

**ALGORITHMS FOR MULTI-CRITERIA GLOBAL  
PATH PLANNING OF AN UNMANNED COMBAT  
VEHICLE**

**SAW VEEKEONG A/L SAW HIN**

**UNIVERSITI SAINS MALAYSIA**

**2020**

**ALGORITHMS FOR MULTI-CRITERIA GLOBAL  
PATH PLANNING OF AN UNMANNED COMBAT  
VEHICLE**

by

**SAW VEEKEONG A/L SAW HIN**

**Thesis submitted in fulfilment of the requirements  
for the degree of  
Master of Science**

**May 2020**

## **ACKNOWLEDGEMENT**

First and foremost, I would like to express my deepest appreciation to my supervisors, Dr. Siti Amirah Abd Rahman, and Dr. Ong Wen Eng, for providing guidance, comments, and suggestions throughout all stages of this research. Without their guidance, the research work would not be conducted successfully. I would also like to take this opportunity to thank the School of Mathematical Sciences (PPSM) and Institute of Postgraduate Studies (IPS), Universiti Sains Malaysia (USM) for providing necessary facilities and services throughout my entire research duration. I was offered a scholarship fund under MyBrain 15 program from the Ministry of Higher Education (MOHE) as a support for my tuition fees. For that I would also like to thank MOHE for providing aid to lessen my financial burden. Besides that, I would like to thank the RU grant 1001/PMATHS/8011017 for providing extra financial supports to cover my expenses throughout the research period. Last but not least, many thanks to all my friends, family, and everybody that support me physically or mentally throughout my research journey.

# TABLE OF CONTENTS

<b>ACKNOWLEDGEMENT</b> .....	ii
<b>TABLE OF CONTENTS</b> .....	iii
<b>LIST OF TABLES</b> .....	viii
<b>LIST OF FIGURES</b> .....	x
<b>LIST OF PLATES</b> .....	xiii
<b>LIST OF SYMBOLS</b> .....	xiv
<b>LIST OF ABBREVIATIONS</b> .....	xvi
<b>LIST OF APPENDICES</b> .....	xviii
<b>ABSTRAK</b> .....	xix
<b>ABSTRACT</b> .....	xxi
<b>CHAPTER 1 INTRODUCTION</b>	
1.1 Introduction to Research Topic .....	1
1.2 Problem Statement .....	2
1.3 Objectives of Thesis .....	3
1.4 Significance of Study .....	3
1.5 Research Motivation .....	4
1.6 Scope and Limitation of Study .....	5
1.7 Organization of Thesis .....	6
<b>CHAPTER 2 UNMANNED COMBAT GROUND VEHICLES</b>	
2.1 Introduction .....	8
2.2 Development of Unmanned Combat Vehicle in Military .....	11
2.2.1 First Mobile Robot .....	11

2.2.2	UGV for Handling IED .....	12
2.2.3	UGV for Reconnaissance, Surveillance, and Target Acquisition (RSTA) .....	13
2.2.4	DARPA Grand Challenge.....	14
2.2.5	Next Generation UGV .....	15
2.3	The Navigation Control of UCV .....	16
2.4	Global Path Planning Process of UCV .....	18
2.5	Representing the Environment in Grid Form.....	20
2.6	Studies Related to Path Planning Problem .....	21
 <b>CHAPTER 3 MODELLING THE UNMANNED COMBAT VEHICLE GLOBAL PATH PLANNING PROBLEM</b>		
3.1	Basic Notions on Graph Theory .....	27
3.1.1	Classification of graphs .....	28
3.1.1.1	Edge direction .....	28
3.1.1.2	Cost function .....	29
3.1.2	Special classes of simple graphs .....	30
3.1.3	Other Graph Terminologies.....	32
3.1.3.1	Adjacency matrix .....	32
3.1.3.2	Path and cycle .....	33
3.1.3.3	Cost of a path and cycle.....	34
3.1.3.4	Successor set and predecessor set .....	35
3.2	Introduction to Path Planning Problems.....	35
3.2.1	Shortest Path Problem .....	35
3.2.2	Multi-Criteria Shortest Path Problem .....	37
3.2.3	Travelling Salesman Problem .....	38

3.2.4	Travelling Salesman Path Problem .....	41
3.3	Basic Notions on Multi-Criteria Optimization .....	42
3.3.1	Concept of Pareto Optimality .....	44
3.3.2	Graphical Visualization of MOP .....	45
3.4	Formulating the UCV GPP Problem .....	47
3.4.1	Constructing the Configuration Space .....	49
3.4.2	Mathematical Formulation of UCV GPP Problem .....	51
<b>CHAPTER 4 SOLUTION TECHNIQUES IN PATH FINDING AND OPTIMIZATION</b>		
4.1	Preprocessing .....	53
4.1.1	Cost normalization .....	53
4.1.2	Weighted Sum Method.....	54
4.1.3	Clustering the Checkpoints .....	56
4.2	Grid-Based Path Searching .....	57
4.2.1	Dijkstra's Algorithm .....	58
4.2.2	Nearest Neighbor Algorithm .....	59
4.3	Improvement Technique.....	60
4.3.1	A* Algorithm.....	61
4.3.2	Repetitive Nearest Neighbor Algorithm .....	63
4.3.3	2-Opt Technique .....	64
4.4	Multi-Criteria Decision Making .....	65
4.4.1	Ideal Point Method.....	66
4.4.2	$\epsilon$ -Constraint Method .....	66
4.5	Summary.....	69

**CHAPTER 5 SOLUTION SCHEME FOR SOLVING THE UNMANNED COMBAT VEHICLE GLOBAL PATH PLANNING PROBLEM**

5.1 Solution Scheme 1: Single TSPP Approach ..... 71

    5.1.1 Preprocessing Phase ..... 73

    5.1.2 Solution Path Searching Phase ..... 73

    5.1.3 Post-Processing Decision Making Phase ..... 75

5.2 Solution Scheme 2: Clustered TSPP Approach ..... 76

5.3 Summary ..... 84

**CHAPTER 6 COMPUTATIONAL EXPERIMENTATION**

6.1 Experimental Set Up ..... 85

6.2 Experiments on Simulated Terrain ..... 86

    6.2.1 Experiment Results and Discussions ..... 88

        6.2.1.1 Computation Time ..... 88

        6.2.1.2 Solution Path Cost ..... 90

6.3 Experiments on a Real-World Satellite Images ..... 97

    6.3.1 Experiment Results and Discussions ..... 98

        6.3.1.1 Computation Time ..... 98

        6.3.1.2 Solution Path Costs ..... 100

        6.3.1.3 Improvements for Solutions Obtained Using SS2 ..... 108

6.4 Summary ..... 111

**CHAPTER 7 CONCLUSIONS AND FUTURE WORKS**

7.1 Conclusions ..... 113

7.2 Future Works ..... 114

**REFERENCES ..... 115**

## **APPENDICES**

### **LIST OF PUBLICATIONS**



## LIST OF TABLES

		Page
Table 2.1	Collection of literatures related to path planning problem. ....	23
Table 4.1	A payoff table for the $k$ -MOP. ....	68
Table 6.1	Computation time for experiments in small-sized simulated terrain ( $15 \times 15$ , $30 \times 30$ , and $50 \times 50$ ). ....	88
Table 6.2	Computation time for experiments in $75 \times 75$ simulated terrain. .	89
Table 6.3	Computation time for experiments in $100 \times 100$ simulated terrain. ....	89
Table 6.4	Solution path costs for experiments in small-sized simulated terrain ( $15 \times 15$ , $30 \times 30$ , and $50 \times 50$ ). ....	91
Table 6.5	Solution path costs for experiments in $75 \times 75$ simulated terrain.	92
Table 6.6	Solution path costs for experiments in $100 \times 100$ simulated terrain. ....	93
Table 6.7	The radius and intercluster edge distance in small-sized simulated terrain ( $15 \times 15$ , $30 \times 30$ , and $50 \times 50$ ). ....	95
Table 6.8	The radius and intercluster edge distance in $75 \times 75$ simulated terrain. ....	95
Table 6.9	The radius and intercluster edge distance in $100 \times 100$ simulated terrain. ....	96
Table 6.10	Computation time for experiments on real world problem. ....	98
Table 6.11	Solution path costs on real-world satellite image. ....	100
Table 6.12	The radius and intercluster edge distance for real-world problem.	106
Table 6.13	Improvement on solution path cost after applying global 2-opt. . .	109
Table B.1	Checkpoints for every problem set in real-world satellite image. .	125
Table B.2	Checkpoints for every problem set in simulated terrains. ....	127

Table C.1	Percentage cost difference (for each attributes) of complete path $c(\pi_{st}^*)$ from ideal cost $c^*$ for experiments on satellite image. ....	131
Table C.2	Percentage cost difference (for each attributes) for experiments on small-sized simulated terrain ( $15 \times 15$ , $30 \times 30$ , and $50 \times 50$ ). ....	133
Table C.3	Percentage cost difference (for each attributes) for experiments on $75 \times 75$ simulated terrain. ....	134
Table C.4	Percentage cost difference (for each attributes) for experiments on $100 \times 100$ simulated terrain. ....	135
Table D.1	Solution path cost for experiments on satellite image after applying global 2-opt. ....	136

## LIST OF FIGURES

		Page
Figure 2.1	The procedure of GPP. ....	18
Figure 3.1	An example modelling problems into a digraph and an undirected graph. ....	29
Figure 3.1(a)	A digraph showing exchange rate between USD (\$), Malaysian Ringgit ( <i>RM</i> ), GBP (£), and Euro (€). ....	29
Figure 3.1(b)	An undirected graph showing distance between several locations. ....	29
Figure 3.2	A graph with three cost factors. ....	30
Figure 3.3	Example of a factory production line modelled into a weighted graph with both vertex and edge-weighted cost functions. ....	31
Figure 3.4	An $3 \times 3$ grid graph. ....	31
Figure 3.4(a)	A 4-connected grid graph. ....	31
Figure 3.4(b)	An 8-connected grid graph. ....	31
Figure 3.5	A complete graph with six vertices. ....	32
Figure 3.6	Solution space of bicriteria MOP. ....	45
Figure 3.7	Classification of Pareto-optimal solutions. ....	46
Figure 3.8	A grid with $M$ rows and $N$ columns. ....	49
Figure 3.9	Grid graph $G$ constructed from $M \times N$ grid in Figure 3.8. ....	50
Figure 4.1	Applying weighted sum method to solve 2-MOP with $\mathbf{w} = (a, b)$ . ....	55
Figure 4.2	Path $\pi_{st}$ before and after swapping the edge $e_{ab}$ and $e_{cd}$ . ....	64
Figure 4.3	Applying the ideal point method to solve a 2-MOP using $L_2$ metric. ....	67
Figure 4.4	Applying $\epsilon$ -constraint method to solve 2-MOP. ....	68
Figure 5.1	Solution Scheme 1. ....	72

Figure 5.2	An example of complete graph formed from GPP problem with $ \Lambda  = 5$ . .....	74
Figure 5.2(a)	Shortest path connecting all pair of checkpoints. ....	74
Figure 5.2(b)	Complete graph $K_5$ . ....	74
Figure 5.3	Solution Scheme 2. ....	77
Figure 5.4	An example of constructing $K_{cls}$ from partitioned checkpoint set in a grid. ....	79
Figure 5.4(a)	Checkpoints that partitioned into clusters. ....	79
Figure 5.4(b)	Cluster complete graph $K_{cls}$ . ....	79
Figure 5.5	An example of shortest Hamilton intercluster path for the clusters in Figure 5.4(a). ....	80
Figure 5.6	Case 1: switching to edge $e_{n_s, y}$ . ....	82
Figure 5.7	Case 2: switching to edge $e_{x, n_1}$ . ....	82
Figure 5.8	Case 3: switching to edge $e_{n_1, y}$ . ....	82
Figure 5.9	Case 4: switching to edge $e_{x, n_s}$ . ....	83
Figure 6.1	Process of creating simulated terrain. ....	86
Figure 6.2	Problem set 4 with $\mathbf{w} = \{0.7, 0.1, 0.2\}$ solved using SS1. ....	103
Figure 6.2(a)	Attribute 1: total cost 90663. ....	103
Figure 6.2(b)	Attribute 2: total cost 73597. ....	103
Figure 6.2(c)	Attribute 3: total cost 83495. ....	103
Figure 6.3	Problem set 4 with $\mathbf{w} = \{0.7, 0.1, 0.2\}$ solved using SS2 with 5 clusters. ....	104
Figure 6.3(a)	Attribute 1: total cost 109556. ....	104
Figure 6.3(b)	Attribute 2: total cost 95287. ....	104
Figure 6.3(c)	Attribute 3: total cost 107230. ....	104
Figure 6.4	Problem set 4 with $\mathbf{w} = \{0.7, 0.1, 0.2\}$ solved using SS2 with 6 clusters. ....	105

Figure 6.4(a)	Attribute 1: total cost 90055. ....	105
Figure 6.4(b)	Attribute 2: total cost 73349. ....	105
Figure 6.4(c)	Attribute 3: total cost 82733. ....	105
Figure A.1	15 × 15 terrain, average cell cost: 5.32 : 3.29 : 3.86. ....	122
Figure A.2	30 × 30 terrain, average cell cost: 4.17 : 3.79 : 2.43. ....	122
Figure A.3	50 × 50 terrain, average cell cost: 3.33 : 3.86 : 4.25. ....	123
Figure A.4	75 × 75 terrain, average cell cost: 4.01 : 3.85 : 4.93. ....	123
Figure A.5	100 × 100 terrain, average cell cost: 4.67 : 4.61 : 3.81.....	123
Figure A.6	Grayscale image profile for three attributes (from left to right: traverse time, risk level, jamming level) with average cell cost 181.67 : 126.43 : 141.38.....	124
Figure E.1	Solution points for Problem Set 1. ....	138
Figure E.2	Solution points for Problem Set 2. ....	139
Figure E.3	Solution points for Problem Set 3. ....	139
Figure E.4	Solution points for Problem Set 4. ....	140
Figure E.5	Solution points for Problem Set 1 after implementing global 2-opt. ....	140
Figure E.6	Solution points for Problem Set 2 after implementing global 2-opt. ....	141
Figure E.7	Solution points for Problem Set 3 after implementing global 2-opt. ....	141
Figure E.8	Solution points for Problem Set 4 after implementing global 2-opt. ....	142

## LIST OF PLATES

		<b>Page</b>
Plate 2.1	THEMIS hybrid UGV (Source: <i>THEMIS Hybrid Unmanned Ground Vehicle</i> (2015)) .....	9
Plate 2.2	Black Knight UGCV (Source: <i>Black Knight</i> (n.d.)) .....	10
Plate 2.3	510 Packbot (Source: <i>iRobot 510 PackBot Multi-Mission Robot</i> (n.d.)) .....	10
Plate 2.4	STRIDE UGV (Source: Abas (2015)) .....	10
Plate A.1	Original satellite aerial image for experiment. ....	124

## LIST OF SYMBOLS

$G$	graph with vertex set $V$ and edge set $E$
$V$	vertex set in graph $G$
$E$	edge set in graph $G$
$v_i$	vertex $i$
$e_{ij}$	undirected edge connecting vertex $v_i$ and $v_j$
$E_{ij}$	directed edge from vertex $v_i$ to $v_j$
$c$	cost function associated to the graph
$K_n$	complete graph with $n$ vertices
$A_G$	adjacency matrix for weighted graph $G$
$A_G^i$	adjacency matrix of $i$ th cost for multi-criteria weighted graph $G$
$\pi_{pq}$	path from vertex $v_p$ to $v_q$
$Cyc(v_i)$	cycle that starts and ends at vertex $v_i$
$\oplus$	path concatenation operator
$\bar{\pi}_{pq}$	partial path from vertex $v_p$ to $v_q$
$\pi_{pq}^*$	complete path from vertex $v_p$ to $v_q$
$c(\pi_{pq})$	cost of path $\pi_{pq}$
$Pre(v_i)$	predecessor set of vertex $v_i$
$Suc(v_i)$	sucessor set of vertex $v_i$
$<_D$	dominates

$\mathbf{w}$	weight vector
$\varepsilon_i$	limit for attribute $i$ ( $\varepsilon$ -constraint method)
$P_{\mathbf{w}}$	weighted sum problem
$X$	feasible set
$Y$	solution set
$\Lambda$	checkpoint set
$\Lambda_i$	clusters
$y^*$	utopia point
$\wedge$	and operator
$\hat{f}_p(x)$	normalized cost for $p$ -th attribute (general)
$c^{\mathbf{w}}$	combined weighted cost
$d(\Lambda_i, \Lambda_j)$	distance between cluster $\Lambda_i$ and $\Lambda_j$
$\pi_{ij}^{cls}$	intercluster path from cluster $\Lambda_i$ to $\Lambda_j$
$r(\Lambda_i)$	radius of cluster $i$



## LIST OF ABBREVIATIONS

ALV	Autonomous Land Vehicle
AOI	area of interest
ATT	Advanced Teleoperator Technology
CBRN	chemical, biological radiological and nuclear
c-space	configuration space
DARPA	Defense Advanced Research Projects Agency
EOD	Explosive Ordnance Disposal
GATERS	Ground/Air TeleRobotic System
GPP	global path planning
GSR	Ground Surveillance Robot
IED	Improvised Explosives Devices
LIMA	Langkawi International Maritime and Aerospace
LPP	local path planning
MICOM	Missile Command
MOP	multi-criteria optimization problem
MSPP	multi-criteria shortest path problem
NNA	nearest neighbor algorithm
RNNA	repetitive nearest neighbor algorithm
RST	Robotics System Technology

RSTA	reconnaissance, surveillance, and target acquisition
SE	supported efficient
SE1	extreme supported efficient
SE2	nonextreme supported efficient
SPP	shortest path problem
SS	Solution Scheme
STRIDE	Science and Technology Research Institute for Defence
STV	Surrogate Teleoperated Vehicle
THeMIS	Tracked Hybrid Modular Infantry System
TOV	TeleOperated Vehicle
TSP	travelling salesman problem
TSPP	travelling salesman path problem
TUGV	Tactical Unmanned Ground Vehicle
UAV	unmanned aerial vehicle
UCAV	unmanned combat aerial vehicle
UCV	unmanned combat vehicle
UGCV	unmanned ground combat vehicle
UGV	unmanned ground vehicle
USV	unmanned surface vehicle
UUV	unmanned underwater vehicle

## **LIST OF APPENDICES**

- APPENDIX A TERRAIN PROFILE FOR COMPUTATIONAL EXPERIMENTS
- APPENDIX B LIST OF CHECKPOINTS FOR COMPUTATIONAL EXPERIMENTS
- APPENDIX C PERCENTAGE ATTRIBUTE COST DIFFERENCE OF SOLUTION PATH FROM IDEAL COST
- APPENDIX D SOLUTION PATH COSTS AFTER APPLYING GLOBAL 2-OPT ON SS2 FOR EXPERIMENTS ON SATELLITE IMAGE
- APPENDIX E DISTRIBUTION OF SOLUTION POINTS IN SOLUTION SPACE FOR EXPERIMENTS ON REAL-WORLD SATELLITE IMAGES

# ALGORITMA PERANCANGAN LALUAN SEJAGAT PELBAGAI KRITERIA UNTUK KENDERAAN TEMPUR TANPA WARGA

## ABSTRAK

Kenderaan Tempur Tanpa Warga (KTTW) merupakan sebuah kenderaan robotik bersenjata tanpa pemandu yang digunapakai dalam pertempuran untuk mengurangkan kes kematian dalam kalangan anggota keselamatan ketika menjalankan misi-misi berbahaya. Salah satu aspek yang penting dalam pembangunan KTTW ialah kemampuannya dalam perancangan laluan. Dalam penyelidikan ini, kami mempertimbangkan perancangan laluan sejagat (PLS) bagi KTTW dengan tiga atribut: masa melintas, tahap risiko, serta tahap gangguan signal. Satu ruangan konfigurasi berdasarkan grid telah dibina dari kawasan sekitar dengan menggunakan kaedah pembahagian sel. Masalah PLS telah dijadikan sebagai masalah laluan jurujual kembara pelbagai kriteria dengan titik mula dan tamat yang unik ( $stMLJK$ ) dengan kelonggaran peraturan.  $stMLJK$  pelbagai kriteria ini telah diringkaskan kepada versi satu kriteria dengan menggunakan kaedah agregat pemberat. Untuk menyelesaikan  $stMLJK$ , dua skim penyelesaian telah dicadangkan. Skim Penyelesaian 1 (SP1) membina graf lengkap dengan menggunakan semua titik lawatan terlebih dahulu. Kemudian, pencarian laluan Hamilton berkos paling rendah di dalam graf lengkap akan diperolehi dengan menggunakan algoritma jiran terdekat berulang. Selepas itu, kaedah 2-opt global akan dilaksanakan untuk meningkatkan kualiti keputusan. Bagi Skim Penyelesaian 2 (SP2),  $stMLJK$  akan ditafsirkan sebagai  $stMLJK$  dua tahap berkelompok dengan semua titik lawatan telah dibahagi kepada pelbagai kelompok. SP2 bermula dengan menentukan susunan lawatan kelompok

terpendek terlebih dahulu. Sesudah itu, laluan Hamilton kelompok dalaman akan dicari bagi setiap kelompok. Selepas itu, laluan-laluan antara kelompok dan kelompok dalaman akan digabungkan menjadi laluan penyelesaian lengkap sejagat. Selain itu, dua cara pembuat keputusan berdasarkan kaedah titik impian serta kaedah batasan- $\epsilon$  telah diperkenalkan bagi membantu pengguna ketika menentukan penyelesaian yang paling sesuai bagi mereka. Untuk menguji prestasi SP1 dan SP2, ujian pengiraan telah dijalankan dalam rupa bumi simulasi serta imej satelit sebenar. SP1 dan SP2 mampu menyelesaikan masalah ujian-ujian dalam masa yang singkat. Apabila saiz masalah semakin bertambah, masa pengiraan bagi SP2 adalah sekurang-kurangnya 18% lebih singkat berbanding dengan SP1. Dalam aspek kualiti, SP2 mudah dipengaruhi oleh cara pembahagian titik lawatan kepada kelompok-kelompok. Dalam kebanyakan masa, SP1 menghasilkan laluan penyelesaian yang mempunyai kos atribut yang paling tinggi sebanyak 25% lebih rendah bagi sekurang-kurangnya satu atribut. Secara amnya, kedua-dua skim penyelesaian mampu menghasilkan laluan penyelesaian sub-optimal bagi masalah PLS dalam had masa yang ditetapkan.

# ALGORITHMS FOR MULTI-CRITERIA GLOBAL PATH PLANNING OF AN UNMANNED COMBAT VEHICLE

## ABSTRACT

Unmanned combat vehicle (UCV) is an armed robotic driverless vehicle deployed in modern warfare to reduce the casualties of safety personnel in dangerous missions. An important aspect in the development of UCV is its path navigation capability. In this research, we consider the global path planning (GPP) problem of the UCV with three attributes: traverse time, risk level, and signal jamming level. A grid-based configuration space is constructed from the environment terrain by using cell decomposition method. The GPP problem is then transformed into a multi-criteria travelling salesman path problem with unique origin and destination checkpoints (*st*TSPP) with relaxed constraint. The multi-criteria *st*TSPP can be reduced into single-criteria version by using weighted sum method. To solve the *st*TSPP, two solution schemes are proposed. Solution Scheme 1 (SS1) first constructs the complete graph using all checkpoints, followed by searching for the least cost Hamilton path within the constructed complete graph using the repetitive nearest neighbor algorithm (RNNA). Then, global 2-opt is implemented to improve the solution quality. For Solution Scheme 2 (SS2), the *st*TSPP is viewed as a two level clustered *st*TSPP with all checkpoints partitioned into multiple clusters. SS2 begins by first determining the shortest cluster visiting sequence, followed by searching for the least cost intracluster Hamiltonian path for every clusters. Then, both intracluster and intercluster paths are combined to form a global complete solution path. Two decision making tools based on ideal point method and  $\epsilon$ -constraint method are also introduced to facilitate users

in selecting the most favorable GPP solution path in decision making process. To test the performance of SS1 and SS2, computational experiments are conducted on both simulated terrain and real-world satellite image. Both SS1 and SS2 are capable of solving problems using little amount of time. As the problem size increases, SS2 uses at least 18% lesser time compared to SS1. Quality-wise, SS2 is easily influenced by the way the checkpoints are clustered. For most of the time, SS1 produces a solution path that has at most 25% lesser attribute cost for at least one of the attributes. In general, both solution schemes are capable of producing sub-optimal solution paths for the GPP problem within the limited time constraints.

# CHAPTER 1

## INTRODUCTION

### 1.1 Introduction to Research Topic

An unmanned combat vehicle (UCV), also known as unmanned combat ground vehicle (UCGV), is a robotic military vehicle with nobody onboard. It is used to replace the direct participation of military personnel in high-risk missions. The deployment of UCVs in the battlefield had reduced the casualty among combatants, especially in dealing with Improvised Explosive Devices (IEDs), which is the main reason for casualty among military personnel (Overton, 2017). Nowadays different types of UCVs have been deployed in missions such as combat logistics, Explosive Ordnance Disposal (EOD), reconnaissance, and also search and rescue mission.

UCV is armed with remotely controlled weapons and military equipment. It can be operated through wireless communication signals from an external control station. In the battlefield, UCVs is used as frontline vehicles to provide protection for allies. It is controlled by the operator in a mobile armored vehicle that stayed behind the UCV. For non-lethal missions, the UCV is usually controlled from a fixed control station or by an operator who stays by the side using a hand-held controller. Nowadays, many countries started to develop UCVs into their military arsenals to increase their combat capabilities.

An important aspect in the development of robotic vehicles is its path planning capability. Likewise, the performance of an UCV in a mission is highly affected by its navigation system. As the UCV is driverless, the path planning algorithms in the navigation system need to be designed in such a way that the requirement of human



supervision and intervention is minimized when the UCV is deployed on a mission. The navigation process of UCV can be classified into local and global path planning (LPP and GPP). The LPP process maintains the vehicle's stability during the journey while GPP plans the overall travel path using the terrain information obtained (Giesbrecht, 2004).

In general, the types of algorithms implemented for unmanned vehicle path planning problems are based on the types of missions conducted as well as the types of vehicles used. For example, Han, Kim, and Lee (2014) presented a label-correcting algorithm for multi-criteria GPP problem. Bae, Kim, and Han (2015) presented a two-phase algorithm for UCV reconnaissance problem with a predefined checkpoint visiting sequence. Park, Kim, and Jeong (2012) presented algorithms for determine patrol paths of an UCV with the objective of minimizing enemies infiltration. On the other hand, for the unmanned aerial vehicle (UAV) path planning, Shetty, Sudit, and Nagi (2008) developed a tabu search heuristic for routing a fleet of unmanned combat aerial vehicles (UCAV). Liu, Peng, Zhang, and Li (2012) introduced an algorithm for route planning problem in deploying the UAV for traffic information collection. Due to the large number of constraints and objectives involved in the path planning process, the research works on the GPP problem poses a challenge among researchers.

## **1.2 Problem Statement**

In this study, we consider the GPP problem of an UCV with multiple visiting checkpoints considering multiple costs attributes. The UCV needs to begin and end its journey at a designated checkpoint, and traversing all the other checkpoints

throughout the journey regardless of orders. The checkpoints can be visited multiple times if necessary. The terrain was associated with three attribute costs: traverse time, risk level and jamming level, which modelled into a multiple costs grid map. We are to search for the sequence of visiting cells within the grid map which represents the UCV travelling path such that all the attribute costs are minimized.

### **1.3 Objectives of Thesis**

The objectives of this thesis include:

1. to study the multi-criteria GPP problem of an UCV with multiple visiting checkpoints. In the study process, relevant topics in graph theory and multicriteria optimization were discussed, followed by the mathematical modelling of the UCV GPP problem.
2. to develop the solution schemes for solving the multi-criteria GPP problem for an UCV. Different solution method and heuristic algorithms used in path planning process and decision making were studied. This is followed by developing a suitable solution scheme to solve the UCV GPP problem.
3. to analyze the performance quality of the proposed solution schemes with varying parameters. The developed solution scheme were implemented into various problem sets to analyze its performance quantitative and qualitatively. The obtained results were analyzed and inference were also made.

### **1.4 Significance of Study**

In this study, the GPP of UCV is modelled into the multi-criteria path planning problem on a grid map with multiple visited checkpoints. This research work covers three different aspects:

1. Multi-criteria optimization: searching for solution paths which optimize multiple cost attributes simultaneously.
2. Travelling salesman path problem (TSPP): shortest path problem with the objective of traversing all given checkpoints (may visit more than one time if necessary) regardless of orders with unique endpoints being provided.
3. Grid-based path finding: the terrain is represented in a grid to preserve the details of surrounding information.

To the best of author's knowledge, most of the previous works do not consider all these three aspects at the same time. Our research work demonstrates how these three aspects will be covered in the path planning problem simultaneously. This study can serve as a useful reference for future work involving multiple checkpoints path planning problem presented in a grid such as automation or robotic path planning problem.

### **1.5 Research Motivation**

This research is motivated by the inadequate of studies in military operation based UCV GPP problems that covers the three aspects stated above. From the research works related to UCV path planning problem, most of it only cover part of these three aspects. GPP problem formulation covered with part of these aspects may cause the problem become less realistic enough to reflect the real-world scenario. Hence, we can see that an integration of these aspects in formulating the UCV GPP problem is required. Thus, this research is focus on modelling the UCV GPP problem using such approach, as well as developing a solution scheme to solve it.

## **1.6 Scope and Limitation of Study**

This research covers the discussion on the history and development of the UCV in military field. Some literature studies and comparisons were done to get a more understanding about the problem. Besides that, topics that are related to the modelling and formulation of GPP problem such as graph theory and multi-criteria optimization were discussed. The terrain is modelled into grid using cell decomposition method. Then, the problem was modelled as a TSPP with unique endpoints. Two different solution schemes were developed to solve the problem from different perspectives. The first solution scheme consider the problem set as a giant network and solve the problem from global view. On the other hand, the second solution scheme treat the problem as a two level clustered TSPP, where checkpoints were grouped into clusters. Decision making technique were also developed to aid the user in choosing the most suitable solution paths if multiple feasible solutions were present. To test performance of the proposed solution scheme, experiment tests were conducted on problem sets consists of simulated terrain and real satellite image with different parameter settings. Finally, experimental results were analyzed and discussions were made to state the possible reasoning and explanation to these results.

As this research integrates multiple aspects simultaneously, all the relevant topics were briefly introduced and a solution scheme with simple algorithm procedures were developed. Thus, it is still bounded by several limitations:

1. Global comparison of algorithms in the proposed solution scheme with other existing solution methods. This is because the focus of this study is to formulate the UCV GPP problem and develop a solution scheme that able to solve the problem in predetermined time constraints. Thus, the algorithms in the solution

scheme were not globally compared other existing solution techniques.

2. The number of clusters (in Solution Scheme 2) were fixed beforehand. For the purpose of simplicity, we predetermine the number of clusters to be formed in the preprocessing of Solution Scheme 2. The relation between number of clusters set and solution quality are still open for study.

## **1.7 Organization of Thesis**

In Chapter 1, the thesis begins with an overview of the research topic, including the brief introduction of UCV in military operations, problems related to the GPP of UCV and various solution approaches used to solve the navigation problems of UCV in prior studies. This is followed by the objectives and significance of the research topic.

Chapter 2 discusses the introduction of UCV and its navigation process. The discussion begins with the development of unmanned vehicle technology from its early days to present. This is followed by discussions on the GPP process of UCV, and also the methods used to construct the configuration space for UCV path planning.

Chapter 3 discusses the basic notions of graph theory and multi-criteria optimization problem (MOP). The discussion begins with some basic terminologies and various types of graphs used in modelling real-life problems. Several types of path planning based problems and its variations are discussed, such as the shortest path problem and the travelling salesman problem. Then, some basic concepts in MOP such as Pareto-optimality and visualization of solution space are discussed. This is followed by the construction of the configuration space for the GPP problem using the cell decomposition method, as well as the mathematical formulation of the multi-criteria GPP problem.

Chapter 4 introduces various solution techniques that will be used in solving the formulated GPP problem. This includes preprocessing the data, grid-based path searching algorithms, solution improvement techniques, and multi-criteria decision making tools. All the discussed solution techniques are modified to suit the GPP problem represented in the grid.

Chapter 5 discusses two solution schemes which are developed to solve the multi-criteria GPP problem. Solution Scheme 1 (SS1) models the GPP problem into a single TSPP and solves it globally. On the other hand, Solution Scheme 2 (SS2) converts the GPP problem into clustered TSPP and solves it in a two-level fashion. The systematic procedure of both solution schemes are discussed.

Chapter 6 contains the experiments of GPP on various terrains. The chapter begins by introducing the procedure of experiment setups. The experiments are conducted on both simulated terrain and real-world satellite images with varying parameters. The experimental results and observations are discussed.

Finally, in Chapter 7, the thesis ends with a brief conclusions of the research.

## CHAPTER 2

### UNMANNED COMBAT GROUND VEHICLES

#### 2.1 Introduction

In the past, before unmanned vehicles were introduced for warfare purposes, military operations often involved the direct participation of combatants on the battlefield. In a warzone, frontline combatants are often faced with unseen threats such as Improvised Explosives Devices (IEDs) and enemy ambushes, thus making them highly vulnerable. The success of the mission often comes with a great price as many frontline personnel is harmed by unseen threats. To reduce the exposure of combatants during the mission, military developers began to explore the potential of unmanned vehicles to replace human combatants in high-risk missions.

The exploration of unmanned technology in military operations began with the development of unmanned ground vehicles (UGV). An UGV is a mechanical platform that moves across the ground surface with nobody onboard. It was designated to carry out repetitive and laborious tasks consistently. An UGV can be controlled by an operator from a control station at a safe distance, preventing injuries while working under extreme conditions. Nowadays UGVs are used in many different fields such as heavy industries, search and rescue missions and space exploration (Gage, 1995; Hirose & Fukushima, 2002; László, 2003). An UGV can be classified into two general classes: autonomous and teleoperated. An autonomous UGV can determine its own course using data collected by onboard sensors in real time while a teleoperated UGV is controlled by a human operator externally via a communication link.

In military operations, UGVs serve as a multipurpose robotic platform to extend the capability of soldiers. Its multipurpose platform can be customized in a number of ways including relay stations, fire fighting robots, and medevacs to suit the needs of different missions. In addition to its supportive role, some UGVs are equipped with lethal weapons such as machine guns and anti-tank missiles. These UGVs with combat capability are known as Unmanned Ground Combat Vehicles (UGCVs), or Unmanned Combat Vehicles (UCVs) in short. Some examples of UGV/UGCV are as follows:

- Tracked Hybrid Modular Infantry System (THeMIS): A hybrid UGV manufactured by Milrem, an Estonia-based security and defence services provider (Plate 2.1).



Plate 2.1: THeMIS hybrid UGV (Source: *THeMIS Hybrid Unmanned Ground Vehicle* (2015))

- Black Knight UGCV: Designed by BAE Systems. It can operate autonomously or from within another vehicle (Valois, Herman, Bares, & Rice, 2008) (Plate 2.2).
- 510 Packbot: Manufactured by iRobot. It was widely deployed in hazardous missions such as Explosive Ordnance Disposal (EOD), chemical, biological radiological and nuclear (CBRN) detection, and HazMat handling (Plate 2.3).
- STRIDE UGV: Developed by Malaysian Ministry of Defense's Science and Technology Research Institute for Defence (STRIDE) in collaboration with





Plate 2.2: Black Knight UGCV (Source: *Black Knight* (n.d.))



Plate 2.3: 510 Packbot (Source: *iRobot 510 PackBot Multi-Mission Robot* (n.d.))

Universiti Kebangsaan Malaysia. It was once exhibited at Langkawi International Maritime and Aerospace (LIMA) Exhibition in 2015 (Plate 2.4).



Plate 2.4: STRIDE UGV (Source: Abas (2015))

The deployment of UCVs in military operations reduced the risk of injuries among military personnel while increasing the efficiency of missions at the same time (Odedra, Prior, & Karamanoglu, 2009). Nowadays, unmanned military vehicles are deployed in different missions such as EOD, CBRN detection, and landmine detection and clearance.

## **2.2 Development of Unmanned Combat Vehicle in Military**

The development of UGV/UCV is a long journey that constantly innovates to improve the vehicle's capability in serving complicated military operations. In this section, some significant events that influence the development of UGV/UCV are presented.

### **2.2.1 First Mobile Robot**

The major development of UGV began in the late 1960s when the first mobile robot *Shakey* was developed in Stanford Research Institute, US (Kuipers, Feigenbaum, Hart, & Nilsson, 2017; Nilsson, 1984). *Shakey* is a computerized wheeled platform equipped with sensors and cameras. It receives a user command to perform simple tasks such as route finding and rearranging objects in a controlled environment. The emergence of *Shakey* greatly influenced the development of modern robotics and artificial intelligence. *Shakey* serves as the function and performance baseline for subsequent UGV development works. In 2004, *Shakey* was elected in Carnegie Mellon's Robot Hall of Fame and it currently resides in the Computer History Museum, California (source: *SRI International's "Shakey The Robot" Selected as Robot Hall of Fame Inductee*, 2004).

In the early 1980s, *Shakey* reappeared in the Defense Advanced Research Projects Agency's (DARPA) Strategic Computing Program as the Autonomous Land Vehicle (ALV). The ALV can travel on various outdoor terrains and perform obstacle avoidance all by itself (Lowrie, Mark, Keith, & Matthew, 1985). However, the ALV program's focus was later shifted from military application towards support in scientific experiments (Douglass, 1988). The navigational systems in ALV were later

adopted by other military vehicle projects. Following this, more mobile robot development efforts were conducted, and this leads towards the emergence of various task-specific UGV.

### **2.2.2 UGV for Handling IED**

In warfare, one of the biggest threats faced by combatants is the IED. An IED may come in various appearances and size, from small parcel bombs to large car bombs. According to Overton (2017), a total of 7,223 IED incidents occurred in 85 countries worldwide from 2011 to 2016, causing more than 23,000 deaths and injuries among armed personnel. Twelve countries have recorded more than 140 IED incidents in the Middle East, Africa, and Asia. This is because IEDs are relatively cheap compared to other firearms. Besides that, IEDs can be built easily from scraps and are difficult to detect as they can blend in daily objects. These factors greatly increase the risk and difficulty in IED detection and EOD procedure. Hence, one of the major applications of UGV is EOD and bomb disposal (Odedra et al., 2009).

In 1972, Lt. Col. Peter Miller developed the first *Wheelbarrow* UGV for the British Army bomb disposal team in Northern Ireland (Odedra et al., 2009). The *Wheelbarrow* was built from a modified lawnmower with a wheelbarrow, from which it gets its name. It is one of the most successful UGVs used in the EOD mission ever. Subsequently, various versions of *Wheelbarrow* UGV were developed. To date, the state-of-the-art model *Wheelbarrow Revolution* has been used by military and public security worldwide in counter-terrorism.

### **2.2.3 UGV for Reconnaissance, Surveillance, and Target Acquisition (RSTA)**

Another important feature that interest military UGV developers are the Reconnaissance, Surveillance, and Target Acquisition (RSTA) applications (László, 2003). In an RSTA mission, soldiers are sent out to scout a targeted location and gather army intelligence. Most of the time they are situated in an unknown environment surrounded by unseen threats, which make them vulnerable. The deployment of UGVs with RSTA application has provided the battlefield commander with the capability of collecting intelligence as well as remote firing weapons from a safe distance while engaging with enemies.

In the early 1980s, two RSTA based project was developed by Naval Ocean System Center (NOSC): the Ground Surveillance Robot (GSR) and Advanced Teleoperator Technology (ATT) Tele-Operated Dune Buggy (Gage, 1995; László, 2003). The GSR system was built on an M-114 armored personnel carrier which is capable of following the leading vehicle and moving human. On the other hand, the ATT Tele-Operated Dune Buggy successfully demonstrated the capability of traversing on complex terrain and operating a mounted weapon system remotely. In 1985, NOSC continued the research work by initiating the Ground/Air TeleRobotic System (GATERS) program to develop the TeleOperated Vehicle (TOV). The TOV consists of a remote vehicle with an operator control station connected by a secure communication link up to 30 km away. The TOV can be controlled by a joystick and is capable of performing long-range RSTA, chemical agent detection, and remote firing weapons.

Following the successful demonstration of several RSTA based UGV, more development programs were initiated to further explore the capabilities of UGV in

other fields. Some examples are as follows:

- **Robotic Ranger:** Developed by Army's Missile Command (MICOM) in early 1982 with the objective to develop robotic systems for battlefield use. Armed with remotely controlled anti-armor missiles which can be used against armored vehicles (Gage, 1995).
- **Surrogate Teleoperated Vehicle (STV):** Developed under Tactical Unmanned Ground Vehicle (TUGV) program by Robotics System Technology (RST) in 1990. It is small enough to be transported by helicopters and Humvee, but still fast enough to keep up with vehicle convoys (Gage, 1995).
- **ARPA DEMO II program:** A UGV demonstration that showcases the multiple vehicle controls capability which conducted in 1996. The program demonstrated multiple vehicles operating cooperatively under supervised autonomy in a scout mission (László, 2003).
- **ROBART I:** The first autonomous site security (sentry) robot developed by Naval Postgraduate School in 1981. Built in with collision avoidance sensors, ROBART I is used for indoor sites patrolling. More security robotic platforms were developed afterwards such as ROBART II, PROWLER and K2A Navmaster (Everett & Gage, 1999).

#### **2.2.4 DARPA Grand Challenge**

Compared to the unmanned aerial vehicle (UAV), unmanned surface vehicle (USV), and unmanned underwater vehicle (UUV), the development of UCV/UGV is the hardest due to the complicated ground surface which poses many unpredictable situations. This requires a large amount of data handling and dynamic variables to

capture all possible configurations exhibited. To promote innovation in the development of unmanned vehicle technology, DARPA has announced a prize competition known as DARPA Grand Challenge (Iagnemma & Buehler, 2006). In this competition, competing vehicles are required to complete an off-road course filled with obstacles within a limited time constraint.

The first DARPA Grand Challenge was held on 13 March 2004 in Mojave Desert, US, with the \$1 million prize reward. In this competition, none of the vehicles are able to complete the entire 142 miles course successfully. The best travel record set only covered up to 7 miles while most of the other teams only traveled up to a few hundred yards (Vance, 2004). This is due to the lack of adaptability of vehicle sensors to sense and react to vast environmental changes compared to indoor controlled lab conditions. This showcased the difficulties in developing UGV/UCV. However, DARPA Grand Challenge has drawn the attention of many developers to come up with different innovations in off-road unmanned navigation systems.

### **2.2.5 Next Generation UGV**

Although the UGV/UCVs developed so far are capable of conducting the required tasks successfully, they are still bound by certain limitations. One of the limitations is that the design of these UGV systems is mostly task-specific (Odedra et al., 2009). The lack of versatility of UGVs in dynamic environments has resulted in the increase of military spending in purchasing a variety of vehicles for a different types of missions. In addition, some older UGV systems come in big sizes which lacks mobility and portability. Thus, a more capable next-generation UGV is needed to provide versatility for combatants to adapt to changes during the mission. Some

examples of future generation UGVs are as follows:

- Remotec Cutlass: Equipped with an upgraded system, Remotec Cutlass can achieve faster travel speed and carry more payloads. It is equipped with an intelligent manipulator arm, where the operator can remotely change the tools attached on its arm based on what is needed. In 2010, 80 Remotec Cutlass were supplied to the UK Ministry of Defence for counterterrorism purposes through a £65 million contract (Odedra et al., 2009).
- AvantGuard UGCV: A variation of Guardium UGV developed by G-NIUS Unmanned Ground Systems in Israel. It is equipped with counter-IED jammer, thermal surveillance camera, vehicle detection radar, and other equipment. It is capable to perform operations such as patrolling, IED neutralization and following a guide soldier or vehicle. (source: *AvantGuard Unmanned Ground Combat Vehicle* (n.d.))
- THeMIS hybrid UGV: By customizing its multipurpose platform, THeMIS can easily transform into various roles such as demining platform, anti-tank platform, supply transport vehicle and medevac.

### **2.3 The Navigation Control of UCV**

One of the important aspects of a modern UCV is its path planning capability. This is because an UCV works differently compared to a human driver. A human driver can make judgments based on their critical thinking skills. On the other hand, the UCV's efficiency depends on its navigation capability under different circumstances. Thus, a wide range of techniques has been developed for UCV navigation and path planning under different circumstances.

Humans have the ability to plan and make decisions that suits them best. For example, we prefer to drive on a longer route with smooth traffic rather than driving on a short route with heavy traffic. This is because we prioritize travel time more than the travel distance. Making priority between choices is one of the cognitive skills possessed by a human being. With other skills such as adapting from past experiences, analyzing trade-offs between choices and making logical deductions, we can make decisions that benefit us in all aspects as much as possible.

In addition, humans also have the ability to interpret and classify objects. A human brain can partition the environment into segments of objects together with its details to use it for problem-solving. For example, we can recognize the details on the map such as relative direction, distance, terrain type, as well as identify objects such as obstacles, possible hazards, and shortcuts. Using these details, we can look for suitable travel paths based on logical deductions and reasoning.

Analogous to a human driver, an UCV has an auto navigation system which works in the same way as a human brain. This navigation system is capable of identifying surroundings, converting it into detailed terrain data, and using it to search for travel routes. The UCV works in a systematic procedure by first recognizing the environment by obtaining terrain data such as elevation, terrain roughness, hazard level, estimated fuel consumption and traversal time. The process is followed by applying path planning algorithms on acquired data to search for an ideal travel route based on user requirement (Giesbrecht, 2004).

There are two types of UCV navigation process: Local Path Planning (LPP) and Global Path Planning (GPP) (Han et al., 2014). LPP uses the UCV surrounding data



obtained from vehicle sensors and cameras to maintain vehicle stability in real time. On the other hand, GPP is a process that uses previously acquired geographical data to plan for long-range travel routes which prevent the UCV from entering or being trapped in harsh environments while minimizing resource consumption at the same time. As the GPP is a deliberate process, it is usually conducted before an UCV begins its journey. Nowadays, UCVs are equipped with high sensitivity local navigator systems that are able to perform LPP processes without requiring much human intervention. In this study, we assume that the UCV is able to perform LPP processes such as obstacle avoidance, stability maintenance and changing direction all by itself.

#### 2.4 Global Path Planning Process of UCV

GPP is an important process in outdoor robotic navigation. The process search for an ideal path in long distance travelling using accumulated terrain information. In general, the path planning process is illustrated in Figure 2.1.

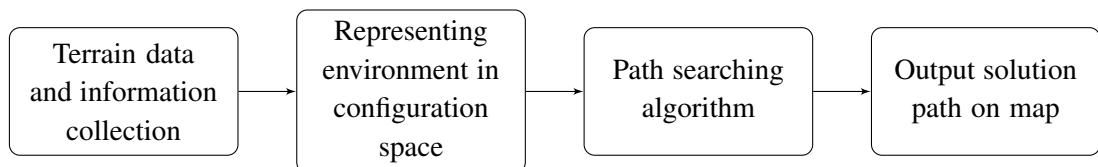


Figure 2.1: The procedure of GPP.

The GPP process consists of two main parts: constructing a configuration space (c-space) and perform path searching algorithm. The GPP process begins by collecting aerial images and terrain data of the region where military operation was planned, which also known as the area of interest (AOI) via satellites or other sources beforehand. The AOI environment is represented in an appropriate manner where the path planning algorithm can be executed by a computerized UCV. From the acquired terrain images, a search space consists of all possible states an UGV may exhibit at

any time, known as configuration space is constructed. The c-space represents each possible situation an UCV can exist in the environment, where each situation in time is given a unique combination of its position and orientation known as configurations.

In c-space, each configuration is represented as a single point associated with the magnitude of the configuration's component such that these terrain informations are digitized. Thus, the computerized UCV reduces the GPP process as the planning of continuous motion of a point. The dimension of the c-space is the number of components considered in c-space, which is decided based on the complexity of the vehicle design and the terrain conditions of the AOI. For example, in path planning of an indoor robot, a three-dimension c-space is usually considered ( $x$ -position,  $y$ -position, and orientation angle). However, the GPP problem complexity grows exponentially with the dimension of the c-space. In high-level robotic UCV path planning, it is sufficient to represent the AOI using two-dimensional c-space ( $x$  and  $y$  position). This helps to reduce the GPP problem complexity to achieve better performance speed.

The path searching algorithm to be implemented on GPP of UCV is determined by how the c-space is represented. In general, there are three categories of c-space representation methods: cell decomposition, roadmap, and potential field (Giesbrecht, 2004). The cell decomposition method divides the AOI into a set of discrete, non-overlapping cells, where the terrain data corresponding to that region is assigned to the corresponding cells. The second representation method, roadmap, implements specific procedures to search for all the significant points in the AOI and uses these significant points to form a network that connects all key locations. On the other hand, the potential field method uses mathematical functions to model the UCV as a point

under the influence of energy fields possessed by the surrounding obstacles and checkpoints. Analogous to the charged particles, a checkpoint poses an attraction force while obstacles pose repulsive force towards the UCV.

Once the c-space is constructed, the GPP process follows by using a path searching algorithm to search for ideal solution paths. The algorithm is executed based on user input. The input parameters usually includes basic information such as coordinates of visited checkpoints, order of visiting checkpoints, as well as various constraints and resource consumption limits. If a solution path that suits the user requirements is found within the c-space, its solution path will be projected onto the terrain map. Otherwise, the algorithm reports failure if no solution paths are found and the user has to readjust the input parameters to recompute.

## **2.5 Representing the Environment in Grid Form**

In military operations, an UCV often travels into unexplored regions such as deep jungles or deserted areas. This is completely different compared to driving in an explored or developed environment where the surrounding information can be accessed easily. Thus, it is important to use a c-space representation method that can store a great deal of information and is flexible and easy in terms of data handling and algorithm implementation. Under such considerations, the cell decomposition method is preferable to be used (Giesbrecht, 2004).

By using the cell decomposition method, the AOI terrain is inscribed in a grid made up of a set of non-overlapping cells of equal size and shape. There are various types of cells such as trellis, hexagonal cell and squared cell. Among these, the squared cell grid is widely used due to its simplicity. This forms a grid map where every cell is

adjacent to other cells. In a grid map, each cell holds the terrain information of the corresponding region in the real-world terrain. To enable the data of each cell to be processed by a computerized UCV, the grid map can be further reduced into a graph, where the center of the cell becomes the node and the path between two adjacent cells be the undirected edge of the graph. Each node is assigned with a vector representing the cost of different attributes on the corresponding cell. The cost of a route can be evaluated by summing up the cost vector of traversed nodes. The constraint limit on each attribute can also be assigned to monitor the attribute level with respect to the traversed path throughout the path searching process.

## **2.6 Studies Related to Path Planning Problem**

A real-world path planning problem is usually an integration of problems from various disciplines such as graph theory, algorithm design, operation research and optimization theory. The variation of path planning problem formulated can be based on aspects such as terrain types, number of agents, visiting rules and resource constraints. Besides vehicle based navigation, path planning problem also being implemented in other fields too. Table 2.1 shows some literatures related to the path planning problems in both military and other fields. The literatures were classified according to several aspects as follows:

- Grid modelling: Is the c-space constructed using a grid based modelling?
- Multiple attributes: Do multiple resources consumption were considered during the path traversal?
- Multiple visiting checkpoints (mvc): Do the path planning involves multiple checkpoints, or just a pair of start and destination checkpoints?

- Hamiltonian (for literatures with mvc only): Do the agent visits all or a subset of the checkpoints?
- Fixed visiting order (for literatures with mvc only): Do the agent has to visits the checkpoints according to predetermined order sequence?
- Multiple agents: Do the literature study consider multiple agents or single agent?

For military based path planning, Shetty et al. (2008) discussed the path planning of a fleet of heterogeneous UAVs in servicing a list of predetermined targets in surveillance mission. The UAV fleet comes with different payload capacity and the targets were given a minimum and maximum service level indicating the amount of ammunition required to inflict sufficient damage on that region. The problem was divided into two separate subproblems: target assignment problem and vehicle routing problem, and it was solved using tabu search heuristic. Park et al. (2012) discussed the UCV patrol path planning problem with the objective of minimizing the time-average risk of enemy infiltration. The terrain are not represented in grid as the traverse paths between each checkpoints are known in advance. The checkpoints were given an importance level and are allowed to be visited multiple times during the planning horizon to minimize the infiltration risk throughout the time. The author developed a two-phase heuristics where in first stage an initial patrol path was constructed and then further improvement was done in second phase.

Han et al. (2014) discussed the UCV GPP problem for a pair of checkpoints that consider three attributes: traverse time, risk level, and signal jamming level which have to be minimized. The problem was modelled in a 8-directed grid graph and the cumulative attribute costs limits were given in advance. The problem was considered as resource-constraint shortest path problem. The author proposed a modified label

Table 2.1: Collection of literatures related to path planning problem.

Author (year)	Grid modelling	Multiple attributes	Multiple visiting checkpoints (mvc)	Hamiltonian (for mvc only)	Fixed visiting order (for mvc only)	Multiple agents	Solution technique / remarks
<u>Path planning in military unmanned vehicles</u>							
Shetty et al. (2008)		✓	✓			✓	Tabu search heuristic (the problem was divided into target assignment problem and vehicle routing problem)
Park et al. (2012)			✓	✓			Two-phase heuristic (the checkpoints are to be visited multiple times during the planning horizon to minimize infiltration risks)
Han et al. (2014)	✓	✓					Modified label correcting algorithm + heuristic to speed up the computation.
Bae et al. (2015)	✓	✓	✓	✓	✓		Two phase optimal solution algorithm + heuristic to speed up the computation.
<u>Path planning in other fields</u>							
Martin et al. (1991)			✓	✓			The printed circuit board production flow was divided into several subproblems which modelled as TSP
Weihua et al. (2005)			✓	✓			The automated robotic inspection system was modelled into two-level TSPP
Liu et al. (2012)			✓			✓	Non-dominated sorting genetic algorithm
Kuby et al. (2014)			✓				Dijkstra's algorithm (a web-mapping and routing tool was presented to solve the problem)

correcting algorithm with a heuristic method to speed up the computation for large problem instances. On the other hand, Bae et al. (2015) discussed a UCV path planning problem for visiting a list of checkpoints in predetermined order with the objective of minimizing the traverse time for a given limit of associated risk level. The terrain was modelled into a 8-directed grid graph with given traverse time and risk level. The author developed an optimal solution algorithm based on dynamic programming for multiple-choice knapsack problem, together with a heuristic algorithm to speed up the computation for large problem instances.

For path planning problem in other fields, we reviewed literatures from both vehicle based and non-vehicle based navigation application. For vehicle based problem, Kuby et al. (2014) discussed the alternative-fuel vehicle (AFV) route planning problem. An online routing tool was developed to plan the road trip based on the initial AFV fuel level, driving range and desired destination. The solution path was searched using Dijkstra's algorithm. The routing tool returns the driving route with AFV refueling stations included along the journey to allow vehicle refueling. Also, Liu et al. (2012) discussed the multiple UAV path planning problem for traffic information collection. The problem's objective is to plan the route for multiple heterogeneous UAVs that minimize the total cruising distance while maximizing the visiting targets. The problem was formulated into multi-objective optimization problem and non-dominated sorting genetic algorithm was developed to solve it.

Path planning problem also being applied in industries. For example, Martin et al. (1991) discussed the optimization problem in the production of printed circuit board (PCB). In the making of PCB, the board needs to be drilled, wired and covered with light sensitive material in a certain pattern using replaceable heads parts. These