UNIVERSITI PUTRA MALAYSIA

COLLISION PREDICTION- BASED GENETIC NETWORK PROGRAMMING -REINFORCEMENT LEARNING FOR MOBILE ROBOT ADAPTIVE NAVIGATION IN UNKNOWN DYNAMIC ENVIRONMENTS

AHMED HASSAN MOHAMMED

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By

AHMED HASSAN MOHAMMED

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

October 2017

DEDICATION

To the memory of my father and sister… who had dreamt to see this thesis completed… but they couldn't

To my mother for her ongoing love and support

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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October 2017

Chairman : Professor Mohammad Hamiruce Marhaban, PhD
Faculty : Engineering

The autonomous navigation of a Mobile Robot (MR) in unknown environments populated by abundance of static and dynamic obstacles with a moving target have tremendous importance in real time applications. The ability of an MR to navigate safely, smoothly, and quickly in such environment is crucial. Current researches are focused on investigating these complex features in static or point-to-point dynamic environments. On the other hand, the salient downside of Q-Learning such as curse of dimensionality (CoD) is aggravated in complex environments.

The objectives of this thesis is to address the issue of Adaptive Reinforcement Learning (RL) approaches in order to meet the requirements of MR navigation. Moreover, it aims to tackle CoD problem of Q-Learning (QL) to be suitable for complex applications. For this purpose, two genetic network programming with RL (GNP-RL) designs are proposed. The first design is based on obstacle target correlation (OTC) environment representation and called OTC-GNP-RL. This provides a perception of the current environment states. The second design is based on the proposed collision prediction (CP) environment representation and called CP-GNP-RL. This representation is designed to provide collision prediction between MR and an obstacle, as well as the perception of current surrounded environment. Besides, it could represent an environment with compact state space and requires ones to measure positions only. Furthermore, the combination of CP and QL (CPQL) can overcome the downside of the CoD problem and improve navigation features.

A simulation is used for evaluating the performance of the proposed approaches. The results show that the superiority of the proposed approaches in terms of the features of MR navigation, where all these features are taken under the design consideration of each proposed approach. Through the evaluation, CPQL, CP-GNP-RL, and OTC-GNP-RL provide significant improvements in terms of safety (7.917%), smooth path (71.776%), and speed (10.89%), respectively, compared with two state-of-arts approaches, i.e. OTC based Q-learning and artificial potential field. In addition, the learning analysis of CPQL shows its efficiency and superiority in terms of learning convergence and safe navigation. Hence, the proposed approaches prove their authenticity and suitability for navigation in complex and dynamic environments.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

REKA BENTUK RANGKAIAN PENGATURCARAAN GENETIK DENGAAN PENGUKUHAN PEMBELAJARAN BERASASKAN RAMALAN PERLANGGARAN UNTUK PENGEMUDIAN ROBOT BERGERAK BERAUTONOMI DI DALAM PERSEKITARAN DINAMIK YANG TIDAK DIKETAHUI

Oleh

AHMED HASSAN MOHAMMED

Oktober 2017

Pengerusi : Profesor Mohammad Hamiruce Marhaban, PhD
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Pandu arah autonomi robot boleh gerak dalam persekitaran tak diketahui, yang dihuni limpahan halangan statik dan dinamik dengan sasaran yang bergerak, mempunyai kepentingan yang besar dalam aplikasi masa nyata. Keupayaan robot boleh gerak untuk mengemudi dengan selamat, lancar, dan cepat dalam persekitaran sedemikian adalah amat genting. Penyelidikan pada masa kini, memberi tumpuan kepada penyiasatan ciri kompleks di persekitaran statik, atau dinamik titik ke titik. Selain itu, keupayaannya diburukkan lagi di dalam keadaan persekitaran kompleks disebabkan oleh kekangan utama Pembelajaran-Q seperti laknat kematraan.

Objektif thesis ini adalah untuk melihat isu pendekatan Pengukuhan Pembelajaran Suai bagi memenuhi keperluan pandu arah robot boleh gerak. Selain itu, hasrat kajian ini adalah untuk menyelesaikan masalah laknat kematraan di dalam Pembelajaran-Q bagi memastikan hasilnya bersesuaian dalam aplikasi kompleks. Untuk tujuan itu, dua reka bentuk rangkaian pengaturcaraan genetik dengaan Pengukuhan Pembelajaran dicadangkan. Reka bentuk pertama adalah berdasarkan perwakilan persekitaran korelasi sasaran halangan, yang diringkaskan sebagai OTC-GNP-RL. Ini dapat memberi penganggapan keadaan persekitaran semasa. Reka bentuk kedua adalah berdasarkan perwakilan persekitaran ramalan perlanggaran yang dicadangkan dan diringkaskan sebagai CP-GNP-RL. Perwakilan ini direka bentuk untuk memberi ramalan perlanggaran di antara robot boleh gerak dan halangan, disamping memberi penganggapan persekitaran semasa yang dikelilinginya. Selain itu, ia dapat mewakilkan persekitaran dengan keadaan ruang yang padat dan hanya memerlukan pengukuran kedudukan. Seterusnya, kombinasi ramalan perlanggaran dan

Pembelajaran-Q dapat mengatasi isu laknat kematraan dan menambahbaik ciri-ciri pandu arah.

Simulasi digunakan untuk menilai prestasi pendekatan yang dicadangkan. Keputusan menunjukkan bahawa keunggulan pendekatan yang dicadangkan dari aspek ciri-ciri pandu arah robot boleh gerak, di mana kesemua ciri-ciri di dalam pendekatan yang dicadangkan telah dipertimbangkan semasa mereka bentuk. Melalui penilaian, CPQL, CP-GNP-RL dan OTC-GNP-RL, setiap satu menunjukkan peningkatan dari aspek keselamatan (7.917%), kelancaran (71.776%) dan kelajuan (10.89%) berbanding dua pendekatan terbaik sebelum ini, pembelajaran-Q berasaskan OTC dan bidang potensi tiruan . Di samping itu, analisa pembelajaran CPQL menunjukkan kecekapan dan keunggulan dari aspek penumpuan pembelajaran dan pandu arah selamat. Oleh itu, thesis ini telah menunjukkan pendekatan yang dicadangkan terbukti kesahihan dan kesesuaiannya dalam aplikasi pandu arah kompleks dan persekitaran dinamik.

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I would like to express my sincere gratitude to my supervisor Prof. Dr. Mohammed Hamiruce Marhaban for the continuous support of my study and research, for his patience, motivation, enthusiasm, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better supervisor and mentor for my PhD study.

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I am very grateful to my family: my mother and my siblings for their unflagging love and support throughout my life. I have no suitable words that can fully describe my everlasting love to them except, I love you all.

Last but by no means least, it gives me immense pleasure to express my deepest gratitude to all my friends for their constant support, encouragement, and prays.

Finally, I would like to thank everybody who was important to the successful realization of thesis, as well as expressing my apology that I could not mention them one by one.

I certify that a Thesis Examination Committee has met on 30 October 2017 to conduct the final examination of Ahmed Hassan Mohammed on his thesis entitled "Collision Prediction-Based Genetic Network Programming-Reinforcement Learning for Mobile Robot Adaptive Navigation in Unknown Dynamic Environments" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

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Declaration by graduate student

I hereby confirm that:

- this thesis is my original work;
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- this thesis has not been submitted previously or concurrently for any other degree at any other institutions ;
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This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
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LIST OF ABBREVIATIONS

AC	Actor Critic
ACO	Ant Colony Optimization
ANFIS	Adaptive Network-based Fuzzy Inference System
ANN	Artificial Neural Network
APF	Artificial Potential Field
ART	Adaptive Resonance Theory
CoD	Curse of Dimensionality
CP	Collision Prediction
CP-GNP-RL	Collision Prediction GNP-RL
CPQL	Collision Prediction based Q-Learning
DCN	Dynamic Cognitive Networks
DFQL	Dynamic Fuzzy Q- Learning
DP	Dynamic Programming
DR	Dead Reckoning
EAPF	Evolutionary APF
EAs	Evolutionary Algorithms
EDA	Estimation of Distribution Algorithms
ED-FCM	Event Driven - Fuzzy Cognitive Map
FCM	Fuzzy Cognitive Map
FIS	Fuzzy Inference System
FLC	Fuzzy Logic Controller
FQL	Fuzzy Q-learning
FS	Fail State
G	The target
GA	Genetic Algorithm
GNP	Genetic network programming
GNP-RL	Genetic network programming with Reinforcement Learning
GP	Genetic Programming
GPS	Global Positioning System

MC	Monte Carlo
MLP	Multi-Layer Perceptron
MR	Mobile Robot
NC	No Collision
NS	Non Safe State
NURBS	Non Uniform Rational B-Spline
OTC	Obstacle Target Correlation
OTC-GNP-RL	Obstacle Target Correlation GNP-RL
PD	Potential Density
PSO	Particle Swarm Optimization
QL	Q-Learning
RL	Reinforcement Learning
SARSA	State-Action-Reward-State- Action
SS	Safe State
TD	Temporal Difference
TFR	Temporal Fuzzy Rules
VD	Visual Domain
VFH	Vector Field Histogram
WS	Winning State

LIST OF SYMBOLS

MR	Mobile Robot
G	Target
O_i	An obstacle
k	Constant
v_{MR}	Velocity of the mobile robot
v_G	Velocity of target
v_γ	Velocity of an obstacle
d_c	Distance of collision
$\mathbb{r}_{MR}$	Radius of the mobile robot
$\mathbb{r}_{MR}$	Radius of an obstacle
$\mathcal{S}$	Safety distance
$d(x_1, x_2)$	Euclidean distance between the positions $x_1$and x_2
d_r	Distance of risk
d_w	Distance of winning
Ri	Orthogonal region, where i can be 1, 2, 3, or 4
R_γ	Region of Obstacle
R_G	Region of Target
R_α	Region of divergence angle
y	Vertical coordinate
x	Horizontal coordinate
m	Slope of a line
b	Constant of a line
D	A distance
R_ς	Region of collision
S	State of an environment
T	Sampling time
L_{RG}	A virtual line connecting the mobile robot and the target
L_{RO}	A virtual line connecting the mobile robot and the target
L_{RC}	A virtual line connecting the mobile robot and the target

L_γ	A virtual line represents the estimated movement of a dynamic obstacle
C_p	A predicted collision point
B	Coverage distance
r	Radius
$\alpha, \beta, \delta,$ and ϕ	Angles
ξ and ψ	Sign {-1,1}
v_{max}	Maximum velocity of the mobile robot
v_{min}	Minimum velocity of the mobile robot
v_{mod}	Moderate velocity of the mobile robot
θ_{RG}	Heading angle of the mobile robot towards the target
n	constant
f	Frequency of the mobile robot processor
NT_i	Node type of the node i of a GNP-RL network.
ID_{ik}	Node function of the sub-node k in node i of a GNP-RL network
k	Constant
m_i	Number of sub-nodes in each node of GNP-RL network.
Q_{ikp}	The Q-value of the parameter p of sub-node k in the node of GNP-RL network.
d_i	The time delay spend in node of GNP-RL network
ε	Probability factor
C_{ikp}	The next node connection number related to the parameter p in sub-node k of node i
R_{ik}	Value of judgment in sub-node k of judgment node i
A_{ikp}	Value of processing in sub-node k of processing node i
θ_Δ	The turning angle of the mobile robot from the virtual line connecting the mobile robot and the target
P_c	Crossover probability
P_m	Mutation probability
d_{max}	Maximum delay can be allowed during one node transition

η	Learning rate of SARSA
μ	Discount rate of SARSA
r_t	Reward function of GNP-RL
C	Constant
$\mathcal{F}$	Fitness function of GNP-RL
n	Constant
m	Constant
$\Delta\theta$	Angle difference between two consecutive steps of the mobile robot
$r(\Delta\theta)$	Rate of steering angle change between two consecutive steps of the mobile robot
ϖ	Balance factor of the mobile robot direction change
$Q(s_t, a_t)$	The Q-value at the current state s_t and action $a_t$of Q-learning
$r(s_t, a_t)$	The reward obtained at the current state s_t when the current action $a_t$of Q-learning is taken
$max(Q, s_{t+1})$	the maximum Q-value calculated for taking all possible actions on the new state at a previous time
λ	Discount factor of Q-learning
$\measuredangle\theta$	The angle turned by the mobile robot
η	Degree of risk
F_{att}	Attractive force
F_{rep}	Repulsive force
P_{tar}	Position of target
$P(t)$	Position of the mobile robot at time t
u	A unit vector
v_{tar}	Velocity of the target
$v(t)$	Velocity of the mobile robot
ρ_r	A positive constant
α_p and α_v	Scalar positive constants
v_{RO}	The relative velocity between the mobile robot and an

	obstacle
v_γ	Velocity of an obstacle
ρ_m	The distance travelled by the mobile robot before its velocity reduces to zero
a_{max}	Maximum deceleration of the mobile robot
P_γ	Position of an obstacle
ρ_0	Positive constant describing the influence range of an obstacle
ρ_s	Shortest distance between the mobile robot and an obstacle

CHAPTER 1

INTRODUCTION

1.1 Overview

Mobile robots (MR's) are category of robots that are capable of moving, sensing, and reacting in an environment [1]. MR's can be used to increase productivity or to reduce human exposure to hazards [2]. Hence, they play an important role in several real time applications [3], for instance, medical services [4], cleaning [5], military [6], mining [7], surveillance [8], remote measurement [9], security [10], industrial [2], rescue [11], and agriculture [12].

Autonomous MR's are the robots that have self-government and emulate to intelligent behavior intelligently and maneuver in unpredictable complex environment, i.e. they have the capability of perception of the surrounding environment and taking the right action at the right time without human intervention. The process of determining collision free path between starting point and target is called MR navigation. This field of research is one of the key challenges of mobile robotics, and it has received a considerable attention over the last two decades [1, 13].

The navigation environment of MR can be classified according to the availability of environment knowledge, which can be known [14], partially known [15], and unknown [1]. In known environment, the coordinates and variables, e.g. positions, velocity, acceleration, and direction, of all obstacles and the target in the environment are predefined to the MR before starting navigation. In contrast, all these coordinates are unknown in most of MR applications [16]. This what motivates researchers to find approaches that can deal with uncertain situations of unknown environment [17].

Another dimension along which navigation of MR approaches can be grouped is concerned with the nature of the environment, static or dynamic [18]. In static environment, the only object that may change its position over time is the MR itself. But, dynamic environment has many particles that are moving and changing their positions over time such that their future trajectories and complete information cannot be known or assumed a priori. Hence, additional challenges of avoiding such obstacles have been added to the navigation of autonomous MR in such environment. Consequently, "A robot's safety cannot be obtained by coming to a standstill in dynamical environments and absolute motion safety is even impossible for the robot "[19-21], where the capability of avoiding obstacles is termed safe navigation [20, 22, 23]. Moreover, MR environments in real applications are considered highly dynamic, where not only the obstacles but also the target is moving [24, 25], where Tahri et al. classified this case as most difficult [26]. Practically, "It is difficult to make a robot intercept a moving target, whose trajectory and speed are unknown and dynamically changing, in a comparatively short distance when the environment contains complex objects."[27].

Some approaches like virtual plane, generalized velocity obstacle, reactive control design, and temporal fuzzy rules [28-31] provide dynamic obstacle avoidance. However all these techniques are based on measuring the velocity of moving obstacles. Practically, this measurement is noisy and difficult to obtain [29, 32, 33] .

To operate autonomously, effective controller must be designed for those MR's. For this purpose, a wide variety of approaches in the literature have been developed to obtain optimal or near optimal safety performance of MR. The approaches that are widely used in MR navigation are soft computing (fuzzy logic, neural network, genetic algorithm, genetic network programming, particle swarm optimization, and ant colony optimization), artificial potential field and Reinforcement Learning (RL). However, these algorithms are applied on either static environment or dynamic environment with a target that is assumed almost stationary. Besides, an increase in the measured variables, computational power, and the required memory incur hindrance to the applicability of these algorithms.

Machine learning paradigms aims to produce intelligent programs through a process of evolving and learning. They can be classified as supervised, unsupervised and RL. Supervised learning has a teacher that takes a known set of input-output data, and seeks to build a model that generates reasonable predictions for the response to new data, whereas unsupervised learning has no teacher but it draws inferences from datasets consisting of input data without labeled responses. Whereas RL is a learning without expert supervision in which MR learns how to map states to actions in an attempt to maximize a numerical reward signal through trial-and-error interactions with its environment. The learner is not told which actions to take, but it must discover which actions yield the most reward by trying them.

In the last decade or so, the application of RL in robotics has spread increasingly [34, 35] and it seems to be a natural choice for learning control policies on MR's [36]. It basically needs a simultaneous assessment of how good or bad the system is doing. Hence, RL seems quite promising because it requires no training data [37] and it is suitable to allow robots to learn from their own practices and environment interaction [38]. Q-Learning (QL), which is a form of RL, is one candidate of the autonomous controller, because it is a model free algorithm [39]. The discrete set of state-action (based on lookup table) method of QL is the popular approach for estimating the value function in QL in which the convergence is guaranteed subjecting to some restrictions on the learning parameters [40, 41]. However, it is not easy to put QL to practical use [42] when the complexity of the considered application is increased, where the state-action pairs of discrete QL are increased exponentially. This increase makes it non-feasible for MR to visit all the potential states at an adequate time to find the most favorable actions for those states. This problem, named Curse of Dimensionality (CoD) [43], causes slowness in learning task and restricts discrete QL applicability on MR navigation that has broad range of variables.

Genetic network programming with RL (GNP-RL) [44-49] is an extension of GNP [50] and it is efficiently combined evolution and learning. Evolutionary computation generally has an advantage in diversified search ability, while reinforcement learning has an advantage in intensified search ability and online learning. GNP-RL is promising in the field of artificial intelligence due to its significant features over other algorithm. Some of these features are: directed graph expression, reusability of nodes, implicit memory function, saving memory consumption and reducing calculation time due to its compact structure, and it is not causing bloat, unlike genetic programming, because of its predefined number of nodes. It also provides combinations between offline and online learning, and diversified and intensified search. However, it has only been applied on navigation of MR in static environment.

In this thesis, MR navigation has been studied in completely unknown (no prior knowledge) environment containing several dynamic and static obstacles. The movement of dynamic obstacles is unpredictable and random. During this navigation, the MR is chasing a continuously moving target which can be observed by MR at each time instant without knowing or predicting its future movement. Meanwhile, MR senses the surrounding environment by laser range finders. It is assumed that the velocity of MR is greater than that of the target and greater than or equal to that of obstacles.

Safe navigation, smooth path, and fast movement are crucial demands in MR navigation. The desire to avoid collision occurrences with an obstacle (dynamic and/or static), which threatens the safe navigation of MR, makes it moves in sharp turning angles and reduces its speed significantly producing zigzag path with large fluctuating in speed set points. On the other hand, in the designs that are based on certain tuning angle during obstacle avoidance and/or constant speed throughout navigation, largest possible turning angle is used to avoid collisions and constant speed restricts the obstacle avoidance capability of MR.

1.2 Problem Statement

To operate autonomously, effective controller must be designed for MR's. From the surveyed papers, a wide variety of approaches in the literature have been developed to obtain optimal or near optimal safe performance of MR in avoiding obstacles. However, the autonomy of an MR still encounter many challenges in learning and execution phases, where the research of MR navigation in static environment is almost matured [51, 52], and it is still in progress for dynamic environment [28, 33]. Besides, "In most real applications, the environment is dynamic. This means not only the obstacles are moving, so does the target. In such situations, the most common methods ignore the trend of moving target and obstacles."[53]. The considered environment in this study is completely unknown, populated by abundant obstacles (unpredictable and random moving obstacles and static obstacles), and contained a moving target. Consequently, many challenges will encounter MR to do its navigation in such environment. Hence, the problems of MR navigation that represent the thesis problem statement can be summarized as follows.

MR environments in real applications are considered highly dynamic, where not only the obstacles but also the target is moving [24, 25, 53, 54]. Therefore, "a robot's safety cannot be obtained by coming to a standstill in dynamical environments and absolute motion safety is even impossible for a robot "[19-21]. Hence, safety movement of MR takes a considerable attention from researchers. However, the effectiveness of most researches in the literature are devoted on static environment. Limited number of researches are applied on point to point navigation (stationary target) in dynamic environment, and it is seldom number of researches investigated obstacle avoidance in dynamic environment with a moving target. Besides, an increase in the measured variables [28-31, 55, 56], computational power [54-57], and the required memory [58-60] incur the applicability of these algorithms [61, 62]. Consequently, it becomes crucial demand to introduce approaches of MR navigation in the considered environment in this thesis that have effective obstacle avoidance feature with reducing the requirements of measurements.

Smooth path is another important features of MR navigation. Although it generally does not investigated widely, it is investigated in static environments more than in dynamic environments. In addition, such investigation does not exist for dynamic environment including a moving target. Besides, the tendency of some researchers [25, 43, 63-65] to use fixed and large steering angles to avoid obstacles conflicts with the desire to provide smooth navigation paths. Moreover, discarding previous steering angles from the calculations of the current steering angle contributes mainly in producing tortuous navigation path during obstacle avoidance. Obviously, this feature is not widely included in the designs because of the difficulty in compromising between safety and smoothness features. These facts introduce a big challenge to combine these two crucial features of MR navigation in one algorithm.

MR speed is one of the variables that should be controlled to meet the requirements of navigation. However, limited number of works investigated MR speed, where the majority of these works are applied on static environment, low rate of them are applied on dynamic environment contains stationary target, and seldom of them studied it for dynamic environment with a moving target. Moreover, some researches [25, 38, 39, 43, 63, 64, 66-69] assumed that the speed of MR during navigation is constant. This assumption has a negative impact on the degree of safe property of avoiding obstacles and/or on the consuming time in implementing navigation task. On our knowledge, there is no work integrated these three features (safety, smoothness, and speed) in one design. Therefore, this variable should also be controlled during MR navigation and integrated with the other two features; safety and smoothness.

QL is a seductive approach to solve the problem of MR navigation in dynamic environment due to its generality and ability to teach MR an optimal behavioral strategy through direct interaction with its environment without prior knowledge of the problem to be solved rather than collecting precise input/output data set. However, it is beleaguered by "Curse of dimensionality" [39, 43, 63, 70-74], which refers to the exponential inflation in state-space with each additional variable or dimension that describes the problem. Due to the high dimensionality and complexity of the environment being studied, curse of dimensionality impedes QL applicability. This leads to slowness of learning, slowness in taking decision, and large memory requirement. This problem takes a considerable attention from researchers. However, they focus mainly on solving it in static environment, and few of them studied it for dynamic environment. Therefore, solving this problem for the considered environment is encouraging.

GNP-RL [44-49] provides significant features such as: combinations between offline and online learning, and diversified and intensified search. Besides, its compact structure reduces memory requirement and computation time. These feature make it suitable to be applied on MR navigation in dynamic environment. However, it has been applied on navigation of MR in static environment only. Therefore it is encouragingly to formulate its gene structure and introduce suitable fitness function to be applied on dynamic environment.

Therefore, the integration of enhancing obstacle avoidance property, optimizing the movement and speed of an MR during the avoidance of an obstacle, tackling the CoD problem of QL, and utilizing the features of GNP-RL will lead to enhance and improve the features of MR navigation in the considered environment.

1.3 Research Objectives

The objectives of this research are:

1. To improve obstacle avoidance capability of an MR navigating in an environment, which involves dynamic and static obstacles, while it is chasing a moving target.
2. To smooth the navigation path of an MR during avoiding dynamic and static obstacles.
3. To optimize the speed performance of MR during obstacle avoidance to obtain fast navigation.
4. To eliminate the negative impacts of QL's dimensionality curse problem, which results from applying QL in highly dimensionality and complex dynamic environment.
5. To develop a design of GNP-RL suitable to control navigation of an MR in a dynamic environment.

1.4 Research Scope

This research concentrates on navigating an MR in unknown and dynamic environment containing a moving target. The dimensions of this environment is unlimited. Many challenges faced by an MR that navigates autonomously in such environment. The first and the most important feature is the successful avoidance of different types of obstacles (static and dynamic) during chasing a moving target. This avoidance conflicts with other two challenges that are; maintaining smooth navigation path and driving MR with high speed. This research focuses on the integration of obstacle avoidance, smooth path and MR speed, with taking under the consideration the mitigation of measurements. Figure 1.1 shows the parameters of research scope.

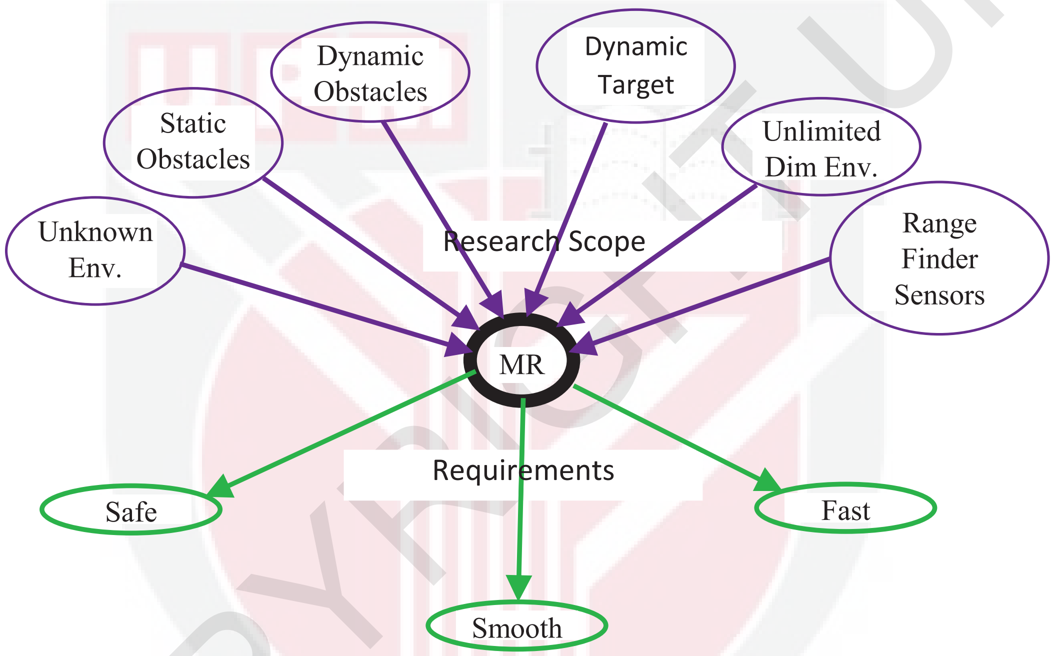

Figure 1.1 : Research Scope Parameters

1.5 Limitations

The proposed approaches enhance the navigation performance of an MR in several directions, such as improving the safety of MR during navigation, enhancing the smoothness of navigation path and MR speed, and speeding up the learning convergence. However, in some circumstances the performance of the proposed approaches is degraded due to:

1. The proposed approaches are dedicated to address the obstacle avoidance problem of one obstacle at a time. That is, the nearest obstacle is only taken under the consideration of avoidance. However, in case two or more critical obstacles

disturb MR at the same instance, MR avoids these obstacles sequentially, but it doesn't avoid all of them in parallel way.

2. Since the avoidance of dead end static obstacle has been studied intensively in the literature, the proposed approaches are focused on avoiding the static obstacle but this special case of obstacles are not taken under consideration.

1.6 Organization of the Thesis

This thesis is organized into five chapters. **Chapter 2** presents a detailed review on MR navigation algorithms, namely, soft computing, reinforcement learning, and artificial potential field. The algorithms currently used for controlling MR are then analyzed along with the research works devoted to manage MR navigation. In addition, the demerits of these algorithms are presented along with the current researches that attempt to solve the bottleneck problems, safe navigation, smooth path, fast navigation, and curse of dimensionality. **Chapter 3** presents the mathematical model of the proposed environment representation, as well as another referenced representation, provides the methodologies of the proposed approaches with the required mathematical models, as well as two state of arts, and introduces the design of the workspace that is used to test the proposed approaches. **Chapter 4** shows the simulation evaluations to prove the efficiency of the proposed algorithms compared with two state-of-arts in terms of safe navigation, smooth path, fast navigation, and learning convergence. Finally, a comprehensive comparison and discussion are presented among the results of all approaches being studied. Lastly, **Chapter 5** concludes the work and recommends some promising directions for future research.

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