Chapter 1

Literature Review

Font and centering issue.

2.0 Introduction

In this chapter, the uncertainties in manipulators and the state-of-the-art approach to model and manage the uncertainty are elaborated and discussed.

In an industrial environment, the uncertainty of an industrial robot is managed by isolating the manipulator into work cells. It lacks predictive behavior and only function in a predefined setup (Miseikis et al. 2017). Such a system is fragile to unpredictable changes such as an accidental introduction to an object in its environment. The robot system often costs more because of constant reprogramming if predefined changes are required.~~Iare exploring into solutions~~ that enable the manipulator system to react appropriately to changes in the environment while taking account the uncertainty of its internal state. With these solutions, ~~I believe~~ a robot manipulator ~~can~~ work in a more efficient setting, ~~i.e., involves~~ less reprogramming and ~~is~~ capable of working in close proximity to a human operator safely. Thus, the purpose of this review is to look at possible solutions to such a flexible system that can manage uncertainty admirably. In this review, I will use the terms error and uncertainty interchangeably.

I classify the uncertainty into two categories; uncertainty in the manipulators state and uncertainty in the manipulators environment. The uncertainty in a state is often caused by indirect measurements of the manipulators joint parameters because of the limitation of sensor choice (Jassemi-Zargani and Necsulescu 2002; Hebert et al. 2012; Rigatos 2009; Janabi-Sharifi and Marey 2010; Du, Zhang, and Xueqian Wang 2014) and the characteristic of the manipulators joints and links (Lertpiriyasuwat, Berg, and Buffinton 2000; Ulrich 2011; Lightcap and Banks 2010; Biber 2003; Sawada, Kondo, and Watanabe 2012) The solutions to handling the uncertainty of a manipulators state involve filtering techniques. For uncertainty in the environment, the cause of the uncertainty is much more relaxed. The uncertainty is often related to a lack of information about the environments state. However, the solutions to manage uncertainty in an environment are elaborate and non-trivial. I outline this review on how the uncertainty of a manipulator is managed by using an extended Kalman filter, unscented Kalman filter, and particle filter. I will also look into how the uncertainty of the environment is managed by using point clouds, occupancy grid map, and its variants.~~Ithen~~ look into simultaneous localization and mapping solutions as a framework for more unified uncertainty management in a manipulator robot.

1.1 The Planning for 6R Robots in Dynamic Environment

In this review, we will look into ~~a small number of~~ research papers that delve into motion planning in a dynamic environment for robot manipulators in three dimensional space, $\mathbb{R}^3$. We pay close attention to algorithms derived from sampling-based planner which use stochastic approach to query the configuration space. The planning algorithms for robot motion in a dynamics environment dated back to 1985, albeit mainly applied on mobile robot (Mohanan and Salgoankar 2018).

Some planning algorithms that is non-probabilistic for robotic arm are also observed which are based on representation space (Su and Xie 2011; Liu et al. 2016), sequential expanded Langrangian homotopy (Dharmawan, Foong, and Soh 2018), and real-time adaptive motion planning (RAMP) (Vannoy and Xiao 2008). These works provide a new method of planning and tackle the problem at the local planning and at lower level of control to solve problems with the aid of a simulated environment. Their simulated environment, or a map model of the environment, includes dynamic objects that are then filtered and disregarded in the map registration pipeline. Their experimentation approach will be adopted in this research where, the map is informed with the presence of obstacles that are moving in the workspace without having another sub-module of the system tracking the object via motion tracking.

1.1.1 The Probabilistic Motion Planning

Kavraki et al. (1996) is the first group of researchers that used probability model for sampling the configuration space for holonomic robot motion such as a manipulator robot. The planner are called the probabilistic roadmap (PRM) motion planning. The algorithm construct a graph structure to find path between an initial pose to a goal pose in two-dimensional configuration space, $n = 2$. Kavraki et al. (1996) also proof a more general solution for higher dimensional configuration space, $n > 2$. With graph structure, more than one path connect the initial pose to the goal pose. Therefore, PRM is a multi-query type planner.

Kunz et al. (2010) improve PRM by redefining the distance metric of a robot manipulator so that the robot can move around a moving obstacle in real-time. Their approach performs well in an uncluttered environment. Kunz et al. (2010) also redefined the distance function of the PRM to address dynamic objects, such as a walking person, into a two-dimensional map. Although the configuration space of the manipulator is in $\mathbb{R}^3$, the map , constructed from a two-dimensional LiDAR scan, is in $\mathbb{R}^2$.

In retrospect, the RRT was formulated for non-holonomic motion (LaValle 1998) targeting problems addressed in diffential-constrained motion such as a car on a plane. However, given the model of its metric space and consequently the configuration space, RRT are tractable for higher dimensional problem such as manipulator motion in 3D space (Wei and Ren 2018). RRT assume as static environment but Wei and Ren (2018) successfully change the way RRT samples a robot metric space so that it is fast enough to react with a changing environment. Also, unlike PRM, RRT works well in a cluttered environment because of the randomized sampling on the robot configuration space in the metric space.

Researchers have been modifying the PRM (Klasing, Wollherr, and Buss 2007; Likhachev et al. 2005; Jaillet and Siméon 2004; Pomarlan and Sucan 2013) and the RRT (Otte and Frazzoli 2015; Ferguson and Stentz 2007; Ferguson, Kalra, and Stentz 2006; Bekris and Kavraki 2007) to facilitate better performance. Unlike Kunz et al. (2010) and Wei and Ren (2018), so few have applied their planning algorihtms on a robot manipulator despite both algorithms provides mathematical framework for .

We will use the method demonstrated by Kunz et al. (2010) and Wei and Ren (2018) to design our experiment of a moving obstacle collision avoidance with the implementation of the vanilla RRT to solve motion for robot manipulator in three-dimensional space, $\mathbb{R}^3$. Different from the implementation by Wei and Ren (2018) our method implement the vanilla RRT where we do not represent the obstacle configuration space.

1.2 Uncertainty Management Through State Estimation

Filters are estimation tools used to observe the state of a system. For a manipulator robot, the state of the robots end effector or its end point is usually confirmed by direct measurement of the joint position. If this direct measurement is unavailable, the state of the robot is measured or estimated using observer or filters.

Filtering techniques uses probabilistic model or framework to handle and manage the uncertainty of observing the state of the manipulator robot. It is often based on Bayes rule where a model of the state is conditioned based on incomplete or indirect measurement. Here, the model of the state is often called a prior and the indirect or incomplete measurement is often regard as the update of a filter. If a prior of a filter is defined by another measurement, we consider the application of the filter as a data fusion technique. After conditioning the measurement update, the state estimation of the robot is ascertained by applying Bayes rule. A filter often involves linearization like the case of an extended Kalman filter. They are also recursive in nature such that the previous estimation is used as the new prior during successive sampling.

In this section, I will look at how extended Kalman filter, unscented Kalman filter and particle filter are used to manage uncertainty for data fusion, state estimation for flexible links and joints, visual servoing and other estimation problems.

1.2.1 Extended Kalman Filter for Manipulator's State Estimation

Jassemi-Zargani and Necsulescu (2002) used extended Kalman filter to fuse data from high resolution joint resolver. A joint resolver is a control unit that performs calculation of the inverse transformation of a manipulator from data obtained from the end effector. They use the data from two accelerometers to estimate the position of each joints in their manipulator and use these measurements in their extended kalman filter observer to estimate the acceleration of the end effector that has jerking motion. Their use of two sensors in extended Kalman filter is an example of data fusion technique.

Lertpiriyasuwat, Berg, and Buffinton (2000) used extended kalman filter to estimate the position of the end effector of two axis robotic arm together with the joint measurement for highly flexible links in real time. The uncertainty in their system is caused by the flexible links. They use a two-link manipulator. Each joint has optical encoder and the end point has a reflective infrared-light emitter. The deflection of each links is modeled using the deflection beam model. The dynamic equations of the manipulator are derived from Kane's method. They linearized the dynamic equation by eliminating the non-linear terms that involve the generalized elastic coordinates and their derivatives in the inertial matrix and the velocity vector. They coined the linearization method as a 'ruthless linearization'. The extended kalman filter is used to estimate the position of the end effector using the differential equation solution of the dynamic equation which was solved using Runge-Kutta method. Their result shows that with ruthlessly linearized model, the extended Kalman filter can estimate the position of the end effector consistently during low-speed and high-speed slew maneuvers compared to continuously linearized model of the dynamic model. From this research, linearization of model before the use of extended Kalman filter affects the performance of the filtering technique.

Ulrich (2011) proposed the use of extended Kalman filter to estimate joint positions and velocities for flexible joint positions and velocities for flexible joint space robotic manipulator. The joint flexibility in manipulators for space robots are obvious because they are lightweight which introduce uncertainty in estimating joint position. Thus, they extend the design of extended Kalman filters based on nonlinear joint models for use with an adaptive controller. By using this combination, they increase the accuracy of the closed-loop estimation and control of a flexible joint space robot.I observe that the uncertainty of their joints also comes from the linearization of a nonlinear behavior of the flexible joint of their space robots. Although nonlinear joints can be approximated by representing joint flexibility by a linear spring model, the researchers argue that such assumption is inaccurate. Accordingly, they add nonlinear stiffness, soft-windup, frictional loses, inertial cross-coupling to their joint model. They presented a converging error for a non-linear based extended Kalman filter technique used with linear and nonlinear joint model. However, the error diverges for linear based extended Kalman filter techniques with the same model coupling.

Lightcap and Banks (2010) attempted to estimate the position of rigid links and flexible joint (RLFJ) manipulator using discrete-time extended Kalman filter as an observer for the robot model and control system. Because of the flexible joints, direct measurement from the encoders cannot represent the position of the joint directly making the position of the robots end effector nonlinear. The authors use extended Kalman filter to estimate the pose of the end effector and manage the uncertainty of the flexible joint through linearization. The uncertainties of the link and the motors' dynamics are modeled into the manipulator's dynamic equations. The authors stress that extended Kalman filter has non-optimal estimation as is the case of any algorithm that requires linearization. They performed a simulation and reiterate their models and algorithm on a Mitsubishi PA10-6CE manipulator experimentally. They observed improved tracking performance for highly flexible joints (joints under high torque) and low tracking performance for rigid joints. Thus, the authors introduce a mixed rigid-joint/flexible joint model to the EKF-RLFL controller which improved the overall tracking performance.

During visual servoing of a manipulator, the pose of the end effector is determined from an intial estimate of its position. Janabi-Sharifi and Marey (2010) demonstrate an adaptive iterative extended Kalman filter (AIEKF) in the absence of accurate initial pose, noise matrix, and covariance matrix at variant sampling rate during robotic visual servoing. Visual servoing is a process of estimating the configuration of a manipulator using images or visual feedbacks. They experimented on a six degree of freedom cartesian manipulator, AFMA-6, with eye-in- hand camera configuration. The robot moves at a predefined trajectory under different condition. Each separate experimentation involves increasing the velocity of the end effector, changing the covariance matrices, changing the sampling time for estimation, and changing the initial positions of the end effector. They compared three other Kalman filtering techniques (extended Kalman filter, adaptive extended Kalman filter, and iterative extended Kalman filter) with the IAEKF. They conclude that IAEKF can improve pose estimation during uncertain initial position, uncertain covariance matrix estimation, high motion and slow sampling rate.

1.2.2 Unscented Kalman Filter for Manipulator's State Estimation

Haghighipanah, Li, et al. (2015) address nonlinearity problem of an elastic cable as power transmission between a motor and a joint for a surgical arm. The coupling between the motor and the robot joint reduce armature mass, inertia and size for expert surgery but the cableelasticity introduces uncertainty and nonlinearity to the kinematics and the dynamics of the surgical arm. They introduce an estimation method that uses a standard unscented Kalman filter (UKF) and a square root Kalman filter (srUKF) to estimate cable coupling parameter and the position of the end effector (end point) in real-time. The authors implement their method using the Raven-II, a seven degree of freedom serial manipulator, as their surgical arm. The surgical arm is equipped with an optical encoder attached to the motors and position sensor on each joint for data validation. In their research, the authors only address the first three joint for state estimation of the Raven-II. They model the armature dynamics using forward and inverse dynamics with Newton-Euler equations. Their inverse dynamic solution is based on the recursive Newton-Euler algorithm. The Newton-Euler equations requires model parameters. The authors identify the initial inertial matrices, mass and the center of mass of the system using a computer aided design model and use srUKF to estimate the joint angle and joint position of the surgical arm online. Also, the authors apply the standard UKF to estimate the coupling parameter offline. They compute spring constant, damping constant, coulomb and viscous friction of the motor side and the joint side empirically. They validate their method experimentally using three different design. The first two experiments involve changing the cable tension and the third experiment involve picking an object of the mass 100 g under high cable tension. They compared the result of the three experiment between the dynamic model that uses their UKF estimation and the dynamic model that has no filtering technique. They improved the accuracy of the joints position to 1.4333 respectively. The authors also observe that whe the flexible joint are model as a rigid body, the performance of their unscented Kalman filter deteriorate. They repeat the same problem mix rigid-flexible cable model and replace the encoder with stereo camera (Haghighipanah, Miyasaka, et al. 2016). They improve the accuracy of the joint position to 43.142, 3 respectively.

1.2.3 Particle Filter for Manipulator's State Estimation

Biber (2003) present the design of two filtering techniques to estimate the acceleration and the jerk of five-bar linkage manipulator with flexible joints. These estimations help in designing a better control. Unlike a rigid joint, the flexible joints are time variant hence highly nonlinear. The nonlinearity introduce uncertainty to the dynamics of the manipulator making prediction of higher order dynamics such as accelerations and jerks uncertain. This is because a nonlinear system has no closed form solution and require linearization. The authors suggest the use of Euler-Langrange equations to represent the model of the manipulator dynamics given that each joint are model by torsional spring. To better estimate the acceleration and jerk of each link in the four-bar linkage, the linearization is manage using extended and unscented Kalman filters. The author validated their observer model by simulation and conclude that the accelaration and jerk of the manipulator's linkages are successfully estimated.

Rigatos (2009) uses particle filter to fuse data from an IMU and joint encoders to estimating pose of the end effector. The purpose of this paper is to estimate the state vector of a three degree of freedom industrial robot using accelerometer and an encoder for each joint. The estimated state vector is used to generate appropriate control signal for the manipulators. Accelerometer are notorious for being nonlinear. Also, with encoder as the primary feedback for joint measurements, the state of the manipulator becomes nonlinear and uncertain. The authors use particle filter to perform data fusion between an accelerometer and an encoder to estimate the pose of the end effector. Readers should note that both accelerometers and encoders has non-gaussian behavior. This behavior is stronger for flexible joints because they introduce nonlinearity to the state (position of the end effector) of the manipulator. Particle filter is used simply because it is nonparametric. This mean that the parameter of a normal distribution are not assumed. Instead, particle filter performs the estimation based on the sampled data and generate the distribution from these samples. The method of sampling provide a general solution that has no presumption of sensor characteristics. This also means that with particle filter, more accessible sensors such as an accelerometer or an IMU can be used without scaling down accuracy. The state vector estimation was compared with extended kalman filtering technique. The authors observe higher accuracy in estimation of the state vector for the particle filtering technique compared to the extended Kalman filter technique. However, the author caution that the selection of particles numbers may improve accuracy with the expense of computational load.

1.2.4 Miscellaneous Estimation Problem in Manipulator Robot

Du, Zhang, and Xueqian Wang (2014) Use particle filter to estimate pose for a visual servoing application. The motivation behind this paper is to introduce contactless and markerless control of a manipulator using computer vision. The researcher uses 3D camera (Kinect sensor) to translate a human arm motion into a motion of a manipulator and Camshift program library to track hand position. The particle filter is used to estimate the hand position and orientation. The particle filter handles the noise error from the Kinect sensor and the accumulated error introduced from the Camshift method of tracking. The robot inverse kinematics are solved numerically using Levenberg-Marquardt algorithm (LM algorithm)

Du and Zhang (2014) uses extended Kalman filter to handle kinematic errors in manipulators. Kinematic errors occur because of imperfection in serial robot components, their wear, misalignment and other factors. The extended Kalman filter allows auto-calibration without strenuous technique and expensive sensors when the kinematic errors are considered. In their method, the IMU and the position sensors are attached at the end point of the six degree of freedom GOOGOL GRB3016 robot. The authors also explain data fusion algorithm for their IMU attached at the end point of their serial robot where a particle filter is used to estimate the orientation of the end point of the serial robot and a Kalman filter is used to estimate the position of the end point of the serial robot. A Kalman filter is the base of both extended and unscented Kalman filter which can only perform well for linear system. The extended Kalman filter is used to optimize the position and orientation estimation of the end point of the robot. By using the Jacobian matrices, the authors estimate the kinematic erros of the serial robot to manage the uncertainty of using IMU measurements. Du, Zhang, and Xueqian Wang (2014) compare their extended Kalman filter approach to a linear least square technique for their estimation of each joints in the robot. The extended Kalman filter has lower error for all six joint parameters estimation. The author acclimate that their method of using IMU and position sensor, via position markers, reduce the complex steps of auto-calibrating a manipulator, increase better accuracy, convenience, and effectiveness.

Hebert et al. (2012) present data fusion algorithm using unscented kalman filter to estimate the manipulator tool and the manipulated object simultaneously. The fusion algorithm is used to manage the uncertainty of the end effector location as a result of uncertain actuation because of unknown weight of the manipulated object. Also, the authors use Barret WAM manipulator that introduce further uncertainty in actuation as a result of tendon actuation similar to flexible cable actuation. These uncertainty prompts the use of two type of sensors as feedbacks, visual and tactile sensing. They use unscented Kalman filter to fuse image features that covers dense range, visual appearance, silhouette of manipulator arm, multi-figered hand and grasped object. To fuse these measurement, the authors model three measurements: (1) the measurement model for manipulators hand tracking by using appearance, shape and silhouette, (2) the object tracking measurement using point cloud association like iterative closest points, and (3) the tactile measurement model to represent a binary state of contact between the fingers of the manipulator and the manipulated object. They use DARPA ARM-S with Barret WAM manipulator to validate their methods experimentally. The experiment involves the tasks of grasping a hand-driller and drilling a red hole on a wooden block with the grasped drill. The authors report an average of $9.3mm$ drilling deviation when the sensor measurements are incorporated into the tasks and an average of $47.5mm$ drilling deviation without the aid of any sensor.

Hu and Xiong (2017) use a new apporach, a distubance Kalman filter, to estimate the force acting on the end effector for a compliant human-robot motion. In their approach, Hu and Xiong (2017) modified the Kalman filtering technique by using rigid body dynamic model and its disturbances as the update stage. The authors use inverse dynamic model (IDM) as a prior to the force. The approach also models the sensor using rigid body dynamic. The only feedback data used as update state of their novel disturbance Kalman Filter are the joint positions and the torque measurement from the sensor. The Disturbance Kalman filter takes into account the uncertainty from the disturbance dynamics. The authors successfully implement the disturbance Kalman filter for the force estimation on a six degree of freedom Kinova Jaco2 arm robot.

Sawada, Kondo, and Watanabe (2012) present a technique of collision avoidance using unscented Kalman filter for a two-link flexible manipulators. The researchers use sliding mode controller to control the motion of the manipulator. They also investigate the use of extended Kalman filter to manage the uncertainty introduced by the flexible beams of the manipulator which affects the motion trajectory of the manipulator's end effector. They introduce a collision input into the observation model of the UKF. The collision is detected by a piezoelectric sensor attach at the base of the links. An abnormal reading from the piezoelectric sensors would trigger the collision input and change the parameters of the UKF to suspend control of the manipulator. This approach, regrettably, expects collision rather than avoiding it. However, this is inevitable considering piezoelectric sensors require contact to detect changes. They confirmed that, through two numerical simulation, the algorithm for their collision detection via UKF successfully increase efficiency.

1.3 Map-Building Approach to Uncertainty Management

A robot in an industrial environment is isolated. The robot is barricaded because of its massive built which impose danger to human operator. ButIargue that with flexible workcell where a robot where a robot manipulator in the industry can manage the uncertainty of its environment through map-learning or map-building, this robot system can potentially reduce cost of operation.

I discover that there are two methods to mapping an unknown environment of a manipulator. The first method is by using point clouds Um and Ryu (2013) and Xinyu Wang et al. (2017). and the other by using occupancy grid map together with its variants such as octomap.I must mention that most of the researches on manipulators mapping are not in immediate industrial setting. Yet,I are confident that these solutions can be used in industrial robot.

1.3.1 Point Clouds Mapping

Mapping with point clouds use direct data from sensor to model the environment. Often these metrical data are translated and combined from multiple scans by using iterative closest point to construct the global representation of the environment.

Um and Ryu (2013) uses point clouds to map the environment. The paper presents a simultaneous planning and mapping for a three degree of freedom manipulator in an unknown environment. The paper argue that their method handles the uncertainty of the unknown environment by using virtual skin concept. The manipulator explores the environment using a mono-vision infrared proximity array (IPA) sensor which replicate the characteristic of a tactile- sensitive skin. From this exploration, the robot would model its configuration space (c-space) and use it as the input for their best-next-move algorithm to optimize path planning.The IPA sensors are attached on each links of the manipulator. Readers should note that an IPA sensor has limited range and noise bound output which add more uncertainty to the estimation of the manipulators c-space. The researchers address the noise in the sensor using group average feature (GAF). The point clouds generate from the IPA go through GAF algorithm to produce a more confident map of the c-space. The generated map of the c-space is used to provide motion planning for the robot manipulator. The rapidly-exploring random tree (RRT) path planning algorithm use the map as an input to plan the motion of the manipulator. The authors optimized the RRT algorithm with their best next move (BNM) algorithm. BNM is reactive and does not use any inverse kinematic solution. They validate the method using and compare the RRT-BNM method with RRT method by simulation and showed that the RRT-BNM method has higher mapping efficiency. They defined mapping efficiency as percentage of map built compared to the actual map, over the number of point clouds in the c-space. Due to the GAF decompression method, the RTT-BNM produce map with less point clouds. The author, however, did not repeat the RRT experimentally. Despite the higher efficiency ofRTT-BNM path planning, the map produce does not represent an accurate geometric information of the unknown environment explored by the manipulator.I believe this is because there is a lack of pose estimation of the manipulators link since the research disregard the use of inverse kinematics, bayesian or non-bayesian filtering techniques to reconcile with the path planning.

Xinyu Wang et al. (2017) present a method using point clouds to perform self-identification using k-means clustering method and obstacle detection and obstacle avoidance. The point cloud is used to generate the skeleton and the sphere along the skeleton. The point clouds are sparse and noisy which introduce uncertainty to the self-identification. However, the uncertainty is eliminated using a filter based on the density of the point cloud. The detection of the obstacles is based on the negation of point clouds that are not a part of the skeleton and the sphere that shape the manipulator. This segmentation is the base of their approach to obstacle avoidance. They tested their algorithm by performing three experiments sequentially using a Baxter manipulator robot with eye-in-hand configuration. These experiments involve the validation of their self-identification algorithm, obstacle detection algorithm, and obstacle avoidance algorithm.

1.3.2 Occupancy Grid Map: The Map of Uncertain Environment

Direct use of point clouds to map an environment is inefficient and requires a considerable amount of computational expense. This is not the case of an occupancy grid cell where the point clouds are used to statistically parameterized the grid cell of the map. A grid cell or a voxel is a cubic primitive that represent the environments geometrical characteristic. Occupancy grid map consider the uncertainty of mapping sensor such as a sonar, a camera, or a laser range finder to represent the environment probabilistically (Moravec 1989). An example of the use of occupancy grid map is by Matuszek et al. (2011) that uses occupancy grid map in presenting an environment of a chess playing robot manipulator. The construction of occupancy grid map often requires data fusion or sensor fusion where two or more sensors are fused together using Bayesian rules or any filtering techniques. Rybski et al. (2012) use a variant occupancy grid map and handle uncertainty of the environment by fusing measurements from a Swissranger SR4000's ranger and two Tyzx G3 EVS stereo cameras to estimate the occupancy of a grid cell.

I, accordingly, define this problem under the uncertainty managing the unpredictable environment unlike Janabi-Sharifi and Marey (2010) which uses the state of the robots joint position as the visual feedback of their visual servoing). Kalman filtering technique is used to help track an object on a flat surface. The use of extended Kalman filter aside from the trajectory control of the end point of the robot increase certainty of the pose estimation and the accuracy of thetracking. A camera is mounted on the end point of

CRS Plus SRS-M1A robot system. The robot is presented with a task to follow the object using the eye-in-hand camera. The visual feedback from the camera is use with their control strategy. The extended Kalman filter is used to predict the relative position of the object while it is moving. Since the researcher maintain a constant velocity to the object, the tracking can use a Kalman filtering technique without linearization. However, since the tracking of the object requires the movement of the camera, given the nonlinearity of an inverse kinematic solution of their robot system, the use of extended Kalman filter is justified. The filter maintains the estimation of the end effector's pose. Although the robot manages to follow the moving object in their experimentation, the authors did not compare and reiterate their experimentation with other estimation method.

Burns and Brock (2007) present a method of sample-based motion planning on top of an occupancy grid map. The sampling-based planner take regard the uncertainty of sensor measurements and incorporate the uncertainty into the occupancy grid map. Their method is iterative; the planner considers and incomplete information about the world and constantly update changes in their map model and configuration space. The authors use the concept of utility and cost to weight the probability of an edge. A* algorithm is used to search the most optimal path from randomly sampled node in the configuration space. During edge validation of the roadmap is witheld before the A* algorithm complete its query. They validate their planner by simulating three separate experiments, two of which, involve manipulators with ten degrees of freedom and fourteen degrees of freedom respectively. The planner is specified to solve 50 planning queries given a start and a goal configurations. They report that building a planner on top of a occupancy grid map increase the accuracy of completing the path from the start configuration to the goal configuration. They conclude that, compared to PRM, their method able to eliminate the possibility of invalid edges in their roadmap because they introduce error model of the sensor at hand.

Kruse, Gutsche, and Wahl (1996) present a method for exploring an unknown environment using either a mobie robot or a manipulator robot. Their method uses a planning-sensing-updating cycle. This research uses an occupancy grid map to represent the unknown environment. Their rating approach is similar to Burns and Brock (2007) utility and cost concept. However, they relate their rating function with the manipulator's configuration space by introducing constraint for fast exploration.

Paul et al. (2011) present a path planning strategy to perform autonomous grit-blasting as a part of bridge maintenance process. They develop a framework called Autonomous eXploration to BUild a Map (AXBAM). AXBAM define the uncertainty in an unknown environment as the measurement of information that has not been discovered in the environment by using Shanon's entropy definition of information theory. This is an appropriate concept to use in modeling an unknown environment since the theory help in optimizing the exploration and path planning of a manipulator. The authors use Occupancy Grid map concept to handle uncertainty for path planning in the unknown environment based on the entropy definition. The authors implement ellipsoid force-field planner to plan collision free roadmap. Another problem addressed by the authors states that there are possibilities for multiple goal configuration and use their entropy model to arrive to a single goal configuration with the highest information gain prediction. Despite the use of occupancy map in managing the control of their manipulator under uncertain environment, the mapping model in this paper uses direct pointclouds for detailed geometric representation of the unknown environment. However, the author fails to show any optimization technique when registering local scans into a global scan. We believe without this optimization, if the pose of the end effector is uncertain, their map may have diverging misalignment. The authors use Hokuyo Laser Range Finder (Hokuyo URG-04LX) as a scanning sensor attached on a six degrees of freedom Denso VM-6093 manipulator arm with eye-in-hand configuration. The 5th joint rotates to facilitate the initial scanning of the environment before exploration commence. Based on this initial scan, the robot will start exploring. By using AXBAM, the authors claim to reduce computation in decision making during exploration.

1.3.3 Octomap: The definitive Uncertainty Management Dynamic Environment

A number of researchers represent the environment using an Octree model to facilitate path planning strategy;(Faverjon 1984; Hamada and Hori 1996). Similar to Occupancy grid map, octree represent the environment with discrete cell that divides into smaller details. Payeur et al. (1997) use octree based representation of occupancy grid map to reduce computational load so that the grid map can be used efficiently to represent 3D scenes.

Hornung et al. (2013) improves the use of octree probabilistically by introducing relaxed logit function for uncertainty management in mobile robots.Octomap represents the uncertainty in the environment and the sensor that maps the environment. Although Octomap has been exhaustively used in mobile platform, researchers have introduce its use in robot manipulators. By using Statistical Outlier Removal algorithm, Miseikis et al. (2017) use Point clouds from cameras to construct and environment based on octomap. They proceed by merging point cloud data from two 3D cameras

(Kinect Sensor) using iterative closest point. Iterative closest point (ICP) is often used in mobile robot to combine two scans collected at different position together. They use forward kinematic to assist in replacing point clouds corresponding to the robots chassis with cylindrical shapes. The map of the environment is modeled using octomap and embedded with a decaying occupancy value. The decaying cost value are used to represent danger zone, a mediary zone, and a non-danger zone in the map for a reflexive and predictive behaviors. Building their path planning on top of these map provides a responsive motion even if the robot workspace is populated by moving objects. The authors use 6DOF UR5 robot with eye-to-hand configuration. They validate their method by simulating a predefined back and forth motion between a start configuration and a goal configuration. The first simulation act as the baseline or the benchmark of their path planning approach using only Rapidly-exploring Random Trees (RRT). The second and the third experiments introduce a moving object into the robot's workspace. Experiment 2 and experiment 3 use the reactive path planning and the reflexive-predictive path planning approaches respectively. They conclude that although experiment 3 performs at the shortest time, the result was not significant.

1.3.4 Miscellaneous Mapping Techniques

In this section, I present papers that has unconventional way to manage the uncertainty oftheir environment. Cohen, Chitta, and Likhachev (2010) and Meeussen et al. (2007) use graph theory to their mapping technique, while Petrovskaya et al. (2006) and Koval et al. (2013) interact directly with the environment using force sensor to localize object in the robots configuration space. Corrales, Candelas, and Torres (2008) track a human operator in its environment. Ruhr et al. (2012) introduce the element of learning to help manipulate dynamic object in the environment. Cohen, Chitta, and Likhachev (2010) present a search-based planning as an oppose to sampling-based motion planning. They use examples of motion planning in lower dimensionality problem or problems in low-dimensional manifold as a heuristic for motion planning in higher dimensional manifold. From this heuristic, they define motion primitives, a predefined motion of a single joint, and used them to minimize the cost function so that the most optimal path can be realized. This method eliminated the multiple solution to start-to-goal configuration by selecting the most feasible path that avoids collision which may not have the shortest path. Their searching-based planner follows anytime repairing A* (ARA*) search algorithm. ARA* is different from A* algorithm because A* always aims at getting into a goal configuration at the shortest traversal. ARA* consider a factor of the most optimal path initially which can be rectified at further path sampling. They use occupancy grid map to decrease the intractability of their algorithm so that the ARA* motion planner produces the most optimum solution in path planning. They manage the uncertainty of multiple path solution by eliminating it using cost function as constraint to their path planning algorithm. They validate their approach by simulating manipulation in a cluttered tabletop and conclude that their approach are only optimal for three degree of freedom pose (translational) rather than a full six degree of freedom pose (translational in x,y, and z directions together with orientation about the x, y and z lines) They also perform the same experimentation on a PR2 robot with seven degree of freedom manipulator.

Meeussen et al. (2007) present an approach to generate a path planning by human demonstration for a sensor based manipulator. A tool containing optical markers are tracked during demonstration phase using a 3D vision sensor (a Krypton 6D Optical System). The tool is attached to a geometrically uncertain object in a controlled environment. The use of 3D vision sensor, and the estimation of the state of the tool and indirect estimation of force asserted by the tool based on the state of the tool introduce uncertainty. To compromise the uncertainty, the authors use particle filtering technique to estimate the pose and twist of the manipulated object via tracking of the manipulating tool the force between the contacting object. The researcher addresses their previous work on the same problem and optimize the particle filter with topological graph called contact-state graph to predict the next best configuration of the object being moved or contact formation. They observed that the contact-state graph reduces the number of particles used during sampling which decrease computational load and increase accuracy in their estimation. The paper however did not replicate their simulation in an experimentation with an actual manipulator

Petrovskaya et al. (2006) use particle filter to estimate the position of their end effector and at the same time ascertain the position of an object by using tactile sensor. The sensing by touching follows a heuristic where a person increases its confident of the shape and the position of an object by feeling it with his or her hand at different location. From this heuristic, the authors express their algorithm with the help of particle filtering technique. Particle filter depends on sampling approach where the prior or a believe is increased by each successive samplling. They modified the particle filtering technique to assist a highly sparse sparse measurement fromtactile sensor and called their technique as scaling series particle filters. In SSPF, the initial filtering steps has the lowest resolution of accuracy and the highest uncertainty. Based on the initial sampling, the following sampling increase increase the certainty of the position of an object by sampling at a different position. The authors tested their algorithm by simulation and experimentation. In the experimentation, SSPF manage to help a manipulator localize and grasp a box at 70% success rate, and identify and handle a door knob at 98% success rate.

Koval et al. (2013) present a situation where constant contact and manipulation of an object, by pushing the object, can be used to estimate the state of the object; i. e. the position and the orientation of the object. They term the process as contact manipulation. They argue that with the absence of more conventional observation from sensors such as a laser range finder and a vision camera, tactile based sensor can perform state estimation using appropriate filtering technique. Since tactile sensor has non-gaussian characteristic and highly nonlinear, the authors used particle filter as their estimator. The use of tactile sensor, however, introduce uncertainty because the sensor has low spatial resolution or low manifold. This is regarded as a low-dimensional manifold problem where the state estimation has higher dimensionality (two for position on a plane and one for orientation). Although intuitively increasing the resolution of the tactile sensor may decrease the spatial uncertainty, it is not the case for tactile sensing with particle filtering technique. Thus, the authors introduce manifold particle filter (MPF). An MPF reduce the dimensionality of the state estimation by marginalizing the probability distribution of the state of the object based on the observation from the tactile sensing and use it as a prior estimate. To implement the MPF, the state estimation follows three steps:

(a) assumption of the state of the object by evenly weighting particles

(b) action which involve pushing the object

(c) observation where the MPF use the pressure profile during pushing to estimate the state of the object.

They implement the algorithm using OpenRAVE simulation environment and evaluate it with a simulated BarrettHand. They then run an experiment using Andy, a robot module developed for Darpa ARM-S competition. They compared their result with a conventional particle filter (CPF) and imporved estimation of the object state.

Corrales, Candelas, and Torres (2008) uses kalman filter fusion algorithm to fuse ultra-wideband (UWB) technology and inertial motion capture system to estimate the motion of human operator in industrial environment. The algorithm improves the interaction between a robot and a human operator/user by localizing a human in a manipulator's workspace so that a cooperative interaction can be made. Since the authors use UWB sensor to estimate the location of the human, they use Kalman filtering technique to fuse the information coming from the UWB and the inertial sensors. The filtering technique compensate the low data rate of the UWB and the high error from inertial sensor. Their Kalman filter uses the global position of the UWB as the correction step and the inertial sensor as the prediction step. Their result shows that by fusing two measurements using kalman filter algorithm, the state estimation of the person's location is increased in accuracy.

Ruhr et al. (2012) This paper present solution to manipulation task which involve opening and closing doors and drawers in any kitchen environment. Their approach involves the management of uncertainty of door handling through learning. Within their learning model framework, the authors use 3D point clouds directly to identify door or cabinet handles. Theyuse RANSAC with the point clouds to segments the point clouds to help detect the handles based on identification of planes that parameterized a wall, ceiling, floor, and cabinets. They also implement real-time impedance control and kinematic model learning to estimate the kinematics of dynamic objects in the kitchen. They use a higher level of abstraction in representing the environment via semantic maps. They evaluated their approach using PR2 mobile articulated robot which has 7DOF manipulator. They report out of 104 trials of opening and closing cabinets and doors, the rate of success is 51.9%.

1.4 Simultaneous Localization and Map-Building as a Total Solution to Uncertainty in a Manipulator's State and Environment

I have discussed the uncertainty of a manipulators can be represented and manage using filters. I have also discerned the use of occupancy grid map, point clouds, and octomap to model the environment of a manipulator. Despite rich solution option to uncertainty of a robot state and its environment, the solutions are disjoint and performed separately.

The closest solution for SLAM problem in a manipulator robot is reported by Klingensmith, Sirinivasa, and Kaess (2016). The authors argue that encoders on each joints of a manipulator is not enough to estimate the endpoint of a manipulator due to gear trash, cable stretch non-rigid deformation and others. Their articulated robot motion for simultaneous localization and mapping (ARM-SLAM) uses Truncated signed distance field (TSDF) as part of the scene reconstruction to help estimate the pose of the end effector. TSDF is a variant of Dense Fusion that performs 3D scene reconstruction using multiple depth images and camera poses. With TSDF, each voxel is encoded with a distance to the nearest surface. The voxels are weighted where positive weight means the voxel is outside the surface, negative weight means the voxel is inside the surface and zero distance is when the voxel is on the surface. Their ARM-SLAM adopt eye-in-hand configuration.They conducted three experiments to validate their SLAM solution. In the two-dimensional simulation, they compare pose error between forward kinematics, Dense Fusion algorithm and ARM-SLAM algorithm. The result shows significant error reduction for both of the two algorithms compared to the forward kinematics calculation. ARM-SLAM, however, has the lowest errors. In their 3D simulation experiment, the authors compare results for forward kinematics calculation with kinect fusion and ARM-SLAM. They observed that ARM-SLAM is more robust when loss of data occurs. They also conducted a real shelf scanning. In this experiment, the authors could not conclusively see better pose estimation compared to the forward kinematics calculation. However, they restate that during loss of data, the ARM-SLAM solution produces robust estimation.

Based on Klingensmith, Sirinivasa, and Kaess (2016), I conclude a Simultaneous localization and map- building approach (SLAM) represent the total uncertainty of a manipulator in an environment. I characterize the SLAM problem as the methodology that involve the consideration of robots state uncertainty, its environment uncertainty, and a tractable solution that uses both the formerand the latter. In a manipulator, a SLAM problem can be considered as a model that has tractable solution given the uncertainty of its end effectors pose and the uncertainty of its configuration space. We define that the SLAM solution to a manipulator should have an element of map-learning where statistical and probabilistic approach is considered when estimating the pose of an end effector.

Sun, Chen, and Lau (2016) use large scale direct mono-SLAM (LSD-SLAM) technique to replicate the motion of a human operator. The technique resolves the noise from their measurements using dbscan, a density-based spatial clustering algorithm, to eliminate outlier. LSD-SLAM uses a visual camera to produce point clouds with the help of dbscan algorithm. The scenes generated from the camera are three dimensional. However, the movement of the manipulator is planar. The LSD-SLAM is used to replicate the movement of a human arm. The movement are learned and modeled using Gaussian Mixture Model (GMM) and the parameters of the model are estimated using Gaussian Mixture Regression (GMR). GMM is a probabilistic model that assume all the data points are generated from a mixture of finite number of Gaussian distribution with unknown parameters. GMR uses Expectation maximization iterative learning algorithm to help replicate an output data based on an input. I observe that, by using GMM and GMR, the authors manage to handle the movement uncertainty of the human operator and map the movement into a planar actuation of the manipulator. The authors perform an experiment by recording the movement of the human operator. The LSD-SLAM manage to generate a smooth path for the end effector of the manipulator as prescribed by the GMM and GMR based on the demonstration of the operator.

Nissler et al. (2016) solution to AprilTag tracking is similar to SLAM solution method where AprilTag is used as a feature observed by the measurement to optimize the pose estimation of the end effector and at the same time using the pose estimation to track the AprilTag on a work space. Nissler et al. (2016) demonstrate the use of fully autonomous handling of CFRP material. The authors use RANSAC solution to fuse multiple scene from sensors, an eye-in-hand camera, that may contain outliers. The authors use KUKA KR 210 with a AVT GigE camera attached to the end point. The robot follows three different motion; a horizontal arc, a vertical arc, and an approach motion. A laser tracker is used to calibrate the position of the robot and the markers. A single AprilTag marker was tracked during the motion. The motions were repeated while tracking multiple AprilTag markers. RANSAC method was compared with a least square method. They observed that RANSAC method that they developed for the AprilTag tracking improves the estimation of the end effectors pose.

I also noted that SLAM solution is used for mobile manipulators. Song et al. (2013). This paper present two problems and two solutions. One is on self-localization, a SLAM problem which they solved using EKF-SLAM and the other is on grasping problem. I will only regard the grasping problem since it directly involves manipulation under uncertainty. They use Speed Up Robust Feature (SURF) for object identification and visual servoing using Position-based Visual Servoing (PBVS) to grasp an object and return the object to a person. During object identification, the authors raised the concern of matching error during identification which may result in misleading object recognition. They mitigate the problem using random sample consensus algorithm (RANSAC) to reject outliers and to find the homography matrix. Homography matrix transforms points in one image to the corresponding points in another image when a camera changes in position. The result of their investigation suggests asuccessful object retrieval to a person. They did not, however, present any comparison of their result with other approach for the Grasping problem.

From these papers, I observe that the having to mount a manipulator to a mobile platform introduce localization uncertainty where there is uncertainty on the base location of the manipulator arm, hence propagating the uncertainty to the path planning of the manipulator.

Pilania and Gupta (2015) propose a method of base uncertainty by using their novel hierarchical and adaptive mobile manipulator planner uncertainty called HAMP-U to account for the uncertainty of the base of a mobile robot

I also observe manipulator attached to a mobile platform often regard their grasping solution using two different approach; i.e. a probabilisitic approach for the mobile platform localization and a deterministic approach at the manipulation stage of the robot movement such as grasping (Venator, Lee, and Newman 2013; Gasparri et al. 2006). I also note that the total uncertainty solution presented by SLAM does not extend to path planning approach.

1.5 ~~Closing Remarks~~

~~I conclude that uncertainty management of a manipulator is imperative for a flexible system in an industrial environment.Idiscover~~ that uncertainty of the manipulator is best approached by considering the uncertainty motion of the robot and the uncertainty of its environment. ~~I review~~ papers that manage the uncertainty of both categories separately. ~~I also look into a number of researches~~ that incorporate both uncertainties into one framework by using simultaneous localization and mapping. ~~All of these uncertainties management involves the use of statistical and probabilistic approach.~~ I ~~believe that incorporating both uncertainty categories into one framework using SLAM solution completely represent uncertainty management in a manipulator robot.~~

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