CHAPTER 1

INTRODUCTION

The background of this research centers around shifting the usage of industrial robot from large enterprises to the small and medium size business. This thesis loosely refers an industrial robot as a robot manipulator that is used in automation per definition ISO-8373:2 (2021). Thus, any manipulators with more than three controllable joints used in an automation for production purposes are considered as and industrial robot. However, the stigma prevails; industrial robots are heavy, expensive, inflexible, high maintenance, and hazardous which requires informed safety precautionaries. In practice, a heavy industrial robot is isolated into workcells making the operation of industrial robots rigid, inflexible, and requires tremendous amount of time and resources should a new task or change is introduced in the workcell (Miseikis et al. 2017). This stigma and the reality of owning an industrial robot hinders the confidence of small and medium size business (SME) to adopt industrial robot technology. This thesis attempts to democratize robot technology and automation to the SMEs by introducing an inexpensive, flexible, and safe robotic technology.

I propose a flexible automation system (FAS) to increase flexibility and decrease the cost of operating and maintaining an industrial robot. The FAS is characterized by its ability to react to unpredictable changes in its production floor using a SLAM solution so that my FAS solution can be installed in a large-volumed production floor under an SME setup. The main purpose of the FAS-SLAM is to maintain and manage the uncertainty of the system so that the system will be safe to use at a low cost. In the coming sections I will establish the connection between an FAS system and a SLAM solution. As a primer, there are three aspects of an FAS for an industrial robot; (1) visual feedback, (2) map model and state estimation model of the robot, and (3) path planning model of the robot. Figure 1.1 shows these considerations.

The FAS uses visual feedback, such as visual camera, laser range finder, or a visual-depth camera, to model the workspace and to model the state of the robot.

The second aspect of an FAS is the state estimation model and the map model summarized by figure 1.2. A map model is a mathematical representation of an environment and state estimation model is a process of estimating an industrial robot configuration, location, velocity and acceleration of its end effector. The map model will provide the information for the FAS to manage the movement of a robot arm in its workspace based on the state estimation.

The third aspect of an FAS is the path-planning model. The path-planning model is used to calculate a way to reach a point in space without colliding with any obstructions or obstacles. The path is dependent on the information restored in the map model of the workspace.

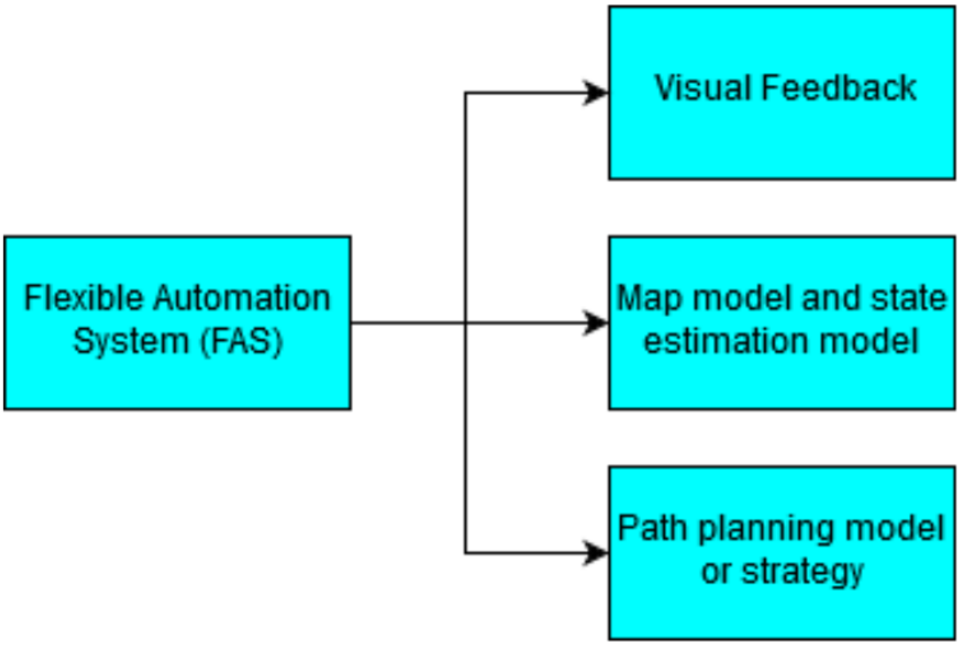

Figure 1.1: Three aspects of an FAS to maintain a safe and cost effective robotic system in a production line.

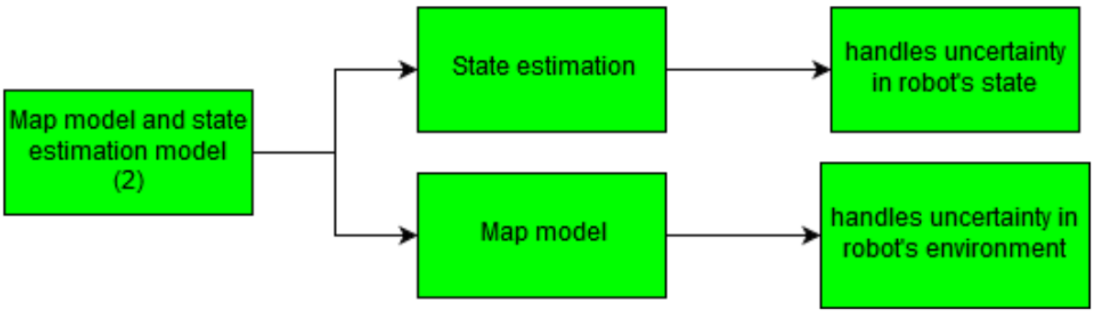

Figure 1.2: The second aspect of an FAS consist of two mathematical model that manage the uncertainty of the workspace of a robot and the uncertainty of the state of the robot.

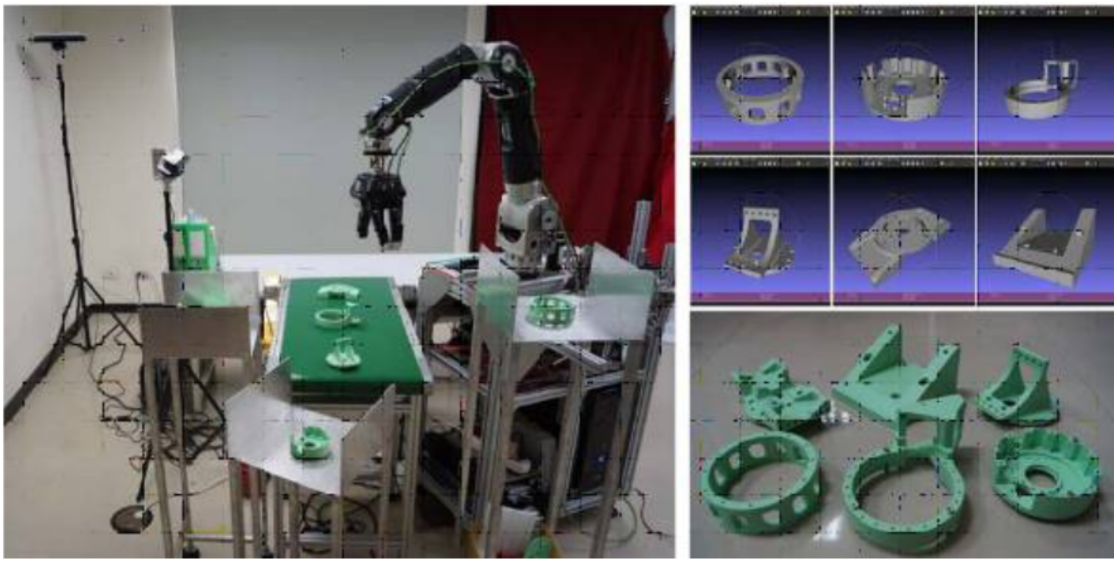

Figure 1.3: Eye-in-hand configuration that uses visual feedback enables an articulated robotic arm to identify objects in its workspace for manipulation.

1.1 The Motivation of Eye-in-Hand Robot Configuration

Placement of the machine vision and the decision of the placement of the vision is non-trivial. The designer can consider, eye-to-hand configuration where the vision sensor is attached to an additional structure that has a vantage point of the robot manipulator and the workspace (Luo and Kuo 2016) or an eye-in-hand configuration where a vision sensor is place on the robot's end-effector or at the last link of the robot arm. The latter configuration requires no additional structure and the visual feedback can be used as a state estimator and a mapping tool abiding the movement of the robot. This makes eye-in-hand configuration more space-efficient. Unlike eye-to-hand configuration, eye-in-hand sensors provide more information gain in terms of the state of the robot and the environment. The feedback from eye-in-hand configuration lacks visual-obstruction where more than one vantage point can be achieve when the sensors move with the end effector. The sensor in eye-in-hand configuration aids task involving reaching and manipulating since both tasks are specific to the end-effector. In the case of eye-to-hand configuration, both reaching and manipulation may be subjected to visual obstruction and extra rigs for the sensor.

As an example, Luo and Kuo (2016) used Microsoft's Kinect, a type of visual-depth sensor (RGB-D), to produce workspace model of their robot system and to identify objects in the workspace. Figure 1.3 shows the rigidity of their setup.

Klingensmith, Sirinivasa, and Kaess (2016) uses the eye-in-hand configuration where an RGB-D sensor is connected at the end effector to auto-calibrate the robot's position and configuration illustrated in figure 1.4. Extra structures were observed in the figure but in this stage of their research, their eye-to-hand sensor setup are not reported in their findings.

Figure 1.4: Eye-in-hand configuration where an RGB-D sensor (blue) is placed on the end-effector link to perform the robot's state estimation via auto-calibration (Klingensmith, Sirinivasa, and Kaess 2016)

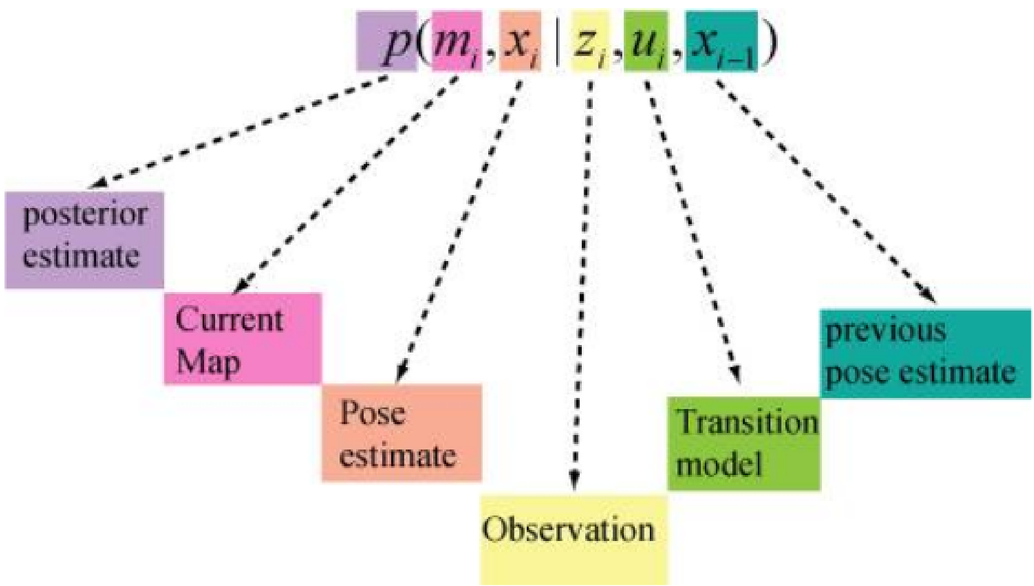

Figure 1.5: The variables parameterizing the SLAM solution

1.2 The Devoid of Unified Solution for Uncertainty Management in State and Workspace of an Industrial Robot

Despite rich solution options to uncertainty of a robot state and its environment, the solutions are disjoint and performed separately. Simultaneous localization and map-building solution (SLAM), however, incorporate both the solution to uncertainty of the robot's state and the solution to uncertainty of the environment into one framework. Equation 1.1 summarize the concept of SLAM:

$$p(m_i, x_i | z_i, u_i, x_{i-1}) \tag{1.1}$$

where p (also known as posterior) is the process of maintaining the map of an unknown environment and estimating the current state or pose of a robot. $m_i \in \mathbb{R}^{3n}$, is the global map model, $x_i \in \mathbb{R}^3 \times \boldsymbol{SO(3)}$ is the state estimation, z_i is the measurement or observation model or visual feedback model of the robot, and u_i is the state transition matrix or state transition model of the robot. x_{i-1} before a new measurement is taken. Figure 1.5 summarizes the arguments of equation 1.1.

In theory a SLAM solution covers the first and the second aspects of the FAS proposed in this research. Figure 1.6 articulates the relevance of SLAM solution to an FAS.

Yet SLAM has only been optimized specifically for autonomous robot to address an unknown environment. The definitive researches on the use of SLAM in articulated robot were introduced by Klingensmith, Sirinivasa, and Kaess (2016), Li, Ito, and Maeda (2019), and Ito, Li, and Maeda (2020). However, they did not consider the uncertainty of the state of the robot, the uncertainty of the robot's environment, and the path planning solution in a single framework. Figure 1.7

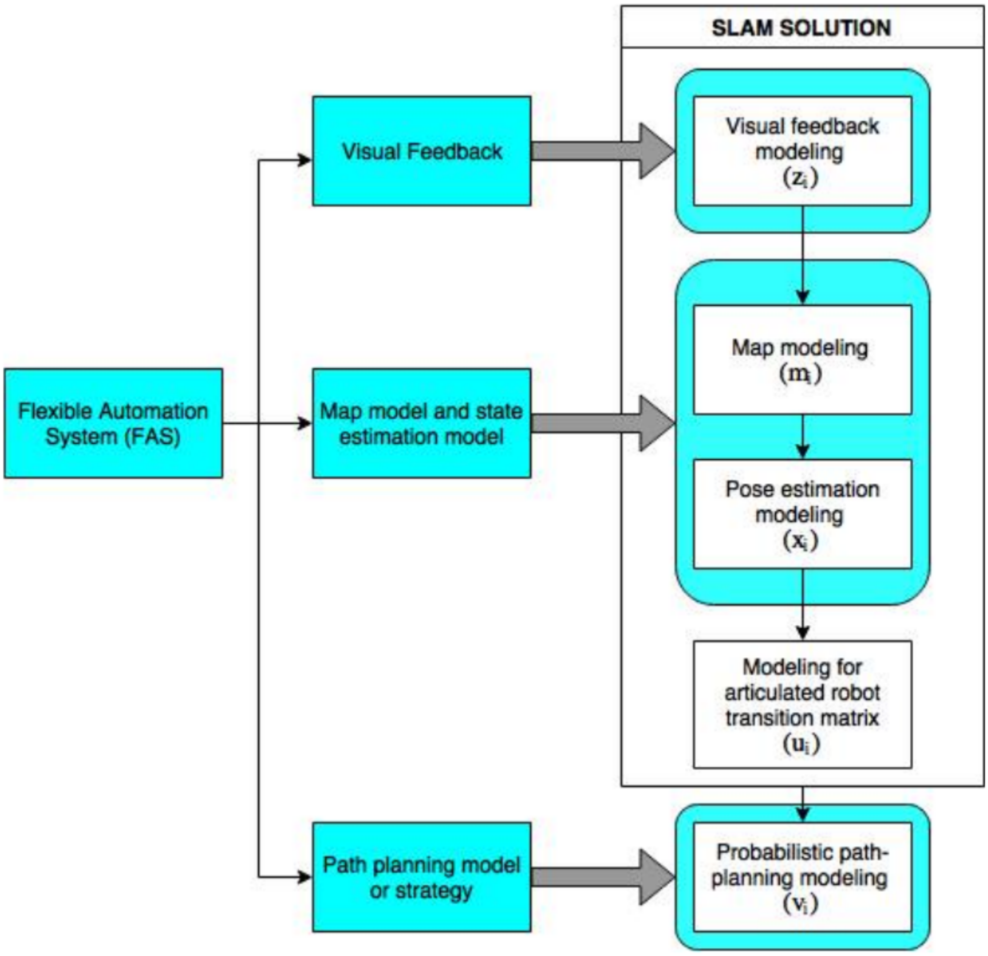

Figure 1.6: The connection between an FAS to a SLAM solution

summarizes the gap in finding a solution to a path-planning under the uncertainty of the state of the robot and the uncertainty of its environment.

1.3 Problem Statement and its Significance

The current state-of-the-art approaches to an industrial articulated manipulator lack a solution that addresses the the safety of the system in a changing environment. SLAM solutions for articulated manipulator have only addressed the issues of accuracy without tackling the high maintenance cost and safety of a robot manipulator specifically on the production set-up. Furthemore, the performance of these solutions against probabilistic path-planner for robot manipulator has yet been reported. This research intend to aspire flexibility and cost effective robot manipulator system for industrial purposes in SME's using sampling-based planner closely coupled with a SLAM solution.

1.4 Research Philosphy

A compliant robotic arm by leveraging the probabilistic mathematical models for map of an environment, the state estimation of a robot, and the path-planning model in controlling the robot motion sustains safety operation and cost-effective production line for SME's.

1.5 Objectives

1. To design a six-axis manipulator and build it as a prototype of a compliant manipulator.
2. To simulate a moving obstacle avoidance capability using a probabilistic planner.
3. To demonstrate the obstacle avoidance capability on the industrial manipulator hardware with a synthetic moving obstacle augmented from a simulated environment.
4. To show the feasibility of using a SLAM solution as a feedback pipeline in motion planning.

1.6 Research Scope

This research uses a back-drivable (compliant) articulated robot with six axes to implement the framework of a fully probabilistic strategy to path-planning and obstacle avoidance. This research only use an RGB-D sensor.

The dynamic environment is a non-reflective and non-specular workspace. In context of designing the workspace as a dynamic environment, the workspace is not share with another robotic arm. Instead, the workspace will be introduced

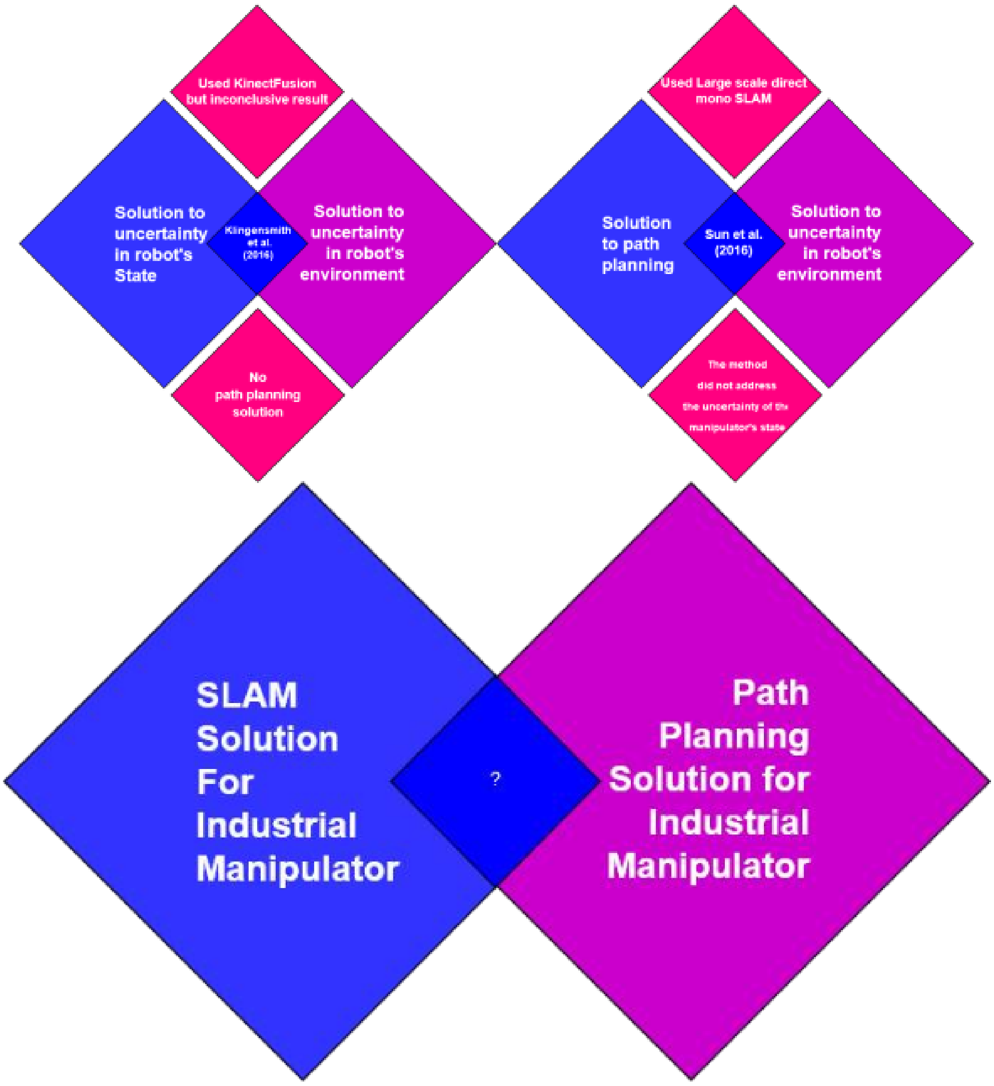

Figure 1.7: The gap (labeled as a question mark "?") of a solution to path-planning for uncertainty in the state of the robot and the uncertainty of the environment of the robot in a single framework hinder a functioning FAS in context of an industrial robot

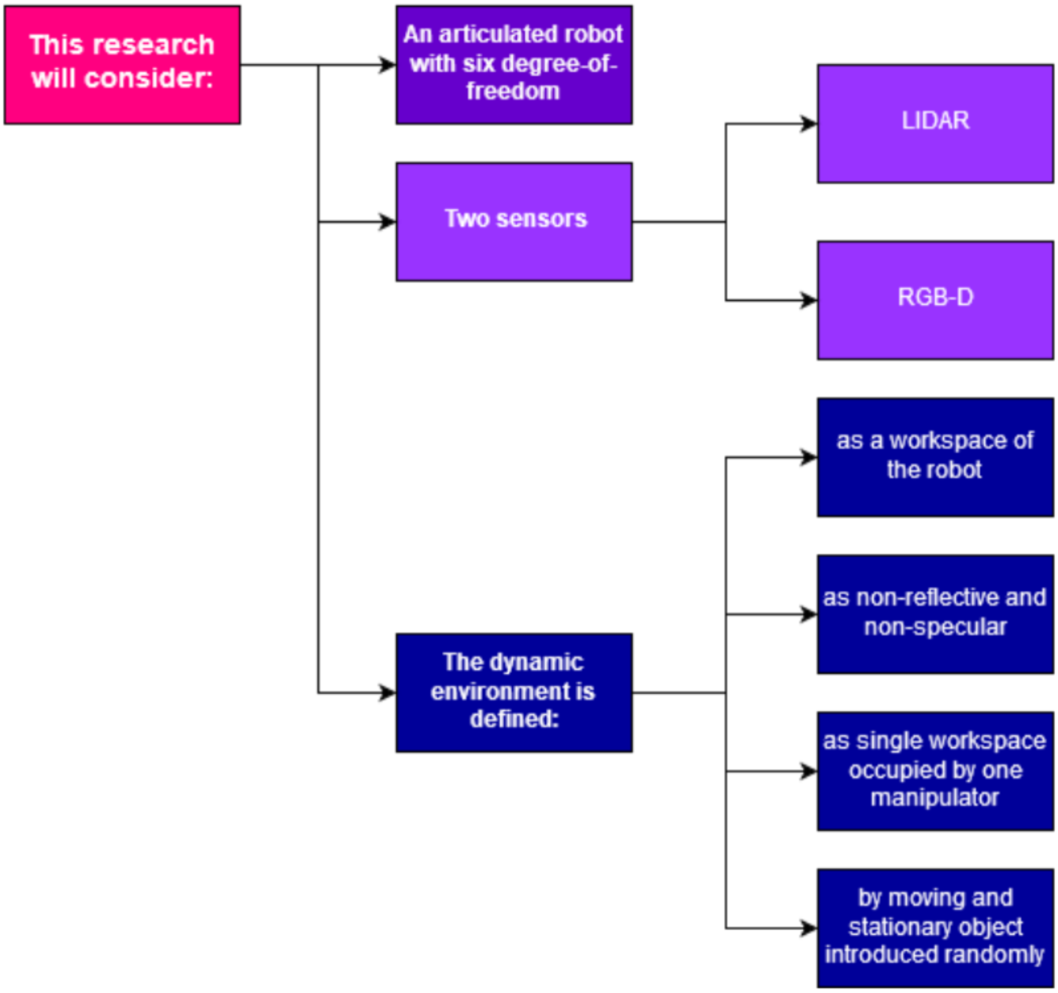

Figure 1.8: The scope of this research and its considerations

with a moving obstacle. Figure 1.8 shows the scope and the considerations of this research.

1.7 Methodology

In this research, the model of a robot kinematics, specifically on the task space (the end-effector frame) of the robot, $C_{ee} \in \mathbb{R}^3 \times \boldsymbol{SO}(\mathbf{3})$ where, $\mathbb{R}^3 \times \boldsymbol{SO}(\mathbf{3})$ is homeomorphic to the special Euclidean group, $\boldsymbol{SE}(\mathbf{3})$. Hence, given $\{C_{ee} = c_{ee}\}$, the task space of the robot manipulator is a set in equation 1.2:

$$\left\{ c_{ee} = \begin{bmatrix} \boldsymbol{R} & \boldsymbol{t} \\ 0 & 1 \end{bmatrix} : \boldsymbol{R} \in \boldsymbol{SO}(\mathbf{3}), \boldsymbol{t} \in \mathbb{R}^3 \right\} \tag{1.2}$$

Thus, since all SLAM solutions for three-dimensional space provide state estimation in the form of $\mathbb{R}^3 \times \boldsymbol{SO}(\mathbf{3})$, their model in equation 1.1 holds for industrial robot arm. Nonetheless, the complete solution for SLAM does not consider the path-planning model of the robot arm, specifically, the mapping of the config-

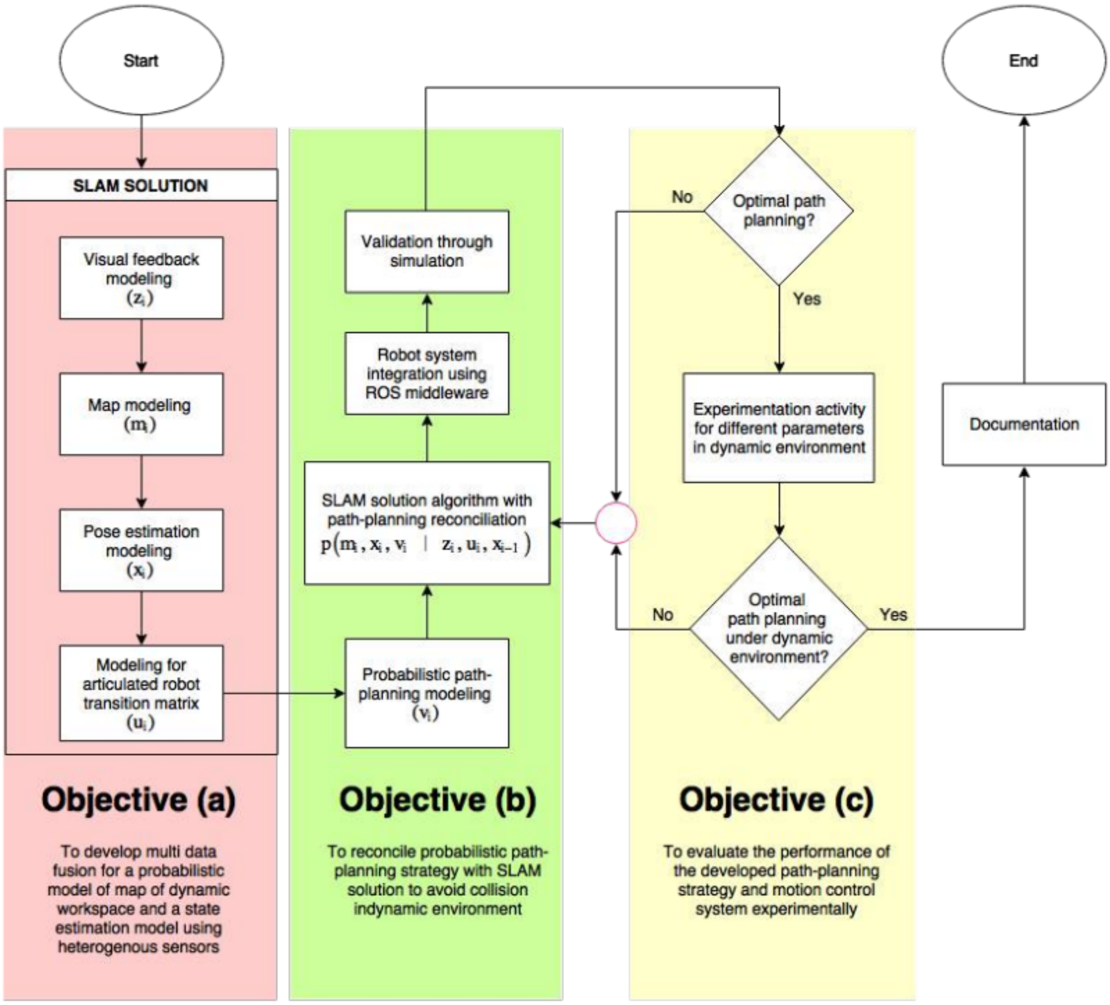

Figure 1.9: Summary of the methodology to achieve the objectives of this research

uration space, $C^n \in \mathbb{R}^6$ into the C_{ee}, where n is the number of rigid body in the robotic arm. Hence, I will investigate the tractability of reconciling probabilistic model of a path-planning strategy with Equation 1.1 such that:

$$p(\mu_i, m|\hat{x_i}, z_i, u_i) \tag{1.3}$$

where p is similar to the process of maintaining the map of a the workspace and estimating the state of a robot concurrently where, $\hat{x_i}$, is the state estimation pipeline of a SLAM solution in equation 1.1.

In equation 1.3, the solution incorporates both SLAM algorithm and a probabilistic path-planning model into a single framework instead of considering the SLAM solution and path-planning algorithm separately. I outline my research methodology based on equation 1.3. An overview of the research methodology against the objectives of this research is presented in figure 1.9.

1.8 The Outline of the Thesis

In this chapter, the concept of FAS is translated into formulating a SLAM solution for a robot manipulator. This thesis will elucidate the SLAM-planner coupling and pipelininig in the coming chapters. The reader is usher to a literature review of the state-of-the-art and the leading papers on state estimation, map-building models and path-planning in **??**. The readers are then introduced with the mathematical foundation in **??**. In **??**, the experimentation are delineated and the chapter continues with the discussion on the findings and result. This thesis concludes with **??** with recommendation on future works.

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