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Dynamic vehicle routing with limited communications

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Defence R&D Canada – Ottawa

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Abstract

Unmanned vehicles are becoming essential platforms for dangerous and difficult tasks reducing the risk for humans. The biggest challenges involve guaranteed mission success despite degraded mission critical hardware and communications networks. The multiple Dynamic Travelling Repairmen Problem (m-DTRP) has applications for unmanned vehicles for search and rescue applications, exploration applications as well as combat scenarios. The m-DTRP has been studied extensively in literature for theoretical scenarios but solutions lack application in mobile robotics applications with impractical communications assumptions. We propose the development of an algorithm for the m-DTRP that relies on local demand and position information and local communications ability to collaborate with other agents to optimize routes. The algorithm uses the transmission of target points with expected service times for agents to decide which demands to take on locally. We expect to observe lower bounds on the number of agents required for system time to converge based on target generation rate and environment area. We expect the algorithm to be a platform for diverse environments with heterogeneous swarms of agents.

Résumé

Les véhicules sans pilote sont en voie de devenir des plateformes essentielles pour accomplir des tâches dangereuses ou difficiles en réduisant les risques pour les personnes. Les principaux défis sont liés à réalisation assurée des missions en dépit des dégradations du matériel essentiel et des réseaux de communication. Le problème des multiples voyageurs commerciaux dynamiques (multiple Dynamic Traveling Repairmen Problem - m-DTRP) s’applique aux véhicules sans pilote dans le cadre de recherche et sauvetage, d’exploration et de scénarios de combat. Le m-DTRP a fait l’objet d’études intensives dans ces scénarios théoriques, mais les solutions s’appliquent mal en robotique mobile en raison d’hypothèses peu réalistes relatives aux communications. Nous proposons le développement d’un algorithme de m-DTRP qui se fonde sur les renseignements locaux sur les demandes et les positions et sur la capacité de communication locale pour collaborer avec d’autres agents dans le but d’optimiser les parcours. L’algorithme utilise la transmission de points cibles et de délais de service prévus pour permettre aux agents de décider quelles demandes elles doivent traitées localement. Nous nous attendons à observer des limites inférieures du nombre d’agents requis pour permettre la convergence des délais du système en fonction de l’environnement et du taux de génération de cibles. Nous prévoyons que l’algorithme sera une plateforme qui prendra en charge divers environnements et des essaims d’agents hétérogènes.

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Executive summary

Dynamic vehicle routing with limited communications

David Pike; DRDC Ottawa CR 2011-184; Defence R&D Canada – Ottawa; December 2011.

The multiple-Dynamic Travelling Repairman Problem is a widely studied in operations research with applications in mobile robotics. Applications include search and rescue operations, planetary and underwater exploration as well as airstrike scenarios. Current solutions for the problem either require full information of the environment or global broadcasting capabilities. These requirements are impractical for some scenarios as larger environments impose demanding hardware capabilities for communications. Also, as problem sizes increase (increased number of vehicles and/or targets), bandwidth requirements increase linearly.

We propose a new problem definition where vehicles rely on local information for path planning and take advantage of limited communications ability. We assume vehicles have a circular sensing ability to recognize targets and a circular communications ability to transmit information to neighbouring vehicles. We propose a communications protocol where vehicles will broadcast realized targets along with an expected service time to nearby vehicles. We will investigate various algorithms for the single vehicle tours and compare results with optimal algorithms with complete information.

The proposed algorithm will be validated through simulation and experimentation. The proposed algorithm will be successful in simulation if we can show convergence under certain parameter constraints. The proposed algorithm will be successful in experimentation if we can implement the communications aspect of the algorithm on four robots with noise present. Our anticipated contribution to literature is an algorithm for the problem relying on local communications and sensing ability and thus more practical for mobile robotics applications.

Sommaire

Dynamic vehicle routing with limited communications

David Pike ; DRDC Ottawa CR 2011-184 ; R & D pour la défense Canada – Ottawa ; décembre 2011.

Le problème des multiples voyageurs commerciaux dynamiques (multiple Dynamic Traveling Repairman Problem) a fait l'objet d'études intensives avec des applications en robotique mobile. Ces applications comprennent les opérations de recherche et sauvetage, l'exploration planétaire et sous-marine et les scénarios de frappe aérienne. Les solutions actuelles du problème exigent des renseignements complets sur l'environnement ou des capacités complètes de télécommunications. Ces exigences ne sont pas réalistes dans certains scénarios où des environnements plus vastes imposent des contraintes en matière de communication. De plus, l'accroissement de la taille du problème (un plus grand nombre de véhicules ou de cibles) entraîne un accroissement proportionnel de la bande passante requise.

Nous proposons une nouvelle définition du problème dans le cadre de laquelle les véhicules utilisent les renseignements locaux pour planifier leur parcours et mettent à profit les capacités limitées de communication. Nous supposons que les véhicules possèdent une capacité de détection omnidirectionnelle qui leur permet de reconnaître les cibles et une capacité de communication omnidirectionnelle qui leur permet de transmettre des renseignements aux véhicules à proximité. Nous proposons un protocole de communications dans le cadre duquel les véhicules diffusent les cibles détectées et le délai de service prévu aux véhicules à proximité. Nous étudierons divers algorithmes de parcours de véhicules particuliers et comparerons les résultats obtenus à ceux d'algorithmes optimaux fondés sur des renseignements complets.

L'algorithme proposé sera validé au moyen de simulations et d'expériences. L'algorithme proposé sera jugé valide dans le cadre de simulations si nous pouvons démontrer la convergence selon certaines contraintes des paramètres. L'algorithme proposé sera jugé valide dans le cadre d'expériences si nous pouvons appliquer les aspects de l'algorithme relatifs aux communications à quatre robots en présence de bruit. Notre contribution prévue à la littérature sera un algorithme qui répond au problème en utilisant les communications et les capacités de détection locales et qui sera donc plus pratique pour les applications de robotique mobile.

Table of contents

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1 Introduction

Unmanned vehicles are becoming essential warfare and homeland security platforms. They have the potential to significantly reduce risk to humans by replacing them in dangerous tasks within the Canadian airspace and combat zones.

The most significant challenges with current unmanned vehicle implementations are ensuring missions success despite degraded operations of vehicle components and disruption of communication networks.

The multiple travelling salesman problem (mTSP) has various applications for swarms of mobile robots. Swarms of robotic agents could employ the mTSP for searching numerous points of interest to find survivors of a disaster or delivering a payload to various targets during an air strike. The mTSP can also be extended to scenarios with heterogeneous agents.

The travelling salesman problem (TSP) was first defined mathematically by Karl Menger [1] in 1930. Held and Karp [2] later showed the Hamiltonian cycle problem to be NP-complete; implying the TSP to be NP-hard. The single travelling salesman problem was extended to m salesman problem visiting n cities.

Exact solutions for the mTSP have been found with integer linear programming solutions [3, 4, 5] as well as branch and bound algorithms [6, 7]. While exact solutions to the m-TSP are efficient, algorithms are expensive computationally and require complete information of the environment making them poor candidates for distributed solutions.

Gorenstein [8] was the first to transform the multiple TSP into the single TSP. Literature contains many transformation solutions for the mTSP [9, 10, 11, 12, 13, 7] requiring algorithms for determining the minimum spanning tree of targets within the environment [14, 15]. Algorithms solving the minimum spanning tree operate with an approximation factor of the optimal TSP tour. An algorithm has an a-approximation factor if the time to complete is a times that of the optimal tour. The algorithm by Christofides [15] is primarily used in literature [16, 17] for determining the single vehicle tour. Christofides algorithm solves the single vehicle tour within an approximation factor of 1.5 in $O(n^{2.5})$ (where n is the number of cities). Transformation solutions for the mTSP are feasible computationally for mobile robotics applications however require total information of the environment.

Literature contains heuristic solutions for the mTSP requiring less computation time and achieving more efficient solutions. Russell [18] was one of the first to address the mTSP problem with a heuristic approach, extending the work of Lin and Kernighan [19] for the TSP. The authors solved the single depot case with a static demand extending the work done by Christofides et al. [15] by altering the paths taken by the salesmen based on side conditions. The algorithm iteratively optimizes the paths for the multiple salesmen case by comparing with the single salesman case. The algorithm outperforms the Christofides algorithm for problems with and without distance and time constraints. Neural network approaches have been used [20, 21, 22, 23, 24, 25] with the best performance achieved by

Torki [24] with optimality factor of 1.065 for worst-case scenarios and a 1.04 optimality factor on average. Other heuristic approaches include the use of Tabu search [26], genetic algorithms [27], simulated annealing [28] and neuro-fuzzy systems [29].

2 Preliminaries

The Dynamic Travelling Repairman Problem (DTRP) is an extension of the TSP first introduced by Bertsimas and Ryzin [30] in 1991. The TSP was extended by continually adding cities to the demand of the salesman. The authors later introduced the multiple Dynamic Travelling Repairman Problem (m-DTRP) with multiple salesmen visiting cities. We will refer to the salesmen as agents and cities as targets for our purposes. We define n to be the number of targets and m the number of agents in the workspace. For the m-DTRP, agents start in random locations within the environment. Targets are generated as a stochastic process throughout the environment with a location and service time. Target generation is modelled as a spatio-temporal Poisson process with temporal intensity $\lambda > 0$. The load of the stochastic process generation targets is defined as:

$L = \frac{1}{mn} \sum_{\alpha=1}^{n} \lambda s_\alpha$

where s_α is the service time associated with target α, m the number of agents servicing demands and n the number of targets.

A light load workspace is defined when $L \to 0^+$ and a heavy load workspace with $L \to 1^-$.

Let w_k be the wait time associated with target k. System cost is defined as the summed wait times of all targets. Average wait time is the mean of all wait times in the total demand. Both of these are defined below.

$W = \sum_{k=1}^{n} w_k$

$\bar{w} = \frac{1}{n} \sum_{k=1}^{n} w_k$

A routing algorithm is stable if $\bar{w}$ converges as $t \to \infty$. An algorithm's performance is measured by how the system cost compares to the system cost of the optimal offline algorithm. We refer to the optimal tour as the offline tour and the decentralized tour as the online tour. Let $C(I)$ be the cost of problem instance I. An online algorithm is c-competitive if it's cost on any problem instance is at most c times the cost of an optimal offline algorithm:

$C_{online}(I) \leq c * C_{offline}(I)\ \forall$ problem instances I

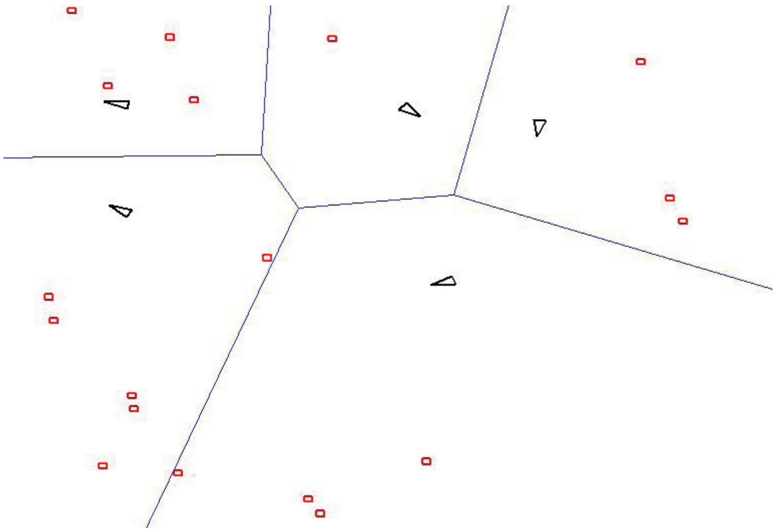

Figure 1: *Environment divided into Voronoi partitions*

Literature primarily focuses on solutions for the m-DTRP that dissect the workspace into regions while vehicles are either assigned dynamically to a region [16] or assigned a priori [17, 31].

3 Related Work

Bertsimas and Ryzin [17] were the first to propose the m-DTRP along with their sequential queue median (SQM) solution. The SQM algorithm divides the environment into m partitions where m is the number of agents servicing targets. The agents are assigned a priori to each region and each agent calculates the optimal single vehicle tour [15] throughout the region. The authors showed the algorithm to be c-optimal in light load conditions.

Bertsimas and Ryzin [32] later presented their Unbiased Travelling Salesman policy (UTSP) operating with known vehicle locations which was shown to be optimal in heavy load conditions. The algorithm divides the environment into $r > m$ wedges meeting a central point. Each agent moves through a subregion in an optimal TSP tour containing n/r targets.

Frazzoli and Bullo [31] used Voronoi partitions in their multi-Receding Horizon (mRH) algorithm and showed their work to be locally optimal for certain stochastic densities. The algorithm works by each agent calculating the tour reaching the most targets within a given time frame. Agents ignore targets outside their assigned Voronoi partition. The mRH algorithm is shown to be locally optimal in light load cases. Figure 1 shows a Voronoi partition between five agents. The SQM and mRH use Voronoi partitions to divide the workspace into regions where each agent performs their single vehicle optimal tour.

Lagoudakis et al.[33] presented an auction framework based on three types of cost functions for the static demand case. The authors derive upper and lower bounds for their six bidding algorithms in comparison with optimal TSP tours. The auction algorithms require each agent to have it's local position, position of all targets as well as the number of agents servicing demands.

Smith and Bullo [34] developed three algorithms for the static demand case for light and heavy load conditions. Their Euclidean Travelling Salesman Problem (ETSP) algorithm operates under full target knowledge but does not require knowledge of neighbouring agents. Each agent computes their optimal TSP tour through the total demand. Agents broadcast their current target, previous target and next target over a limited range. When agents receive broadcasts from other agents, they remove the three targets received from their route. The algorithm was shown to be c-competitive with the optimal m-TSP tour. The authors introduced their Rendezvous algorithm for the static demand case. The Rendezvous algorithm starts with all vehicles meeting in a central location within the environment, dividing up the target locations to each vehicle and carrying out the single-depot mTSP from the central location. The authors developed their Grid Assignment algorithm where the region is divided into cells based on communication range between agents. The Grid Assignment algorithm divides agents into leader and servicing agents. Leader agents are assigned to a cell and communicate targets to servicing agents. The Grid Assignment algorithm was also shown to be c-competitive.

Pavone et al.[16] developed their multi-vehicle Divide and Conquer (mDC) which partitions the environment into $r > m$ partitions of equal area. Agents assign themselves to subregions and perform single-vehicle TSP tours through the outstanding demand points. The algorithm is m-competitive (where m is the number of agents) in heavy load conditions but only sub-optimal in light loads. Since the mDC policy is m-competitive to the offline algorithm, system time grows increasingly inefficient as the number of agents increases. The algorithm is shown to be adaptive to target generation rates. For example, previous works showed control policies to be c-competitive for certain λ values while the mDC policy can adapt and converge to increased λ values.

Bullo et al.[35] presented two algorithms for light and heavy load conditions using region dissection with priority classes of targets. Their separate queues (SQ) policy partitions the environment into m equal regions and assigns one vehicle to each region. When the demand is empty for a specific region, the vehicle occupying that region will move to the median of the region. The algorithm is shown to be within $2n^2$ of the optimal system time.

Arsie et al.[36] introduce an algorithm for the dynamic demand case requiring no communication between agents. The algorithm assumes targets can globally broadcast their positions throughout the workspace. The no-communications (NC) algorithm assigns each agent to the closest target not serviced. As soon as a target becomes serviced, other agents heading towards that target move to the next closest in the demand. The algorithm is shown to be stable in light loads. Arsie et al. [36] extended this algorithm to use Voronoi partitions which they refer to as their sensor-based (SB) policy. The SB policy is shown to be stable in heavy loads.

The solutions discussed above are efficient with regards to distance travelled and service

Table 1: *Decentralized algorithms for the mTSP and mDTRP with inputs*

Authors	**Implementation**	**Information**
mTSP		
Smith and Bullo [34]	ETSP	-Full demand, local communications
	Grid Assignment	-Full demand or local sensing
Lagoudakis et al.[33]	Auction framework	-Local location, Full demand, Number of agents
mDTRP		
Bertsimas,Ryzin[17]	mSQM	-Vehicle positions, full demand
Bertsimas,Ryzin[32]	UTSP	-Vehicle positions, full demand
Frazzoli,Bullo[31]	mRH	-Vehicle positions, full demand
Pavone et al.[16]	mDC	-Vehicle positions, full demand
Arsie et al.[36]	NC	-Full demand
	SB	-Vehicle positions, full demand

time however require impractical information of the environment. The SQM policy [17] requires the vehicle positions of all agents in the field along with full target information. The UTSP [32] requires all vehicle positions and full demand information. The mRH and mDC policies require vehicle positions as well as full target information. The no-communications policy by [36] requires full target information while the sensor-based policy requires all vehicle positions and full target information. Both requirements of all agent positions and full target information are impractical for mobile robotics applications. This will be discussed further in Section 5.4. Table 1 summarizes policies for the m-DTRP along with the information required.

4 Thesis Topic

Our research goal is to develop an algorithm comparable to those proposed in literature while only assuming local communications and sensing abilities. Previous works assume target positions of all agents in the workspace [31] or global broadcasting ability of targets [36]. The algorithm will be simulated in MATLAB and compared against offline algorithms with full information to determine how close the proposed solution is to the optimal solution. Algorithms will be compared in varying load conditions for comparison to literature. The proposed policy will be more practical for mobile robotics applications as global communications assumptions are not present.

5 Problem Definition

Let $\Omega \subset \mathbf{R}^2$ be a convex domain on the plane with non-empty interior. We will refer to Ω as the workspace and $q \in \Omega$ as a target in the workspace. A target q is defined by it's coordinates x, y within the workspace boundaries. We will assume that targets have a negligible servicing time such that as soon as a vehicle reaches a target location, that target is serviced or $s_k = 0 \ \forall k$ where s_k is the service time associated with target k

[17, 31, 36, 16, 35].

A stochastic process generates service requests over time within Ω [17, 31, 36, 16, 35]. These points are referred to as targets. The process generating service requests is modelled as a spatio-temporal Poisson process with temporal intensity $\lambda > 0$ and an absolutely continuous spatial distribution described by the density function $\psi : \Omega \mapsto \mathcal{R}_+$ with bounded and convex support within Ω [36]. The spatial density function ψ is normalized such that $\int_\Omega \psi(q)dq = 1$.

The cost associated from travelling from point q_i to q_j in Ω will be the Euclidean norm where

$c_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$ where (x, y) is a point in Ω

Note also the cost travelling from q_i to q_j is the same as for travelling from q_j to q_i. Therefore, the environment has symmetric costs in Ω.

The robot model will be taken from [31, 36, 34] as omni-directional holonomic points with bounded velocity. Let $p(t) = (p_1(t), \dots, p_m(t)) \in \Omega^m$ be the positions of the m agents within the workspace Ω [36, 31]. We will consider the robots to be omni-directional, holonomic points with the only constraint being the maximum velocity of the robots [36, 31]. The dynamics of the vehicles are given by:

$\frac{dp_i(t)}{dt} = u_i$ with $||u_i|| \leq u_{const}$

Without loss of generality, we will assume $u_{const} = 1$ [31]. Since we are attempting optimal solutions with respect to time, we can assume the robots will either be moving at maximum velocity or be stationary. Therefore:

$||u_i|| \in \{0, 1\}$

We assume that the vehicles have unlimited fuel and can travel an infinite distance within Ω [36, 31].

Let $\mathcal{B}_i(t) \subset \Omega$ be the set of targets serviced by the i^{th} agent up to time t as in [31, 36]. Since one service request can only be serviced by one agent $\mathcal{B}_i \cap \mathcal{B}_j = \emptyset$ for $i \neq j$.

Let $\mathcal{D}(t) \subset \Omega$ be the current demand of the mission at time t. Let $\mathcal{P}(t) \subset \Omega$ be the total set of targets serviced over time as defined below.

$\mathcal{P}(t) = \mathcal{D}(t) \cup \mathcal{B}_1(t) \cup \dots \cup \mathcal{B}_m(t)$.

With the above environment definitions we look at three problems with varying information as inputs for the control policies. The problem we propose to solve is Problem Statement 2 found in Section 5.3.

5.1 Problem Statement 0

We assume agents have full position information of other agents and targets within the workspace. Given p, B_i, D, find the optimal control policy π_i which minimizes $\sum_{k=1}^{n} w_k$ where w_k is the wait time associated with target q_k. This problem was solved with numerous algorithms in literature [17, 31, 16, 36]. Bertsimas and Ryzin [17] presented their mSQM policy optimal in light load conditions along with their G/G/m policy optimal in heavy load conditions. Frazzoli and Bullo [31] presented their mRH policy which they showed to be locally asymptotically stable in the light load case. Pavone et al.[16] presented their mDC policy which they showed to be m-competitive for heavy loads and sub-optimal for light loads.

5.2 Problem Statement 1

We assume agents have only local position information and full demand information in the workspace. Given p_i, B_i, D, find the optimal control policy π_i which minimizes $\sum_{k=1}^{n} w_k$ where w_k is the wait time associated with target q_k. This problem was solved by Arsie [36] for light load conditions (as $L \to 0$).

5.3 Problem Statement 2

We assume agents in the workspace have local communication ability with communication radius r_{comm} and local sensing ability with sensing radius r_{sense}. Figure 2 shows a single agent with communications and sensing range. We assume two agents can communicate when the distance between them is less than r_{comm}. We assume agents can sense demands within sensing radius r_{sense}. We define targets within r_{sense} of agent i at time t as $D_i(t)$.

We call two or more agents within communication range to be in network N. Assume we have two agents within r_{comm} in network N. Let $\hat{a}$ be an agent within network N. We define agent i to be in network N if agent i is within r_{comm} of any agent within network N; i.e.,

$$i \in N \text{ if } \exists \hat{a} \in N : ||p_i - p_{\hat{a}}|| \ \leq \ r_{comm}$$

We assume agents can communicate target positions and expected time of completion across network N. We denote the total realization of the i^{th} agent $\hat{D}_i$. Figure 3 shows three agents within a network with r_{sense} covering a portion of the targets.

Now we formally state the problem we wish to solve. With the proposed algorithm, we wish to investigate load conditions for which system time will converge. Given $p_i, B_i, D_i, \hat{D}_i$, find the optimal control policy π_i which minimizes $\sum_{k=1}^{n} w_k$ where w_k is the wait time associated with target q_k.

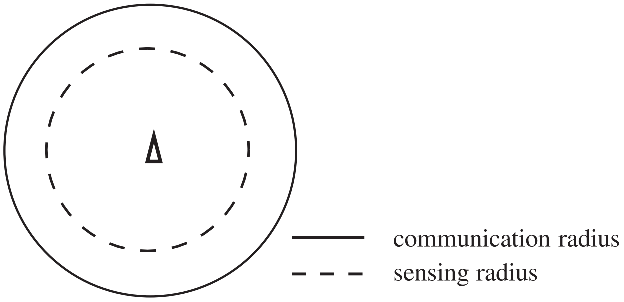

Figure 2: *Single agent with communications and sensing radius*

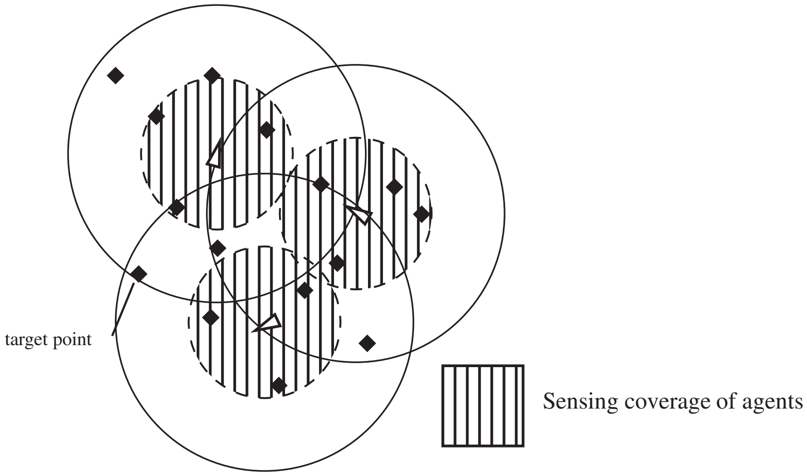

Figure 3: *Network of agents with sensing coverage*

5.4 Motivation

Problem Statement 0 assumes every agent has access to full position information of targets and demands within the workspace. Therefore, an implementation of such an algorithm would require full broadcasting capabilities throughout the workspace. The problem also requires position information of agents and targets, requiring bandwidth to increase with a large number of agents and/or heavy load conditions. Such assumptions are impractical for mobile robotics applications such as for unmanned underwater vehicles (UWVs) where communication capabilities are short range. Problem Statement 0 is impractical in UAV applications where the workspace dimensions exceed communication capabilities. Problem Statement 0 is also impractical for military applications where radio signals can be intercepted or jammed.

Problem Statement 1 assumes every agent has access to full demand information within the workspace. While the assumptions are more practical than for Problem Statement 0, Problem Statement 1 still requires global broadcasting through the workspace to transmit demand locations to each agent. Problem Statement 1 requires an increase in bandwidth as load increases and more targets are broadcasting their positions globally. Similarly as for Problem Statement 0, Problem Statement 1 is impractical for UWV applications, UAV applications with larger workspaces and military applications where signals can be intercepted or jammed.

Problem Statement 2 assumes no global communications throughout the workspace. Control policies of the form $\pi_i : (p_i, \mathcal{B}_i, \mathcal{D}_i) \mapsto u_i$ are completely decentralized with respect to communications and robot positions within the environment. While Problem Statement 0 and Problem Statement 1 achieve near optimal solutions to the m-DTRP, Problem Statement 2 is considerably more practical from an engineering standpoint as mobile robots have less demanding hardware requirements to employ solutions. For example, solutions to Problem 0 and 1 would require a radio transmitter capable of sending signals across the entire workspace. Since communications are only local, increased bandwidth due to load increase will be distributed across the network of agents as opposed to over the frequency band throughout the entire workspace.

6 Proposed Approach

We propose to use the published solutions [15, 37, 36] for the single vehicle TSP with the information provided in Problem Statement 2. Agents will move through the single vehicle Rahinam tour [37] of targets known in D_i. Agents will receive additional targets outside of their local realization D_i which we call $\hat{D}_i$. Agents will always move through targets in D_i and consider targets in $\hat{D}_i$. If an agent can service a target in $\hat{D}_i$ before the received service time, the agent will transmit the new service time through the network and add the target to D_i. For agent i, targets will remain in D_i unless agent i receives information through the network that another agent can service the target faster. After agents move through D_i and cannot service targets in $\hat{D}_i$ faster than their neighbours, they will make an exploration maneuver away from $\hat{D}_i$ based on potential fields.

When agent i and agent j are within communication range, agent i will transmit D_i to agent j and vice versa. D_i will also contain expected service times for each target. Agent i will receive D_j from agent j and add unknown targets to $\hat{D}_i$. Agent i will consider targets in $\hat{D}_i$ after the expected tour through D_i. If agent i can service a target in $\hat{D}_i$ before the expected service time calculated by agent j, agent i will transmit the target along with the new expected service time through the network. When agent j receives the new expected service time, agent j will drop the target from its demand. Otherwise, agent j will continue with it's tour through D_j.

Figure 4 shows the proposed architecture of an agent with local sensing and communication abilities. The local sensing module is responsible for sensing targets within r_{sense} and passing them to the Tour Calculation Module. The Tour Calculation Module solves the single vehicle tour for the targets the agent is responsible for. The Radio Input Module passes targets and expected service times received from neighbouring agents. Once received, the

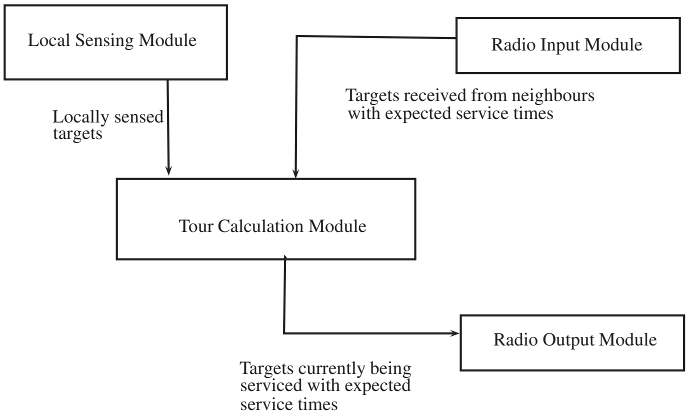

Figure 4: *Proposed communications and sensing model for agent*

Tour Calculation module would check whether the new targets can be reached sooner than the expected service times. Finally, the Tour Calculation Module passes targets currently being serviced to the Radio Output for transmission to neighbouring agents.

The idea is that agents will complete their local tours relying on r_{sense} and optimize when a particular agent has a heavier load than the others around it. Let us suppose agent i has a heavy load, after calculating the tour through D_i, agent i will transmit the locations and expected service times of the targets in D_i to nearby neighbours j and k. If agent j and k have relatively light loads, they will be able to observe the late service time for the later targets in D_i and assume responsibility for these targets. In the case that agents j and k can service targets within r_{sense} of agent i faster than agent i, they will be removed from D_i and assumed by D_j and D_k.

6.1 Validation in Simulation

The algorithm will be coded in MATLAB and compared against offline algorithms constructing the optimal tour for the TSP. Simulations will be run for a finite time and system time will be compared against the offline algorithm with the identical initial configuration and demand locations.

The algorithm will be simulated with various load conditions to determine when the algorithm is successful in completing all targets. Simulations will vary r_{comm}, r_{sense}, load(target generation rate/number of agents) to determine the effects these parameters have on system time and optimality.

The proposed algorithm will be successful if it converges for a specific load condition and performs within a constant factor approximation of the optimal offline algorithm.

Trials will be initialized with random starting locations for the agents with the workspace and have only access to the demand locations within r_{sense}.

Table 2: *Proposed experiment scenarios for final implementation*

Number of Agents	Load
2	0.1
3	0.1
4	0.1
2	0.9
3	0.9
4	0.9

Table 3: *Proposed timeline for critical research activities*

Research Goal	Proposed Completion Date
Code simulations in MATLAB (Section 6.1)	15 October, 2011
Determine lower bounds on m for convergence (Section 6.1)	15 November, 2011
Finish simulation trials (Section 6.1)	31 December 2011
Implement algorithm on Clearpath robots (Section 6.2)	15 March, 2012
Draft thesis report	15 May, 2012
Final thesis report	1 July, 2012

6.2 Validation in Experimentation

The algorithm will be tested in the autonomous vehicles laboratory with four Clearpath robots. The robots have local communications ability. Circular sensing ability can be simulated in experimentation by having the localization system generate target points and place them in the proper local demand when agents are within r_{sense} of the generated targets. The experiment will be performed with two, three and four agents. Table 2 shows the experimental trials to be performed with the developed algorithm.

Through experimentation we wish to determine if the communications network proposed is feasible on a hardware platform. We wish to observe any issues with multiple transmitting robots and attempt alterations in the message passing mechanics to overcome these issues. We hypothesize that given the proposed algorithm works in simulation, three agents operating within the environment will demonstrate more difficulty than two agents.

7 Timeline

Writing the thesis will be done concurrently with research activities. Depending on results, findings will be submitted for publication. Table 3 gives an overview of the critical project milestones along with proposed completion goals. This table will be used as a guide preserving the order of activities as they appear.

8 Anticipated Contribution

Our contribution will be an algorithm for the m-DTRP relying only on local communications and sensing ability. By having only local inputs, the algorithm will be practical for mobile robotics applications by having relaxed hardware constraints.

We anticipate convergent system time given a lower bound on m for a given environment area and target generation rate. Through simulation trials we hope to observe these parameters and find optimal values with regards to distance travelled and total service time.

We anticipate the extension of our solution to environments with heterogeneous agents and multiple types of service requirements. Utilizing the network N described above, agents could use local communications to transmit different service requests and eventually find agents with proper equipment to fulfill them.

Consider a swarm of two types of UAVs delivering different size payloads to extinguish forest fires. We'll say one set of UAVs delivers small water payloads to relatively small fires with many agents while another set of UAVs deliver heavier payloads to greater sized fires. If the swarm uses the proposed communications network, the set of smaller payload UAVs can service small fires while identifying larger fires through r_{sense} and transmitting locations through the network. In this way multiple UAVs can fulfill two types of tasks while all agents can identify target locations and propagate them through the network.

9 Conclusion

The proposed solution would take advantage of the previous works solving the m-DTRP while relaxing assumptions hindering the practicality for real-world systems. Problem Statement 2 requires only local target and position knowledge while able to utilize local communications abilities to optimize routes. The proposed solution would use the local communications medium to transmit target positions and expected service times for demands between agents. Bandwidth increase is scalable with respect to the number of agents and target generation rate. The proposed algorithm will be successful if values for m can be found such that average wait time converges for all targets. It is anticipated that m will be based on the area of the environment and target generation rate. Experimentation will be done utilizing communications hardware while simulating service requests being recognized within r_{sense}. We anticipate the algorithm as a platform for diverse environments requiring multiple servicing requests from multiple types of agents while relying on the same communications routine.

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Unmanned vehicles are becoming essential platforms for dangerous and difficult tasks reducing the risk for humans. The biggest challenges involve guaranteed mission success despite degraded mission critical hardware and communications networks. The multiple Dynamic Travelling Repairmen Problem (m-DTRP) has applications for unmanned vehicles for search and rescue applications, exploration applications as well as combat scenarios. The m-DTRP has been studied extensively in literature for theoretical scenarios but solutions lack application in mobile robotics applications with impractical communications assumptions. We propose the development of an algorithm for the m-DTRP that relies on local demand and position information and local communications ability to collaborate with other agents to optimize routes. The algorithm uses the transmission of target points with expected service times for agents to decide which demands to take on locally. We expect to observe lower bounds on the number of agents required for system time to converge based on target generation rate and environment area. We expect the algorithm to be a platform for diverse environments with heterogeneous swarms of agents.

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