collision detection and avoidance: RViz showed potential collisions between the robot and surrounding objects, which helped to refine movement paths and ensure safe operations.

RViz played an essential role in monitoring how the robot’s performance changed when uncertainties were applied. For example, it visually highlighted the impact of object misalignment (X, Y position uncertainty) or variations in gripper width, allowing for real-time corrections and adjustments [26].

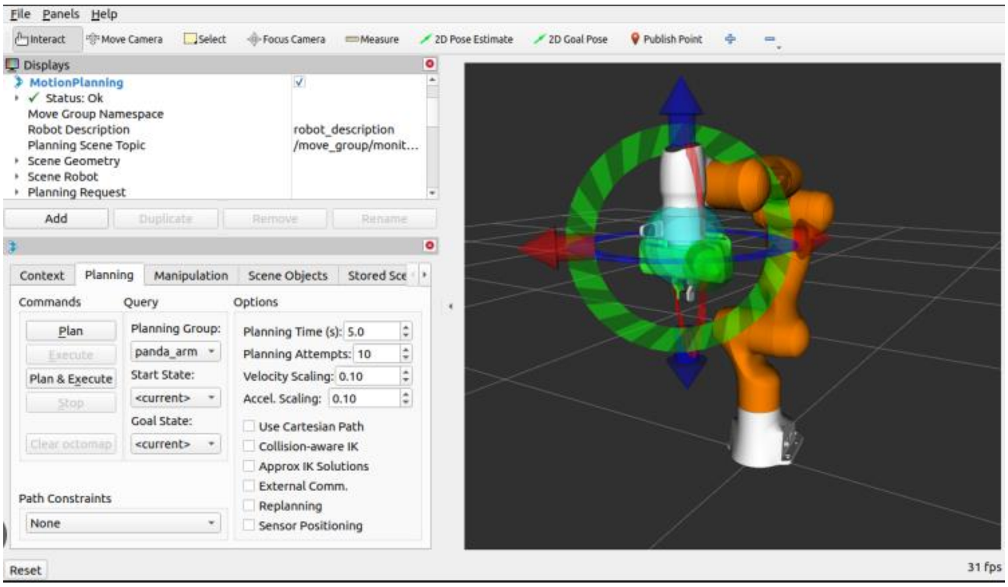

Figure 2.6: Franka Emika Panda Robot in Rviz

2.3.6 Gazebo

Gazebo is an advanced 3D simulation platform that offers realistic physics and environmental modelling. In this study, Gazebo was used to create a virtual environment for the Franka Emika robot to perform its tasks. It allowed for precise modelling of physical interactions, such as object manipulation, friction, and dynamic forces [27].

Features of Gazebo include:

1) Realistic simulation of physics, which enabled us to model how uncertainties affect the robot's grasping and movement.
2) The ability to test different uncertainty scenarios in a controlled environment before applying them to real-world experiments.
3) Integration with ROS, allowing seamless communication between the simulation and the robot’s control algorithms.

Gazebo simulations played a key role in the early stages of experimentation. They provided a safe platform to test various uncertainty models (e.g., Normal, Uniform) for object position, gripper width, and motion parameters. The simulation results gave initial insights into how the robot's performance might be affected by these uncertainties before moving on to real-world testing.

Figure 2.7:Franka Emika Panda Robot in Gazebo

To simulate the pick-and-place tasks, the Robot Operating System (ROS) framework was employed, providing tools for controlling the Franka robot and collecting data. Gazebo, an advanced 3D simulation environment, was used to simulate real-world physical constraints and interactions. The combination of ROS and Gazebo allowed for precise simulation of robot behaviors, including motion, sensing, and environmental interactions. ROS facilitated communication between different modules, enabling seamless integration of control algorithms, while Gazebo provided a realistic simulation environment to test various uncertainty models before physical deployment.

2.4 MoveIt-Framework

MoveIt is a widely-used open-source software package for motion planning, manipulation, and control of robotic systems. It provides a set of tools and libraries that simplify motion planning for robotic manipulators and mobile platforms, allowing users to plan, visualize, and execute complex motion trajectories.MoveIt is integrated with ROS and supports a wide range of robot platforms, including the Franka Emika Panda robot used in this thesis.It provides a user-friendly interface for controlling the robot and planning complex motion trajectories, including collision avoidance and path optimization [28].

MoveIt also offers support for virtual and physical environments, making it a versatile tool for robotics research and development. Its features include inverse kinematics, collision checking, grasping, and trajectory optimization. Users can specify the goals and constraints for the robot's motion with MoveIt, enabling efficient and secure operation.Additionally, MoveIt offers a plugin system that enables programmers to integrate additional software and add unique functionality. MoveIt is a dependable option for robotics applications due to its wide adoption and vibrant community, which guarantee ongoing support and development.

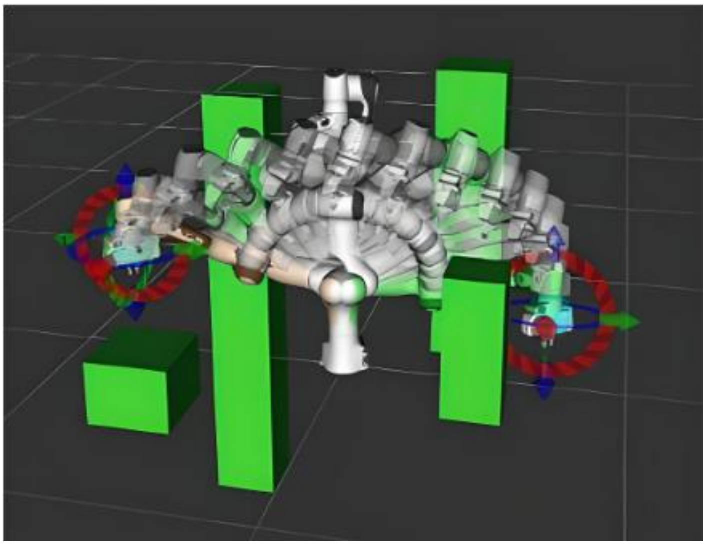

Figure 2.8: Path Planning using MoveIt [29]

2.5 OpenCV

OpenCV is a versatile and powerful open-source library for computer vision and machine learning applications that has been widely adopted in both academic and industrial settings. It provides an extensive set of functions and algorithms that enable developers to perform various tasks related to image processing, computer vision, and machine learning. OpenCV supports various programming languages, including C++, Python, and Java, which makes it accessible to a wide range of developers [30].

One of the most popular applications of OpenCV is object recognition, which involves detecting and identifying objects within an image or video feed. OpenCV provides a range of techniques for object recognition, including feature-based approaches, which are used to extract key points from an image, as well as deep learning-based approaches like convolutional neural networks (CNNs), which can learn to recognize objects from large datasets of labeled images.

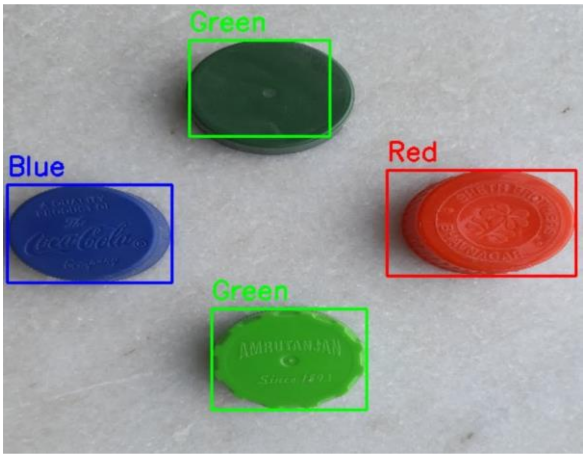

Figure 2.9: Color detection using OpenCV [31]

Another essential feature of OpenCV is its image processing capabilities, which allow users to read, modify, and write digital images and video files in various formats. This includes operations like image filtering, resizing, and color conversion, as well as more advanced techniques like image segmentation, which involves dividing an image into distinct regions based on their characteristics [30].

3 Literature Review

This chapter aims to provide a comprehensive examination of existing research and studies relevant to the challenges and methodologies involved in managing uncertainty in robotic systems. This chapter will explore key concepts from previous work, focusing on uncertainty modeling, risk assessment, and probabilistic approaches that are crucial for improving robotic performance in dynamic and unpredictable environments. By examining the state of the art in these areas, this chapter lays the groundwork for the experimental and theoretical investigations undertaken in the subsequent chapters, positioning this research within the broader context of robotic automation and uncertainty management.

3.1 Uncertainty in Robotics

Uncertainty is an inherent aspect of robotic systems, affecting every phase of operation, from perception to action. This issue is particularly evident in tasks that require high precision, such as pick-and-place operations, where even minor discrepancies in sensor readings or actuator responses can lead to significant performance deviations.

In the field of robotics, uncertainty can be broadly classified into three categories: sensor uncertainty, actuator uncertainty, and environmental uncertainty [32]. Sensor uncertainty stems from the limitations in the precision and accuracy of the sensors used to gather information about the environment. This uncertainty can manifest as noise in distance measurements, inaccuracies in object detection, or errors in positional tracking [33]. Actuator uncertainty, on the other hand, arises due to mechanical tolerances and variations in robot components, such as gripper width or joint movement [34]. Lastly, environmental uncertainty is introduced by external factors, such as unpredictable changes in object position, lighting conditions, or unexpected obstacles in the robot's workspace.

Several approaches have been proposed to manage these uncertainties in robotic systems. Feedback control methods, which continuously monitor the robot’s state and adjust actions in real time, are widely used to mitigate sensor and actuator uncertainties [35]. Additionally, sensor fusion techniques combine data from multiple sensors to provide a more accurate and reliable representation of the environment . Probabilistic planning approaches have also gained prominence in recent years, using stochastic models to account for uncertainty in robot decision-making processes. However, while these methods reduce the effects of uncertainty, they do not entirely eliminate its impact on robotic performance, particularly in dynamic environments.

In the context of pick-and-place tasks, the effects of uncertainty are often amplified due to the precision required to successfully grasp and manipulate objects. Therefore, understanding and modeling uncertainty is critical to improving the reliability of such robotic applications.

In robotics, uncertainty is a fundamental challenge that affects a robot's ability to make decisions, perform actions, and interact with its environment. Unlike humans, who can naturally adapt to changes, robots rely on sensors, algorithms, and mechanical actuators to execute tasks. The challenge arises when these systems are exposed to uncertainty be it from sensor noise, mechanical wear, or unexpected environmental change that introduce variations and errors. These uncertainties complicate a robot's ability to perform tasks with precision and reliability, which can lead to inefficiencies, task failures, or, in extreme cases, damage to the robot or its surroundings.

As robots become more autonomous and are expected to operate in dynamic and unstructured environments, managing and mitigating uncertainty is becoming increasingly critical. In contrast to traditional industrial robots that operate in highly controlled environments (e.g., manufacturing lines), modern robots are now deployed in more complex and unpredictable scenarios, such as service robotics, healthcare, logistics, and autonomous driving. In these environments, uncertainties arise from multiple sources and can significantly affect a robot's performance. Effectively dealing with these uncertainties is a key requirement for achieving robust and reliable robot systems.

3.2 Sources of Uncertainty in Robotics

Robotic systems are composed of various interconnected components, each of which can introduce uncertainty into the robot's overall performance. The primary sources of uncertainty include sensor data, actuator performance, environmental factors, and the robot's control algorithms. Understanding each of these sources is essential for developing techniques to mitigate their effects.

3.2.1.1 Sensor Uncertainty:

Sensors are the primary interface between the robot and its environment. Through sensors, robots can detect the presence and position of objects, measure distances, sense temperature, and gather other important data about their surroundings. However, no sensor is perfect, and each sensor is subject to limitations. These limitations include:

1) Noise: Sensors can introduce random noise into their readings. For example, a camera may capture an image with visual distortions due to lighting conditions or reflection, while a distance sensor (such as LiDAR) may provide inaccurate readings due to environmental obstacles or material reflectivity.

2) Resolution Limits: Sensors have finite resolution, which means that they cannot capture minute details of the environment. For example, if a robot's camera has low resolution, small objects or fine details in the environment may be missed.

3) Environmental Interference: Factors such as changes in lighting, dust, or temperature can affect sensor readings, leading to inaccurate measurements.

A robot relying on visual data from a camera might struggle to detect objects in low-light conditions or in environments with high glare.

Sensor uncertainty can significantly impact a robot's ability to perceive and interact with its environment accurately. For instance, in a pick-and-place task, a camera with sensor noise might misidentify the location of an object, causing the robot to fail in grasping it correctly [36].

3.2.1.2 Actuator Uncertainty

Actuators are the components responsible for executing a robot's physical movements, such as controlling motors that move the robot's arms, legs, or wheels. These actuators are subject to mechanical limitations and variabilities that introduce uncertainty. Factors such as:

1) Mechanical Wear: Over time, the mechanical components of actuators experience wear and tear, which can affect their performance. For instance, a robotic arm might experience slight deviations in its movements due to mechanical slack or looseness in its joints.

2) Power Supply Variability: Actuators require power to function, and variations in the power supply (e.g., voltage fluctuations) can lead to inconsistent actuator performance, causing the robot to move too quickly, too slowly, or inaccurately.

3) Calibration Errors: Actuators must be precisely calibrated to ensure that the robot's movements are accurate. Small calibration errors can lead to large deviations in the robot's intended movements, particularly when performing tasks that require fine control, such as grasping or manipulating small objects.

Inaccurate actuation can have a direct impact on task success. For example, if the gripper of a robot is not correctly positioned due to actuator uncertainty, the robot may fail to grasp the object, or it may apply too much or too little force, leading to a failed task [36].

3.2.1.3 Environmental Uncertainty

Unlike the controlled environments of traditional industrial robots, real-world environments are dynamic and unpredictable. Environmental uncertainty arises when the robot encounters unexpected changes in its surroundings. Examples of environmental uncertainty include:

1) Dynamic Obstacles: Objects or people may move unexpectedly within the robot's workspace, requiring the robot to adapt its trajectory or re-plan its actions in real-time.

2) Changes in Lighting or Temperature: For robots that rely on cameras or temperature sensors, fluctuations in lighting conditions or temperature can affect their perception of the environment. For instance, a robotic vacuum

cleaner operating in a brightly lit room may encounter difficulties when moving into a dimly lit area.

3) Unpredictable Surface Conditions: Changes in the surface on which a robot moves (e.g., wet, uneven, or slippery surfaces) can affect its ability to maintain stability and balance, leading to deviations from its planned path.

Environmental uncertainties are particularly challenging because they are often outside the robot's control. A robot may need to react to these uncertainties in real-time, adjusting its actions and adapting to unforeseen changes to complete its tasks [36].

3.2.1.4 Control Uncertainty

Control uncertainty arises from imperfections in the algorithms that govern the robot's behaviour. The control system is responsible for interpreting sensor data and making decisions about how the robot should act to achieve its goals. However, control algorithms are not immune to uncertainty. Examples of control uncertainty include:

1) Model Mismatches: The control system relies on models of the robot and its environment to predict outcomes and plan actions. However, these models are often simplified or incomplete, which leads to inaccuracies. For instance, a robot may have an incomplete model of the environment, causing it to underestimate the complexity of the task.

2) Estimation Errors: Control algorithms often rely on estimation techniques, such as Kalman filters, to make predictions about the state of the robot and its environment. These estimates are subject to error, especially when the robot is operating in an uncertain or noisy environment.

3) Computational Delays: Control algorithms must operate in real-time to process sensor data and send commands to actuators. Delays in processing or communication between components can introduce uncertainty, as the robot may act based on outdated information.

Control uncertainty can lead to suboptimal decision-making or task execution. For example, if a robot's control algorithm fails to account for the motion of a dynamic obstacle, the robot may collide with the object or be forced to re-plan its trajectory, resulting in delays or task failure [36].

3.3 Probabilistic Distributions in Robotics

Probabilistic distributions are commonly used in robotics to model uncertainty and predict the likelihood of various outcomes. Probabilistic distributions are mathematical functions that describe the likelihood of different outcomes occurring, based on known or estimated data. They are crucial for modelling uncertainty in robotics because they enable systems to account for variations and unknowns in sensor data, object characteristics, and environmental conditions. By representing uncertain parameters as random variables, researchers can simulate real-world conditions and better understand how these uncertainties affect robotic performance [37].

The normal (Gaussian) distribution is one of the most frequently used models in uncertainty analysis for robotic systems. This distribution is suitable for representing uncertainties that arise from random errors or noise, such as slight deviations in object position or variations in actuator performance. Research demonstrated that applying normal distributions to uncertainties in object position could effectively predict grasp success rates in pick-and-place tasks. The mean of the distribution typically represents the expected value of the parameter, while the standard deviation captures the level of uncertainty [38].

In addition to the normal distribution, the uniform distribution is often used to model uncertainty where all possible outcomes within a specific range are equally likely. For instance, uniform distributions are applied when there is an equal probability of an object being located anywhere within a defined area. This is particularly relevant in applications where the robot does not have precise information about the object's position but must operate within certain bounds. While uniform distributions are less common in the literature compared to normal distributions, they provide valuable insights into worst-case scenarios by examining the extreme values within a given range [38].

Comparative studies between these two distributions suggest that normal distributions are more effective in modeling sensor noise and actuator imprecision, while uniform distributions are useful for handling uncertainty in unstructured environments [34]. However, further research is needed to assess how these distributions influence the cumulative effect of multiple uncertainties in complex robotic systems, particularly in dynamic and real-time applications.

Given that uncertainty cannot be entirely eliminated, probabilistic models are commonly used to handle it in robotic systems. These models allow robots to make decisions based on likelihoods and distributions of possible outcomes rather than relying on deterministic calculations.

Several probabilistic approaches are widely used in robotics to represent and manage uncertainty:

1. **Gaussian Distributions**: Also known as the normal distribution, the Gaussian distribution is perhaps the most commonly used probabilistic model in robotics. It is defined by two parameters: the mean (μ) and the standard deviation (σ). The mean represents the expected value of the random variable (e.g., the expected position of an object), while the standard deviation represents the spread or variability around that mean (i.e., how much the actual position might deviate from the expected position). Gaussian distributions are used in applications like sensor fusion, localization, and control algorithms where uncertainty can be assumed to follow a symmetric bell curve around the mean [1].

Example: In the case of a robot using a laser rangefinder to measure distance to an obstacle, the sensor’s readings might be affected by noise, resulting in slight variations in the measured distance. A Gaussian distribution can model the uncertainty in these measurements, with the mean representing the expected distance and the standard deviation reflecting the noise level [37].

2. **Uniform Distributions**: A uniform distribution assumes that all outcomes within a given range are equally likely. This distribution is often used when little information is available about the system or when it is necessary to account for the worst-case scenario [37].

   Example: If a robot must grasp an object but does not have any reliable information about the object’s exact size or weight, a uniform distribution might be used to represent the range of possible sizes or weights.

3. **Discrete Distributions**: These are used when a random variable can take on a finite number of distinct values, making them useful for modelling situations where outcomes are categorical rather than continuous [37].

   Example: A robot in a warehouse could use a discrete distribution to model the probability of picking a specific type of object from a predefined set, such as boxes of different sizes or weights.

4. **Triangular Distributions:** A triangular distribution is defined by a minimum, maximum, and mode (most likely value), making it useful when there is some knowledge about the bounds and central tendency of a parameter, but not enough data to fit a normal distribution [37].

   Example: In robotic grasping, if the exact weight of an object is unknown but is expected to fall within a known range with a most likely value, a triangular distribution could be applied to model the uncertainty in the object’s weight.

5. **Beta and Alpha Distributions:** These distributions are flexible and can model a wide range of uncertainties, particularly when the random variable is bounded between 0 and 1, making them useful for probability-based decision-making processes [37].

   Example: In a robotic system that adjusts its confidence levels in sensor readings, a beta distribution can be used to represent the uncertainty in the robot's belief about the success of a task, based on prior knowledge and accumulated experience. Beta distributions are commonly used in Bayesian updating processes, where the robot continually refines its decision-making as more data becomes available.

6. **Poisson Distributions**: Poisson distributions are used when the random variable represents the number of events occurring within a fixed interval of time or space. It is commonly used in robotics for modelling events that occur randomly but at a constant average rate [37].

Example: A robot navigating through a warehouse might use a Poisson distribution to model the arrival rate of new obstacles (e.g., humans walking by), allowing it to anticipate and react to unexpected events.

7. **Bayesian Networks**: Bayesian networks are graphical models that represent a set of variables and their probabilistic dependencies. They are particularly useful in robotics for reasoning under uncertainty. In a Bayesian framework, prior knowledge about the system is updated with new information (evidence) to produce posterior probabilities, enabling robots to make more informed decisions [39].

   Example: A robot navigating a partially mapped environment can use a Bayesian network to update its belief about its current location as it receives new sensor data (e.g., from a camera or lidar). The robot starts with a prior belief (based on the map) and refines this belief as it encounters new information, leading to a more accurate estimate of its location.

8. **Markov Models**: Markov processes describe systems where the future state depends only on the current state, not on the sequence of events that preceded it. Markov models are widely used in robotics for tasks like localization and path planning.

   Example: In a mobile robot's navigation task, a Markov model can be used to estimate the probability of the robot being in a certain location, given its current position and sensor readings. This is the basis for the well-known Markov Localization algorithm.

9. **Monte Carlo Methods**: Monte Carlo methods are computational algorithms that rely on repeated random sampling to obtain numerical results. In robotics, Monte Carlo methods are used for tasks such as path planning, where uncertainty is high and probabilistic reasoning is needed to account for numerous possible scenarios [40].

   Example: Monte Carlo localization is a technique that uses random sampling to estimate a robot's position in an environment. The robot generates a set of hypotheses (particles) about its location and updates these hypotheses based on sensor data, converging on the most likely position.

These probabilistic models are essential for making robots more robust and adaptable in uncertain environments. By incorporating probabilistic reasoning into their control algorithms, robots can make better decisions, even when faced with incomplete or noisy data.

3.4 Robotic Pick-and-Place Applications

Pick-and-place tasks are fundamental to many industrial and service robot applications, where robots are required to grasp objects from one location and place them accurately in another. These tasks require high levels of precision, dexterity, and reliability, especially when uncertainties in object location, gripper performance, or robot dynamics are introduced.

Grasp planning is a critical aspect of pick-and-place tasks, and uncertainty in the object's position or orientation can lead to grasp failures, misplacements, or dropped objects [41]. Early studies focused on deterministic approaches to grasp planning, assuming that the object's position was known with perfect accuracy. However, as robotic applications expanded into more unstructured environments, researchers began incorporating probabilistic models to account for uncertainties in object detection and localization.

Recent advancements in adaptive grasping have leveraged uncertainty modeling to improve task success rates. Studies have demonstrated that by introducing probabilistic models for object position and gripper width, robots were able to dynamically adjust their grasping strategies, leading to improved performance under uncertain conditions. Additionally, learning-based approaches have emerged as a promising solution, where robots learn to adapt to uncertainties through trial and error, improving their grasp success over time [42].

While significant progress has been made in handling uncertainty in pick-and-place tasks, challenges remain in ensuring the robot's ability to perform consistently in highly dynamic or unpredictable environments. The complexity of these tasks increases when multiple uncertainties (e.g., position, velocity, and acceleration) are considered simultaneously, necessitating further research into integrated uncertainty modeling and control strategies.

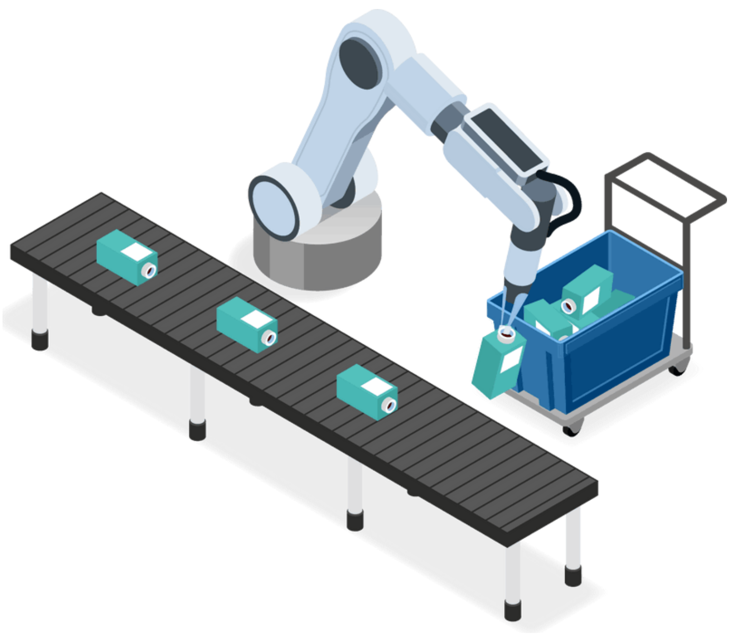

Figure 3.1: Robotic arm in pick and place application [43]

Robotic Manipulator arms as shown in Figure 3.1 perform tasks in various environments, such as assembly lines, laboratories, or warehouses. They utilize advanced sensor technology and precise control systems to interact with their surroundings. This is predicated on their ability to comprehend their operational environment through spatial mapping, sensors, and computational algorithms. Robotic Arms can execute complex tasks, adapt to changes, and circumvent obstacles. The software embedded within the Robotic Arm is user-friendly and governs the arm's operations. These Robotic Arms are swift, efficient, precise, cost-effective, dependable, and resilient [5].

4 CONCEPT

This chapter delves into the core concepts that frame the methodology and experimentation of this research. It outlines the key requirements necessary for the successful execution of the experiments and provides an in-depth overview of the use case scenarios that were developed to assess the impact of uncertainty on robotic pick-and-place tasks. Each requirement and use case scenario are carefully designed to model real-world challenges and uncertainties that robots face during dynamic operations.

4.1 Requirements

Robotic systems that operate in real-world environments are subject to various uncertainties, such as sensor inaccuracies, object positioning errors, and fluctuations in motion control. To systematically assess the impact of these uncertainties on robotic performance, a set of key requirements was identified. These requirements aim to create realistic and meaningful conditions for testing the robot's ability to handle uncertainty in pick-and-place tasks.

4.1.1 Requirement 1: Handling Uncertainty in Object Position

The first requirement is to model and evaluate how the robot performs when there is uncertainty in the position of objects it is required to pick and place. In industrial environments, objects are rarely in exactly the same location due to random disturbances, human interaction, or mechanical inconsistencies. The robot’s ability to detect and handle such variations in object position is crucial for maintaining high task success rates.

In this research, probabilistic models such as Normal and Uniform distributions are used to simulate uncertainty in object position. Specifically, the X and Y coordinates of the object are varied randomly according to these distributions, simulating deviations that the robot may encounter in real-world scenarios. The robot's vision system, integrated with the Framos D400e series camera, plays a critical role in identifying and localizing objects under these uncertain conditions. This approach helps evaluate the success rate of pick-and-place tasks as object position uncertainty increases.

4.1.2 Requirement 2: Adjusting for Variations in Gripper Width

The second requirement addresses the uncertainty in the gripper width. In a real-world scenario, objects may have slight variations in size or shape, and the robot’s gripper must adapt to these changes. The ability of the robot to securely grasp objects of varying widths without failure is essential for efficient task execution.

To simulate variations in object size, the gripper width is subjected to uncertainty modelled using probabilistic distributions. Different gripper width values are generated to reflect potential deviations from the optimal grip, and the robot must adapt in real-time to successfully grasp objects. This requirement ensures that the robot can accommodate minor deviations in object size while maintaining a high success rate in grasping and manipulation tasks.

4.1.3 Requirement 3: Managing Uncertainty in Motion Parameters

The third requirement focuses on understanding how uncertainties in motion parameters, particularly velocity and acceleration, affect the robot's ability to perform precise movements during pick-and-place tasks. In dynamic environments, motion fluctuations can occur due to external factors or internal control variations.

Probabilistic models are applied to simulate uncertainty in velocity and acceleration. Arrays of velocity and acceleration values are generated using Normal and Uniform distributions, and these uncertain motion parameters are introduced into the robot's control system. The objective is to assess the impact of motion uncertainties on the robot's accuracy and success rate in completing pick-and-place tasks. Evaluating how well the robot compensates for these uncertainties will provide insights into its dynamic control capabilities.

4.2 Overview of Use Case Scenarios

The use case scenarios outlined below are designed to rigorously test the robot's performance in handling various uncertainties. Each scenario simulates different aspects of uncertainty, and the robot's ability to adapt and succeed under these conditions is evaluated. These scenarios represent real-world situations where robots must operate in unpredictable and dynamic environments.

Scenario 1: Uncertainty in Object Position

Objective: To assess the robot's ability to successfully perform pick-and-place tasks when there is uncertainty in the position of the object. This scenario explores how variations in the X and Y coordinates of the object affect the robot's performance.

Description: The object's position is subjected to random deviations based on Normal and Uniform distributions. These distributions introduce variations in the object's location within the robot's workspace, simulating conditions where the object is not precisely where it is expected to be. For example, in an assembly line, an object might shift slightly due to vibrations or conveyor belt movements. The robot's vision system, aided by the Framos D400e camera, must detect and adapt to these positional variations.

Key Metrics: The robot's success rate, failure rate, and positional accuracy are recorded to determine how effectively the system compensates for positional uncertainty. The analysis focuses on how increasing deviations in object position affect the overall success of the pick-and-place task.

Scenario 2: Uncertainty in Gripper Width

Objective: To evaluate the robot's ability to handle variations in the width of objects during the grasping process. This scenario tests the flexibility of the robot's gripper in adapting to different object sizes and shapes.

Description: In this scenario, the robot's gripper is configured with varying widths, reflecting uncertainty in the size of the object being grasped. Normal and Uniform distributions are used to generate gripper width arrays that simulate real-world conditions where objects slightly deviate from their expected dimensions. The robot is tasked with picking and placing these objects, and its success in adjusting the grip accordingly is measured.

Key Metrics: The robot's grasp success rate, object stability during manipulation, and failure rates are key metrics used to evaluate performance. The data gathered will provide insights into how sensitive the system is to gripper width uncertainty and whether it can adapt dynamically to changing object sizes.

Scenario 3: Uncertainty in Motion Parameters (Velocity and Acceleration)

Objective: To understand how uncertainties in motion parameters, specifically velocity and acceleration, affect the robot's ability to perform accurate and stable pick-and-place tasks. This scenario examines how fluctuations in these dynamic parameters impact the robot's overall performance.

Description: Arrays of velocity and acceleration values are generated using Normal and Uniform distributions, introducing random variations in the robot's motion control system. These uncertain motion parameters are applied during pick-and-place tasks to simulate real-world disturbances, such as sudden changes in speed or acceleration. The robot's ability to maintain accuracy and smooth movements under these conditions is evaluated.

Key Metrics: Success rate and the smoothness of the robot's movements are used to assess performance. The robot's ability to maintain stable and accurate motion despite variations in velocity and acceleration is critical to its success in dynamic environments.

Scenario 4: Combined Uncertainty (Object Position, Gripper Width, and Motion Parameters)

Objective: To test the robot's ability to handle multiple uncertainties simultaneously. This scenario combines uncertainty in object position, gripper width, velocity, and acceleration to simulate a more complex and realistic operational environment.

Description: This scenario introduces combined uncertainties in object position, gripper width, and motion parameters, challenging the robot to adapt to multiple factors at once. Probabilistic distributions are applied to each variable, creating a scenario where the robot must manage simultaneous uncertainties in all key aspects of the pick-and-place task. This scenario is designed to reflect real-world industrial environments where multiple sources of uncertainty may be present at any given time.

Key Metrics: Combined success rate, failure rate, task completion time, and accuracy across all parameters are used to evaluate the robot's performance. This scenario aims to test the limits of the robot's ability to operate effectively under high levels of uncertainty.

In this chapter, the core requirements for addressing uncertainty in robotic pick-and-place tasks were identified, and several use case scenarios were developed to explore the robot's performance under various uncertain conditions. By introducing uncertainty in object position, gripper width, velocity, and acceleration, the research systematically evaluates the robot's resilience and adaptability. The combined uncertainty scenario provides a holistic view of the robot's capacity to operate in complex environments with multiple sources of variation. The results from these scenarios will inform the development of more robust control algorithms and operational strategies, ultimately enhancing the reliability and precision of robotic systems in industrial applications.

5 METHODOLOGY

The methodology employed in this research is centered on systematically exploring the impact of uncertainty on robotic pick-and-place operations, using the Franka Emika Panda robotic arm as the testbed. This chapter details the experimental design, the tools and platforms used, the uncertainty modeling techniques applied, and the evaluation metrics chosen to assess the performance of the robot under various conditions. The goal of the methodology is to provide a structured approach for both simulation and real-world experimentation, enabling a thorough evaluation of how uncertainties in object position, gripper width, velocity, and acceleration affect task success rates.

The methodology includes several stages: system setup, uncertainty modeling, experimental execution (in both simulation and real-world environments), data collection, and result analysis. Each of these stages is described in detail, with the aim of ensuring that the experiments are replicable and the results are statistically valid.

5.1 System Setup and Architecture

5.1.1 Hardware Components

The primary hardware component used in this research is the Panda robotic arm as shown in Figure 5.1. Known for its dexterity, sensitivity, and collaborative capabilities, the Panda robot was chosen due to its widespread use in industrial and research environments. The robot's high precision and flexibility in performing manipulation tasks make it ideal for testing the effects of uncertainties in robotic pick-and-place operations.

Figure 5.1: Franka Emika Robot [22]

In addition to the robotic arm, the Framos D400e series camera was used for object detection and positioning tasks as shown in Figure 5.2. This depth-sensing camera is based on Intel RealSense technology and allows for accurate depth measurements in real-time, which are crucial for pick-and-place tasks where object positioning is a critical factor. The camera provides visual input to the robot, enabling it to detect, locate, and interact with objects in its environment.

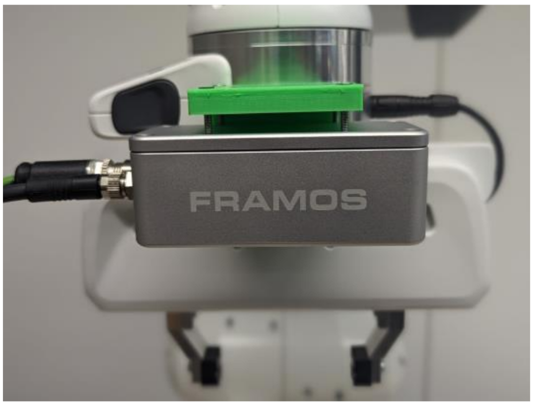

Figure 5.2: Camera mounted to robot

5.1.2 Software Components

The experiments were conducted using the Robot Operating System (ROS), a widely adopted framework that provides essential tools and libraries for building and controlling robotic systems. ROS was used to manage the communication between different components of the system, including the robotic arm, camera, and the data logging modules. It enabled real-time control of the robot and facilitated the collection of experimental data.

Gazebo was used as the simulation platform, providing a virtual environment where the Franka Emika Panda robot could be tested under controlled conditions before real-world experiments were conducted. Gazebo supports realistic physics-based simulations, including collisions, joint movements, and environmental interactions, making it an ideal platform for evaluating robot performance under various uncertainty conditions without risking hardware damage.

MoveIt, a motion planning framework integrated with ROS, was utilized for trajectory planning, allowing the robot to calculate optimal paths for picking and placing objects. MoveIt's built-in inverse kinematics solver, along with its collision checking and optimization tools, was crucial for ensuring that the robot could perform these tasks efficiently, even under uncertainty.

OpenCV was employed for processing visual data captured by the Framos D400e camera. This computer vision library provided the algorithms necessary for object detection, recognition, and tracking, ensuring that the robot received accurate information about object positions in the workspace.

To simulate the pick-and-place tasks, the Robot Operating System (ROS) framework was employed, providing tools for controlling the Franka robot and collecting data. Gazebo, an advanced 3D simulation environment, was used to simulate real-world physical constraints and interactions. The combination of ROS and Gazebo allowed for precise simulation of robot behaviors, including motion, sensing, and environmental interactions. ROS facilitated communication between different modules, enabling seamless integration of control algorithms, while Gazebo provided a realistic simulation environment to test various uncertainty models before physical deployment.

5.2 Uncertainty Modelling

The core of this research lies in understanding how various uncertainties affect the performance of the robot in pick-and-place operations. To achieve this, uncertainties were introduced into the system in the form of probabilistic distributions applied to key variables such as object position, gripper width, velocity, and acceleration.

5.2.1 Object Position Uncertainty

In real-world environments, object positioning can be imprecise due to factors such as sensor noise or environmental disturbances. To model these uncertainties, the X and Y coordinates of the object were varied using Normal and Uniform distributions. In the Normal distribution case, the object position was perturbed by random noise cantered around the true position, with varying standard deviations (0.005, 0.01, 0.015, and 0.02) to simulate different levels of uncertainty. In the Uniform distribution case, the object position was allowed to varying for scales (0.005, 0.01, 0.015, and 0.02), simulating real-world scenarios where the robot may not have perfect knowledge of an object’s exact position.

5.2.2 Gripper Width Uncertainty

The precision of the robot's gripper in picking up objects depends on the correct setting of the gripper width. Variations in gripper width can affect the robot’s ability to grasp objects securely, leading to task failures. The uncertainty in gripper width was modelled using Normal distributions with standard deviations (0.0025, 0.005 and 0.0075) around the optimal gripper width (0.03m). For uniform uncertainty, gripper width values were varied within a range around the optimal value to represent real-world deviations due to mechanical tolerances or calibration issues.

5.2.3 Motion Parameter Uncertainty (Velocity and Acceleration)

Robotic motion involves both velocity and acceleration, and uncertainties in these parameters can cause the robot to deviate from its intended path, resulting in poor task performance. Velocity uncertainties were modelled using a normal distribution centred around a mean velocity of 0.5m/s, with a standard deviation of 0.3. Acceleration uncertainties were modelled using a uniform distribution with a scale of 0.5, capturing the variability in the robot's dynamic motion behaviour. These uncertainties were applied both independently and in combination to assess their impact on task success rates.

5.2.4 Combined Uncertainty

To understand the compounded effects of multiple uncertainties, scenarios involving combinations of object position, gripper width, velocity, and acceleration uncertainties were tested. For instance, one scenario combined uncertainty in both object position and gripper width, while another combined uncertainty in object position, velocity, and acceleration. A final scenario tested the simultaneous application of uncertainties across all four parameters.

5.3 Experimental Design

5.3.1 Simulation Setup in Gazebo

In this research, the Gazebo simulation environment was utilized primarily for coding and understanding the robotic system's operational flow, rather than for conducting uncertainty tests. Gazebo provided a realistic platform for setting up the Franka Emika Panda robot and simulating its interactions with the environment. The primary focus during this phase was to familiarize ourselves with the ROS framework, the robot's kinematic structure, and how to effectively integrate the different software components necessary for the implementation.

The simulation environment helped to develop and test the control algorithms for the Franka Emika robot in a safe, virtual setting. Using Gazebo, 3D model of the workspace was created, including the robot's operational area and the objects involved in the pick-and-place tasks.

Throughout this stage, a significant emphasis was placed on understanding the flow of data between the various components of the robotic system. By leveraging Gazebo, we were able to visualize how the robot's sensors would interact with the environment and how data would be processed through the ROS nodes. This comprehension was crucial for identifying the roles of different software modules and ensuring seamless communication between them.

The simulation environment served as a preparatory stage for the actual implementation of the robotic system using the Franka Emika Panda robot. By thoroughly developing and refining the code in Gazebo, potential issues were mitigated that could arise during real-world testing. The insights gained from the simulation setup, including how to adjust parameters and optimize the robot's movements, were critical for enhancing the robot's performance in practical applications.

While Gazebo did not serve as a direct testing ground for uncertainties, it laid the foundational knowledge necessary to conduct real-world experiments effectively. By understanding how the system operates in a controlled virtual environment, we were better equipped to anticipate challenges and design experiments that could accurately assess the impact of uncertainties on robotic performance in real-life scenarios.

5.3.2 Real-World Experimentation Setup

Following the preparation and coding phase in Gazebo, we proceeded to set up the real-world experimentation environment using the Franka Emika Panda robot. The objective was to validate the insights gained from the simulation and assess the robot's performance under real-world conditions. This phase involved careful planning and configuration to ensure that the robotic system could operate effectively while dealing with uncertainties in object positioning, gripper width, velocity, and acceleration.

The physical workspace for the real-world experiments was designed to closely resemble the simulated environment in Gazebo. This included setting up a designated area where the robot would perform pick-and-place tasks. The workspace was equipped with a variety of objects, specifically selected to mimic the conditions tested in the simulation phase. Standardized cubes were used as the primary objects to be manipulated, providing consistency in the testing process.

The setup was carefully arranged to facilitate easy access for the robot while ensuring that potential obstacles were minimized. Additionally, lighting conditions and the arrangement of the camera system were optimized to enhance the robot's ability to perceive and interact with objects accurately.

During this phase, the control algorithms developed in Gazebo were uploaded to the robot, allowing it to execute the same movements and tasks simulated earlier. The ROS framework facilitated seamless communication between the camera, robot, and the algorithms responsible for processing visual data and controlling the robot's movements.

5.4 Data Collection Methods

Data collection was automated using ROS logging tools during both the simulation and physical experiments. Key metrics such as grasp success rate, failure rate, task completion time, and positional errors were recorded after each iteration. For each scenario, 50 iterations were performed to ensure statistical significance. In addition to logging numerical data, visual data was captured through Gazebo’s visualization tools and the Franka robot's onboard cameras. The data was stored in JSON format for easy analysis and comparison between different scenarios.

5.5 Evaluation Metrics

The performance of the robot was evaluated using the following metrics:

- Success Rate: The percentage of successful grasps in each experiment.

- Failure Rate: The percentage of failed grasps, defined as cases where the robot either missed the object or dropped it during the task.
- Positional Error: The deviation between the target position and the actual placement of the object after each successful grasp.

These metrics were compared across different uncertainty models and distributions to determine the impact of each parameter on system performance.

6 USECASE AND ANALYSIS

This chapter presents the results and analysis of the experiments conducted to evaluate the impact of uncertainties on robotic pick-and-place tasks using the Franka Emika Panda robot. The experiments aimed to investigate the effects of uncertainties in object position, gripper width, velocity, and acceleration, both individually and in combination. Through the application of probabilistic distributions, various uncertainty scenarios were tested, and the robot's performance was assessed based on success rates in grasping and placing objects.

The chapter is structured to provide a clear breakdown of the experimental scenarios, the setup for each experiment, and the results obtained. This is followed by an analysis of the results, comparing success and failure rates across different levels of uncertainty. Each section corresponds to a specific type of uncertainty or a combination of uncertainties, allowing for a detailed examination of their effects on robotic performance.

6.1 Experimental Scenarios Overview

The experiments were designed to test the impact of uncertainties in key parameters object position, gripper width, velocity, and acceleration on the success of robotic pick-and-place tasks. These uncertainties were modelled using probabilistic distributions, with each scenario designed to isolate the effects of one or more uncertain parameters. The goal was to quantify how these uncertainties affect the robot’s ability to grasp and place objects accurately and consistently.

The following scenarios were considered:

- **Scenario 1: Uncertainty in Object Position** – Testing the impact of uncertainty in the X and Y coordinates of the object.
- **Scenario 2: Uncertainty in Gripper Width** – Evaluating the effect of variations in the robot's gripper width on task success.
- **Scenario 3: Uncertainty in Motion Parameters (Velocity and Acceleration)** – Analysing the influence of uncertainties in dynamic parameters on task accuracy.
- **Scenario 4: Combined Uncertainties** – Assessing the compounded effect of uncertainties in object position, gripper width, velocity, and acceleration.

Below is the Table 6.1 representing each scenario and cases within the scenario for different distributions. Each scenario was executed multiple times, with 50 iterations per experiment, using varying distributions and uncertainty parameters. The results were measured in terms of success and failure rates, providing a comprehensive understanding of the robot’s performance under different conditions.

Sr. No	Scenario	Uncertainty Modelled	Distributions Used
1	**Object Position Uncertainty**	X and Y coordinates of object position	**Normal:** Std dev. (0.005, 0.01, 0.015, 0.02)
			Uniform: Scale (0.005, 0.01, 0.015, 0.02)
2	**Gripper Width Uncertainty**	Gripper width deviations from 0.03 m	**Normal:** Std dev. (0.0025, 0.005, 0.0075)
			Uniform: Scale (0.005, 0.01, 0.015)
3	**Motion Parameters Uncertainty**	Velocity and/or acceleration	**Case 1:** Velocity (Normal) →Std dev (0.3)
			Case 2: Acceleration (Uniform) → Scale (0.5)
			Case 3: Both (Velocity + Acceleration) simultaneously
4	**Combination Scenarios**	Multiple uncertainties combined	**Case 1:** Object position + gripper width
			Case 2: Position + velocity + acceleration
			Case 3: Position + gripper width + velocity + acceleration

Table 6.1: Usecase overview

6.2 Scenario 1: Uncertainty in Object Position

6.2.1 Objective

The objective of this scenario was to analyse how positional uncertainties in the X and Y coordinates of the object affect the robot's grasping success rates. By introducing uncertainty in object position, we aim to simulate real-world conditions where precise object placement may not always be guaranteed.

6.2.2 Experimental Setup

In this scenario, uncertainties in the X and Y coordinates of the object were introduced using two probabilistic distributions:

- **Normal Distribution**: Standard deviations of 0.005, 0.01, 0.015, and 0.02 were applied to model positional uncertainties.
- **Uniform Distribution**: Uncertainty was modelled for specified scale of 0.005, 0.01, 0.015 and 0.02 to assess the impact of uniformly distributed variations in object position.

The robot was tasked with grasping an object placed at uncertain positions within its workspace. The gripper width, velocity, and acceleration were kept constant to isolate the effects of object position uncertainty.

6.2.3 Results

The results for each standard deviation in the normal distribution and for each range in the uniform distribution are presented below:

1) **Normal Distribution**:

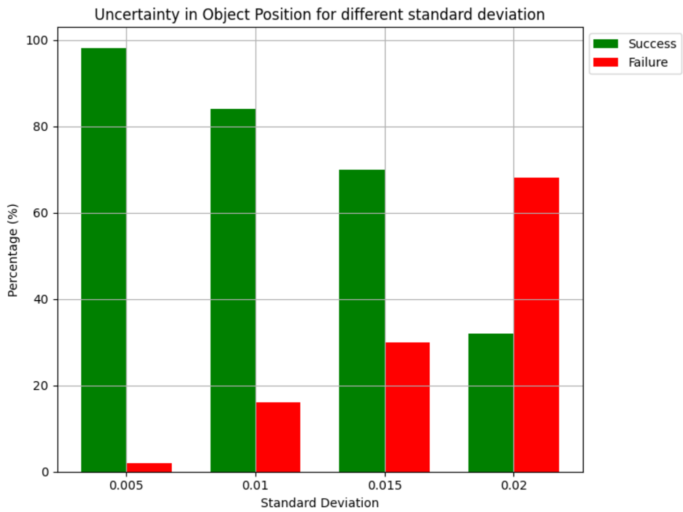

Figure 6.1:Uncertainty in object position for normal distribution

In the above Figure 6.1, at standard deviation of 0.005, the success rate was high (98%), with minimal impact on grasp performance. As the standard deviation increased to 0.01, 0.015, and 0.02, the success rate gradually dropped to 84%, 70%, and 32%, respectively as shown in Table 6.2. Hence, we can see that as the standard deviation increases the success rate reduces. In order to have better success rate the uncertainty in object position must be minimal so that the task is done without failure.

Standard Deviation	Success (%)	Failure (%)
0.005	98	2
0.01	84	16
0.015	70	30
0.02	32	68

Table 6.2: Uncertainty in object position for normal distribution

This scatter plot in Figure 6.2 illustrates the impact of uncertainty in object position with a normal distribution and a standard deviation of 0.015. The X-axis represents the sampled position values along the X-coordinate, while the Y-axis represents the sampled position values along the Y-coordinate. In this scenario, the green dots indicate successful grasps, and the red dots signify failed grasps.

The initial object position is marked at (X, Y) = (0.488, 0.08), which serves as the reference point for the sampled positions. As observed from the plot, the region close to the initial object position tends to have a higher success rate for grasping, as indicated by the concentration of green dots. Conversely, the farther the sampled positions deviate from the initial object position, the higher the failure rate, reflected by the increased occurrence of red dots.

This relationship between the distance from the initial object position and grasp success demonstrates that proximity to the reference point is critical for reliable grasping under conditions of uncertainty. The success rate for this scenario is 70%, while the failure rate is 30%, indicating that while the majority of sampled positions result in successful grasps, deviations from the object's original position significantly affect performance.

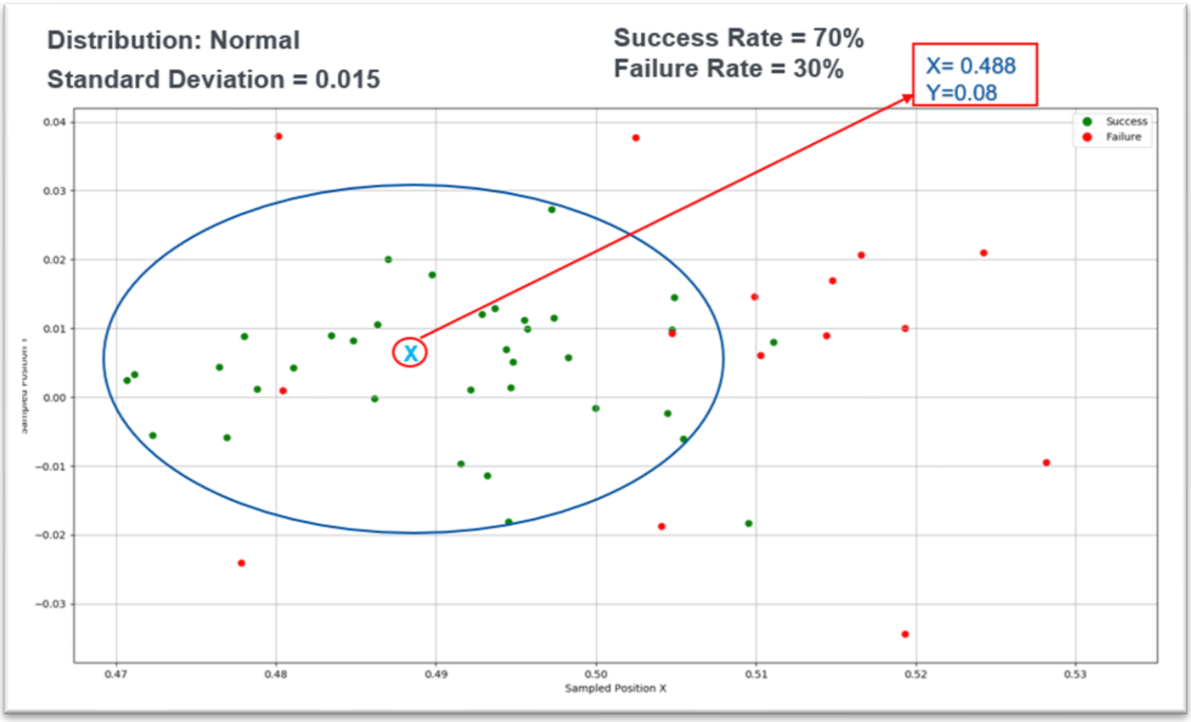

Figure 6.2: Uncertainty in object position for normal distribution of 0.015

2) **Uniform Distribution**:

Figure 6.3: Uncertainty in object position for uniform distribution

In Figure 6.3 we observe that, at a scale of 0.005, the success rate was 94%. As the scale increased to 0.01, 0.015mm, and 0.022mm, the success rates fell to 90%, 80% and 72%. Hence, we can see that in Table 6.3 as the scale increases the success rate reduces. In order to have better success rate the uncertainty in object position must be minimal so that the task is done without failure.

Scale	Success (%)	Failure (%)
0.005	94	6
0.01	90	10
0.015	80	20
0.02	72	28

Table 6.3: Uncertainty in object position for uniform distribution

The scatter plot in Figure 6.4 depicts the results of object position uncertainty modeled with a uniform distribution and a scale of 0.02. Similar to the previous analysis, the X-axis shows the sampled position values along the X-coordinate, and the Y-axis shows the sampled position values along the Y-coordinate. Green dots represent successful grasps, while red dots represent failed grasps.

The initial object position is (X, Y) = (0.488, 0.08). Here, the success rate is 72%, and the failure rate is 28%. The concentration of green dots closer to the initial object position highlights that successful grasps are more frequent near this reference point.

As the sampled positions deviate from the original object position, the likelihood of failure increases, as indicated by the larger number of red dots in those areas.

In contrast to the normal distribution, the spread of successful and failed grasps is more uniform, as expected from the nature of the distribution, but the overall trend still suggests that proximity to the initial object position is critical for successful task completion. The uniform distribution provides a slightly higher success rate compared to the normal distribution, but failures become more frequent with larger deviations from the original position.

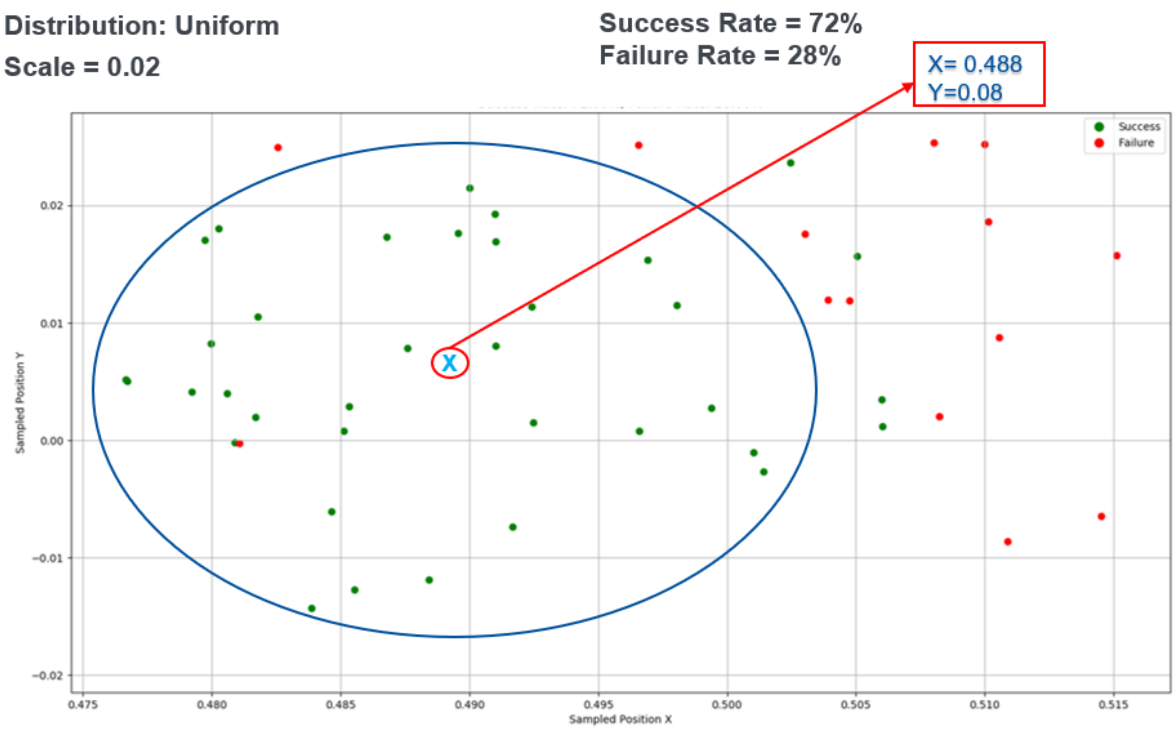

Figure 6.4: Uncertainty in object position for uniform distribution of 0.02

6.2.4 Analysis

The results show a clear trend: as positional uncertainty increases, the robot's success rate in grasping objects decreases. In both normal and uniform distributions, small positional deviations (e.g., standard deviation of 0.005 or scale of 0.005) had minimal effect on the robot's performance. However, as the deviations grew larger, the robot struggled to locate and grasp the object accurately. This highlights the importance of precise object localization in ensuring the success of pick-and-place tasks.

6.3 Scenario 2: Uncertainty in Gripper Width

6.3.1 Objective

This scenario focused on evaluating how variations in gripper width affect the stability and success of the robot's grasp. In real-world applications, gripper width may vary due to calibration errors or mechanical wear, making it important to understand how these variations influence task performance.

6.3.2 Experimental Setup

Two distributions were used to model uncertainty in gripper width:

1) **Normal Distribution**: Standard deviations of 0.0025, 0.005 and 0.0075 were tested.

2) **Uniform Distribution**: Gripper width was varied uniformly for scale of 0.005, 0.01 and 0.015 around the optimal width of 0.03m.

The robot's object position, velocity, and acceleration were kept constant during these experiments to isolate the effect of gripper width uncertainty.

6.3.3 Results

1) **Normal Distribution**:

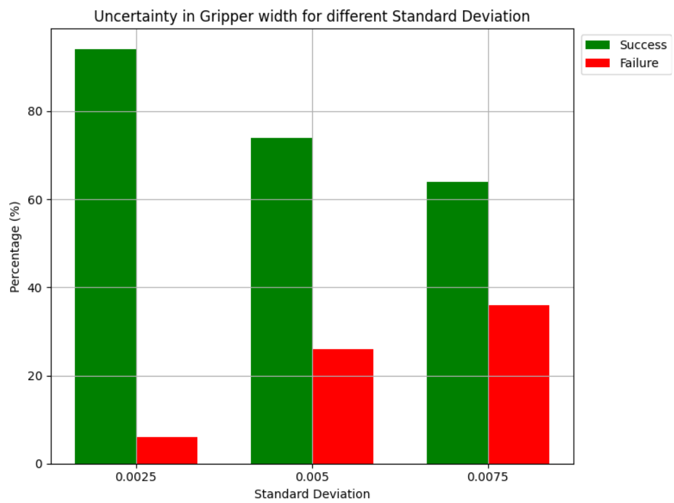

Figure 6.5: Uncertainty in gripper width for normal distribution

In Figure 6.5 we can observe that for a standard deviation of 0.0025, the success rate was 94%, with minimal grasp failures. As the standard deviation increased to 0.005 and 0.0075, the success rates dropped to 74% and 64% respectively. Hence, we can see that as the standard deviation increases the success rate reduces as shown in Table 6.4. In order to have better success rate the uncertainty in gripper width must be minimal so that the task is done without failure.

Experiment No:	Standard Deviation	Success Rate (%)	Failure Rate (%)
1	0.0025	94	6
2	0.005	74	26
3	0.0075	64	36

Table 6.4: Uncertainty in gripper width for normal distribution

This scatter plot in Figure 6.6 illustrates the impact of uncertainty in gripper width for a normal distribution with a standard deviation of 0.0025. The X-axis represents the sample number along the X-coordinate, while the Y-axis represents the sampled gripper width values along the Y-coordinate. In this scenario, the green dots indicate successful grasps, and the red dots signify failed grasps.

The standard width of the object is 0.03m which serves as the reference point for the sampled gripper width. As observed from the plot, the region up to 0.034m as indicated by the concentration of green dots. Conversely, the region above 0.034m have higher the failure rate, reflected by the increased occurrence of red dots.

This relationship between the gripper width and grasp success demonstrates that the range from 0.03m to 0.034m is critical for reliable grasping under conditions of uncertainty. The success rate for this scenario is 90%, while the failure rate is 10%, indicating that while the majority of sampled gripper width result in successful grasps, and the ones outside the critical range resulted in failed grasp.

Figure 6.6: Uncertainty in gripper width for normal distribution of 0.0025

2) **Uniform Distribution**:

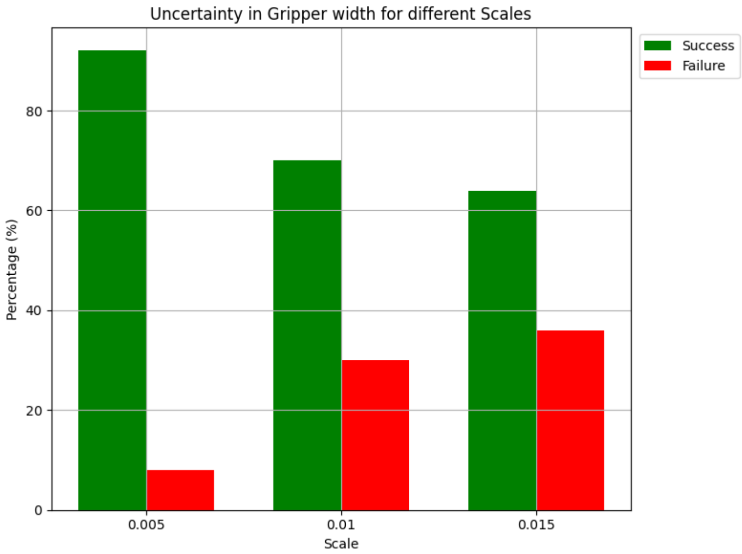

Figure 6.7: Uncertainty in gripper width for uniform distribution

In Figure 6.7, we can see that for a scale of 0.005 around the optimal width, the success rate was 92%. As the range increased to 0.01m and 0.015, the success rates dropped to 70% and 64%. Hence, we can see that as the scale increases the success rate reduces as shown in Table 6.5. In order to have better success rate the uncertainty in object position must be minimal so that the task is done without failure.

Experiment No:	Scale	Success Rate (%)	Failure Rate (%)
4	0.005	92	8
5	0.01	70	30
6	0.015	64	36

Table 6.5: Uncertainty in gripper width for uniform distribution

This scatter plot in Figure 6.8 illustrates the impact of uncertainty in gripper width for a uniform distribution with a standard deviation of 0.015. The X-axis represents the sample number along the X-coordinate, while the Y-axis represents the sampled gripper width values along the Y-coordinate. In this scenario, the green dots indicate successful grasps, and the red dots signify failed grasps.

The standard width of the object is 0.03m which serves as the reference point for the sampled gripper width. As observed from the plot, the region up to 0.034m as indicated by the concentration of green dots. Conversely, the region above 0.034m have higher the failure rate, reflected by the increased occurrence of red dots.

This relationship between the gripper width and grasp success demonstrates that the range from 0.03m to 0.034m is critical for reliable grasping under conditions of uncertainty. The success rate for this scenario is 64%, while the failure rate is 36%, indicating that while the majority of sampled gripper width result in successful grasps, and the ones outside the critical range resulted in failed grasp.

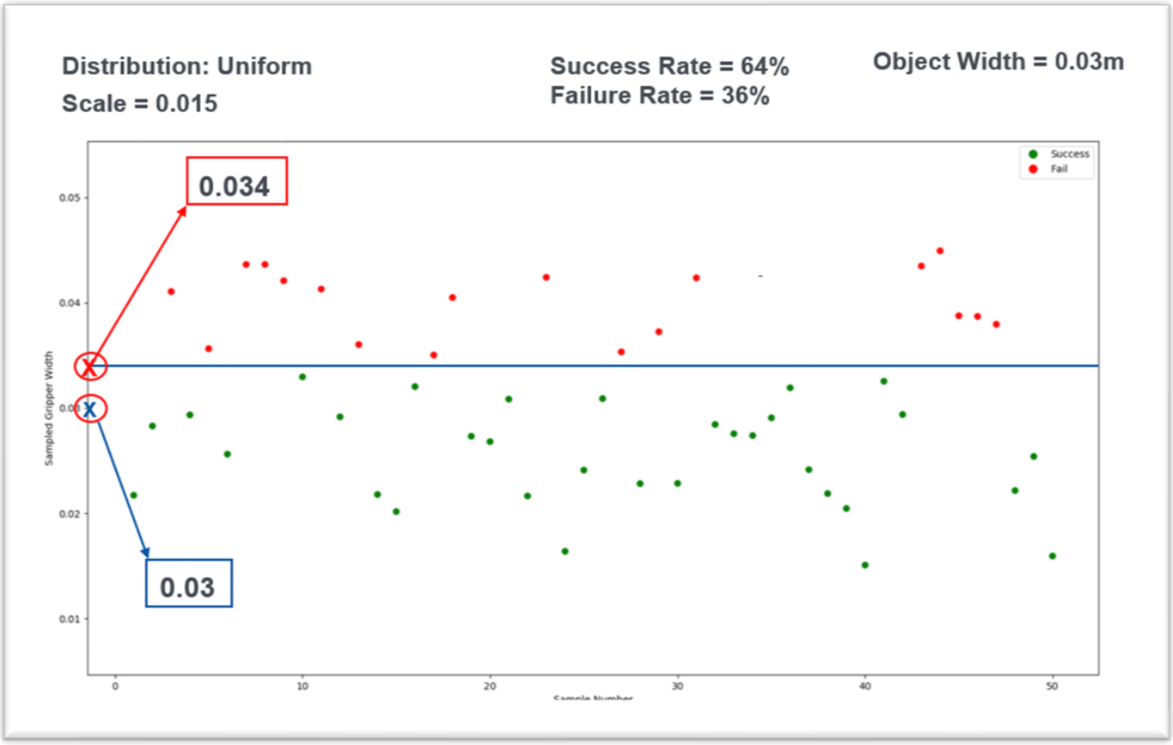

Figure 6.8: Uncertainty in gripper width for uniform distribution of 0.015

6.3.4 Analysis

The results indicate that even small deviations in gripper width can significantly affect grasp success. The robot performed well when the gripper width was close to its optimal value of 0.03m. However, as the deviation from the optimal width increased, the success rate decreased. Larger deviations resulted in failed grasps, where the object either slipped or was not securely held. This suggests that accurate gripper calibration is critical for ensuring consistent performance.

6.4 Scenario 3: Uncertainty in Motion Parameters (Velocity and Acceleration)

6.4.1 Objective

This scenario aimed to determine how uncertainties in velocity and acceleration affect the robot's ability to complete pick-and-place tasks. Dynamic parameters such as velocity and acceleration are crucial for maintaining smooth and controlled motion, and any uncertainty in these parameters can lead to performance degradation.

6.4.2 Experimental Setup

Uncertainty in velocity and acceleration was introduced using the following distributions:

Case 1: Uncertainty in Velocity

- In this scenario, uncertainty was introduced only in the velocity while keeping acceleration constant at 0.1m²/s. The velocity arrays were generated using a normal distribution with a standard deviation of 0.3 around a mean velocity of 0.5 m/s.
- Both the object position and gripper width were kept constant at their optimal values.

Case 2: Uncertainty in Acceleration

- Here, uncertainty was modelled in the acceleration parameter using a uniform distribution with a scale of 0.5, while velocity was kept constant at 0.5 m/s.
- Similar to the first scenario, the object position and gripper width were fixed.

Case 3: Combined Uncertainty in Velocity and Acceleration

- In this case, uncertainties in both velocity and acceleration were introduced simultaneously, using the same arrays as in Scenarios 1 and 2.
- The object position and gripper width remained constant.

6.4.3 Results

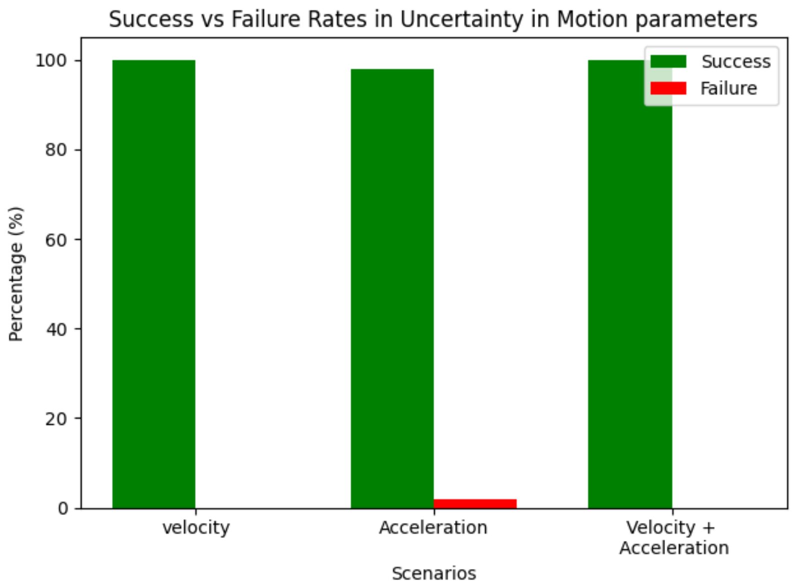

Figure 6.9: Uncertainty in motion parameters

The success rate in case 1 was 100%, as shown by the green bar in Figure 6.9, indicating that the uncertainty in velocity had minimal impact on the robot's performance in this case. In case 2, The robot's success rate was 98%, showing that even with variability in acceleration, the pick-and-place task was nearly unaffected, though there was a slight increase in the failure rate compared to Scenario 1. And in the final case, the results show a success rate of 100%, demonstrating that the robot could handle combined uncertainties without any significant degradation in performance as mentioned in Table 6.6.

Case	Scenario			Results (%)	
	Parameter	Distribution	Scale/ deviation	Success	Failure
1	Velocity	Normal	0.3	100	0
2	Acceleration	Uniform	0.5	98	2
3	Velocity	Normal	0.3	100	0
	Acceleration	Uniform	0.5		

Table 6.6: Uncertainty in motion parameters

6.4.4 Analysis

The results show that uncertainty in motion parameters like velocity and acceleration did not have any major impact on task success. Erratic or unstable motion caused by acceleration uncertainties can lead to grasp failures, highlighting the need for tight control over dynamic parameters in robotic tasks.

6.5 Scenario 4: Combined Uncertainties

6.5.1 Objective

The objective of this scenario was to evaluate the impact of multiple uncertainties like object position, gripper width, velocity, and acceleration when applied together. This scenario simulates the real-world conditions where multiple factors are uncertain simultaneously.

6.5.2 Experimental Setup

The following uncertainty models were applied:

Case 1: Uncertainty in Object Position and Gripper Width.

- In this scenario, uncertainty is introduced in both the object's X and Y positions as well as the gripper width, while velocity and acceleration are kept constant.
- For object position, a normal distribution with a standard deviation of 0.01 was applied to generate the X and Y values.
- For the gripper width, uncertainty was modelled using a Uniform distribution with a scale of 0.01.

Case 2: Uncertainty in Object Position, Velocity and Acceleration

- In this case, uncertainty was introduced in the object's X and Y positions, as well as in velocity and acceleration, while the gripper width remained constant.
- The object's X and Y coordinates were generated using a normal distribution with a standard deviation of 0.01.
- Velocity uncertainty was modelled using a normal distribution with a standard deviation of 0.3 around a mean velocity of 0.5 m/s.
- Acceleration uncertainty was introduced using a Uniform distribution with a scale of 0.5.

Case 3: Combined Uncertainty in Object Position, Gripper Width, Velocity, and Acceleration.

- In the final scenario, uncertainty was introduced across all four parameters: object position, gripper width, velocity, and acceleration.
- For object position, a normal distribution with a standard deviation of 0.01 was used to generate the X and Y values.
- Gripper width uncertainty was modelled using a Uniform distribution with a scale of 0.01.
- Velocity uncertainty was modelled using a normal distribution with a standard deviation of 0.3 around a mean velocity of 0.5 m/s.
- Acceleration uncertainty was generated using a Uniform distribution with a scale of 0.5.

6.5.3 Results

The success rate in case 1 was 52%, indicating a moderate level of task success under combined uncertainties in object position and gripper width as shown in Figure 6.10. In case 2, the robot achieved a success rate of 80%, demonstrating its resilience to uncertainty in these motion parameters. In case 3, since all the four parameters had uncertainty, it drastically reduced the success rate to 50%. This shows the compounding effect of uncertainty in robotics.

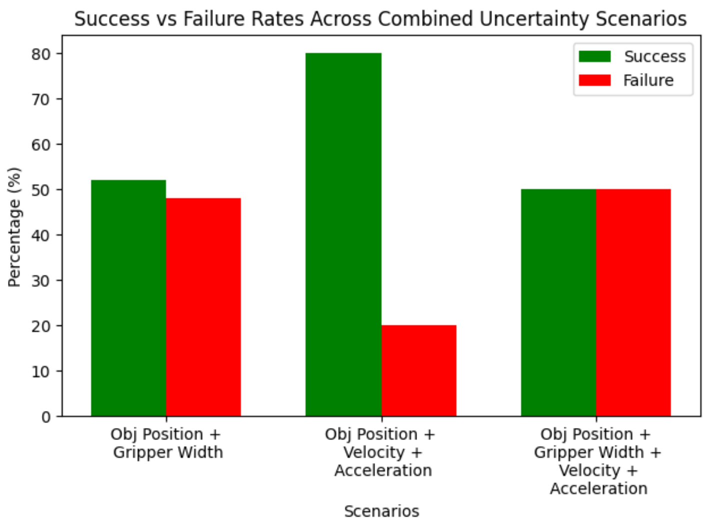

Figure 6.10: Combined uncertainty

Case	Scenario			Results (%)	
	Parameter	Distribution	Scale/ deviation	Success	Failure
1	Object Pos	Normal	0.01	52	48
	Gripper Width	Uniform	0.01		
2	Object Pos	Normal	0.01	80	20
	Velocity	Normal	0.3		
	Acceleration	Uniform	0.5		
3	Object Pos	Normal	0.01	50	50
	Velocity	Normal	0.3		
	Acceleration	Uniform	0.5		
	Gripper width	Uniform	0.01		

Table 6.7: Combined uncertainty

From Table 6.7, when comparing Case 1, which introduces uncertainty in object position and gripper width, with Case 3, where all four parameters object position, gripper width, velocity, and acceleration are subject to uncertainty, we observe that the success rates in both cases are nearly identical, with only a minor difference. This indicates that the inclusion of velocity and acceleration uncertainties in Case 3 has a negligible impact on the overall grasp success rate. The results suggest that variations in velocity and acceleration do not significantly affect the outcome of the pick-and-place task. This finding further supports the conclusion that the primary factors influencing grasp success are object position and gripper width, while velocity and acceleration have a minimal effect on the task's overall performance.

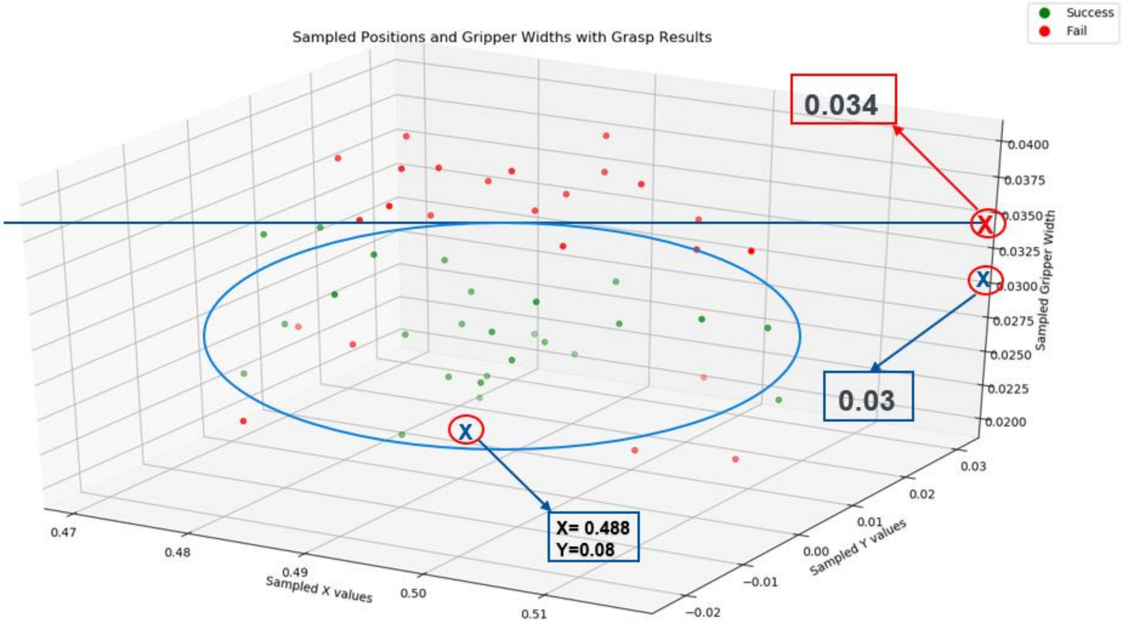

Figure 6.11: Combined uncertainty for object position and gripper width

The 3D scatter plot in Figure 6.11 visualizes sampled positions in the X and Y directions, along with varying gripper widths (Z-axis). The green dots scattered across the plot represent successful grasps, while the red dots indicate failed grasp attempts. The purpose of the chart is to highlight the regions in the parameter space that lead to success or failure under combined uncertainty conditions.

The X-axis and Y-axis denote the sampled positional uncertainties in the object’s location, while the Z-axis indicates varying gripper widths. As these three parameters are adjusted within specific ranges, the robot's ability to successfully grasp the object fluctuates, with some parameter combinations leading to failure (shown in red) and others to success (shown in green).

Within the plot, there are three notable failure points marked with "X." These points represent combinations of initial object position (X,Y) =(0.488, 0.08), default gripper width (0.03m) and the gripper width up to which the robot is able to grasp object (0.034m). The plot also includes a blue elliptical region, which provides a boundary for the successful grasp space, showing how the robot can perform well within certain uncertainty ranges but begins to fail as uncertainties in the object position and gripper width increase. The ellipse visually captures the compounding effect of these uncertainties on the robot's grasping performance, emphasizing the transition between success and failure at its boundaries.

6.5.4 Analysis

The combined uncertainties had a significant compounding effect on the robot's performance, leading to a lower success rate. The robot struggled to compensate for multiple uncertain parameters, which caused greater variability in task outcomes. This highlights the complexity of managing multiple sources of uncertainty in real-world robotic applications. The success rate for the combined uncertainties was 50%, indicating a substantial decrease in task performance compared to scenarios where only one or two parameters were uncertain.

6.6 Compounding effect of combined uncertainty

Case	Scenario			Results (%)		Individual Success %
	Parameter	Distribution	Scale/ deviation	Success	Failure	
1	Object Pos	Normal	0.01	52	48	84
	Gripper Width	Uniform	0.01			70
2	Object Pos	Normal	0.01	80	20	84
	Velocity	Normal	0.3			100
	Acceleration	Uniform	0.5			98
3	Object Pos	Normal	0.01	50	50	84
	Velocity	Normal	0.3			100
	Acceleration	Uniform	0.5			98
	Gripper width	Uniform	0.01			70

Table 6.8: Compounding effect of combined uncertainty

Table 6.8 demonstrates the compounding effect of multiple uncertainties on the success rate of robotic grasping. The "Individual Success %" column represents how each parameter such as object position, velocity, acceleration, and gripper width performs independently in terms of its grasp success rate.

In Case 1, uncertainty is introduced in object position and gripper width. Individually, object position has an 84% success rate, while gripper width has a 70% success rate. However, when these uncertainties are combined, the overall success rate drops to 52%, showing a significant compounding effect. This demonstrates how multiple uncertainties interact to reduce the overall success rate.

In Case 2, uncertainty is applied to object position, velocity, and acceleration. Object position maintains an 84% individual success rate, and both velocity and acceleration have high success rates of 100% and 98%, respectively. Despite this, the combined success rate is 80%, which is higher than in Case 1 but still indicates some compounding effect due to the interaction of uncertainties.

In Case 3, all four parameters (object position, gripper width, velocity, and acceleration) are uncertain. Individually, success rates remain high, especially for velocity (100%) and acceleration (98%), but the combined success rate drops to 50%. This significant drop indicates that even though certain individual parameters, like velocity and acceleration, perform well, when combined with others (object position and gripper width), the compounding effect drastically reduces the overall success rate.

The table clearly shows that even if individual parameters perform well in isolation, their combined uncertainties have a substantial impact on the success rate. The interaction between these uncertainties introduces additional complexity, making the task more prone to failure, which is particularly evident in Case 3. This underscores the importance of considering multiple uncertainties collectively rather than evaluating them independently.

6.7 Analysis Summary

Each scenario demonstrated that increasing uncertainty in any parameter object position, gripper width, velocity, or acceleration led to a decrease in success rates. However, the magnitude of this impact varied depending on the parameter. Across all cases, object position uncertainty consistently had the largest impact on success rate. Even small deviations in the object’s position significantly reduced the chances of successful grasps. Despite adding uncertainty to velocity and acceleration, these parameters did not have a substantial effect on grasping performance. This suggests that within the tested range, the Franka Emika Panda robot is highly robust to variations in movement speed and force.

The most critical finding was the compounding effect observed when multiple uncertainties were present. While individual uncertainties might seem manageable, their combined effect results in a significant performance drop, particularly in Case 3. This highlights the need for a holistic approach to uncertainty mitigation in robotic systems.

The type of probability distribution plays a role in how uncertainties affect the system. Normal distributions, with their predictable centre, allowed for better performance compared to uniform distributions, which introduced more randomness and unpredictability. Although the simulation provided a controlled environment for testing uncertainties, the real-world experiments revealed additional challenges, such as sensor noise and mechanical imperfections, which further reduced task success rates.

In conclusion, the analysis shows that while individual uncertainties in parameters such as velocity and acceleration might not drastically affect robotic grasping success, the combined effect of multiple uncertainties can lead to significant performance degradation. Object position uncertainty was found to be the most influential parameter. This insight is valuable for designing more reliable and adaptive control algorithms, particularly in unpredictable environments.

Future work could explore more advanced uncertainty mitigation techniques, such as machine learning-based adjustments or enhanced sensor integration, to further reduce the impact of uncertainties on robotic performance. Additionally, further experiments with different robots and tasks would help generalize these findings across various applications in robotics.

7 CONCLUSION

7.1 Summary

This thesis has explored the critical role of uncertainty in robotic systems, specifically focusing on its impact on the performance of pick-and-place tasks using the Franka Emika robot. As industries increasingly rely on robots to perform tasks in dynamic and unpredictable environments, managing uncertainty has become crucial to ensure operational efficiency, safety, and reliability. This research has successfully addressed the challenges posed by uncertainties in object position, gripper width, velocity, and acceleration by applying probabilistic distribution models and evaluating their effects on task performance.

The key findings of this research are as follows:

- **Object Position Uncertainty**: The introduction of uncertainty in object position, modelled using normal and uniform distributions, demonstrated that small deviations had minimal impact on success rates. However, larger positional uncertainties significantly reduced task success rates, underscoring the importance of precise object localization.

- **Gripper Width Uncertainty**: Variations in gripper width revealed that minor deviations around the optimal value (0.03 m) maintained high success rates. However, larger deviations from the optimal width resulted in a sharp decline in grasping success, highlighting the need for accurate gripper calibration.

- **Motion Parameter Uncertainty**: In experiments with uncertainty in velocity and acceleration, the robot's success rate was notably impacted. While small uncertainties in velocity alone had little effect, the combination of velocity and acceleration uncertainties led to decreased performance. This demonstrated the need for precise control over dynamic parameters in motion planning.

- **Combined Uncertainty**: Scenarios that combined uncertainties in object position, gripper width, velocity, and acceleration presented the most significant challenge. Success rates dropped considerably when multiple uncertainties were introduced, indicating the compounding effect of uncertainties and the complexity of managing them simultaneously.

Overall, the results highlight the need for robust and adaptive control algorithms capable of mitigating the impact of uncertainties. The probabilistic models used in this thesis have provided valuable insights into the types and scales of uncertainty that most affect robotic performance. Understanding these factors enables the design of more resilient robotic systems that can function reliably in uncertain environments.

7.2 Future Work

While this research has made significant contributions to understanding and managing uncertainty in robotic systems, several avenues for future research remain:

1. **Improved Uncertainty Modelling**: Future work can focus on exploring more advanced probabilistic models that incorporate time-varying or dynamic uncertainties. For example, uncertainty could be modelled as a function of the robot's operating conditions, which may fluctuate over time or under different environmental conditions.

2. **Real-Time Adaptation**: Developing adaptive control algorithms that can respond to uncertainties in real-time is a key area for future exploration. While this thesis used pre-determined uncertainty models, real-world applications would benefit from systems that continuously learn and adjust based on sensor feedback.

3. **Multi-Robot Collaboration under Uncertainty**: The research can be extended to scenarios involving multiple robots working collaboratively. In such cases, managing uncertainties related to robot-to-robot interactions, communication delays, and task coordination would become critical.

4. **Extended Scenarios and Applications**: While this thesis focused on pick-and-place tasks, the insights gained can be applied to other robotic applications such as assembly, welding, and inspection tasks. Future work could explore how uncertainties affect these types of operations and develop solutions tailored to each application.

5. **Integration of Machine Learning**: The integration of machine learning algorithms could allow robots to predict and adapt to uncertainties more effectively. By learning from past failures and successes, the robot could improve its decision-making and task execution in real-time.

6. **Safety-Critical Applications**: As robots increasingly enter safety-critical domains such as healthcare and autonomous driving, ensuring reliable performance under uncertainty becomes even more essential. Future research could focus on enhancing safety mechanisms that account for uncertainty in these high-stakes environments.

7.3 Final Remarks

This research has demonstrated that addressing uncertainties in robotics is a multifaceted challenge that requires a combination of robust modeling, careful experimental design, and advanced control strategies. The findings provide a solid foundation for improving robotic system performance in uncertain environments, paving the way for more reliable and adaptable industrial automation solutions.

The integration of uncertainty management into robotic systems is not merely a technical challenge but a practical necessity. As robots become more autonomous and interact with unpredictable environments, the ability to anticipate and adapt to uncertainty will be key to their successful deployment in real-world applications. The contributions made by this thesis mark a significant step forward in this direction, but much work remains to be done to fully realize the potential of robotics in uncertain, dynamic environments.

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