2009 IEEE International Conference on Robotics and Automation
Kobe International Conference Center
Kobe, Japan, May 12-17, 2009

A Protocol for Decentralized Multi-Vehicle Mapping with Limited Communication Connectivity

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***Abstract*—This paper addresses the problem of communication range limitations for decentralized multi-vehicle mapping. We present a novel integrated communication and planning protocol that enables all vehicles to form a common global map. The fusion of mapping information is facilitated through the Information Filter and performed over a connected acyclic wireless communication network with limited communication range. The formation of the acyclic connected communication network is achieved by partitioning the landmark graph using graph theoretic tools during the planning phase. We provide results that illustrate the effectiveness of our approach over different distributions of landmarks.**

I. Introduction

The planning and control of multiple vehicles for information gathering tasks over landmarks has had great attention in recent years. Benefits of vehicle autonomy have been combined with coordination and planning systems to employ a real time multi-vehicle strategy to remove human operators from potentially dangerous situations, or mundane tasks. Multi-vehicle systems have found application in search, rescue and disaster management [1], surveillance [2], tracking, mapping and exploration [3]. The information on each landmark that is to be mapped could be positional information, and/or landmarks feature details like chemistry, temperature or human occupancy.

Decentralized data fusion (DDF) algorithms involving the Information Filter have been applied with great success to fuse data gathered from the different vehicle in a multi-vehicle system [4]. The benefit of the Information Filter, which is of interest to this paper, is that information integration across vehicles is additive (a communicative operation) thereby the specific order in which vehicle updates are applied is irrelevant. The difficulty then lies in tracking the information updates through the system as, without an acyclic communication network, information can be double counted and give over confidence in map estimates.

Traditional methods to address this issue is to assume large wireless communication ranges so vehicles communicate newly gathered information directly with all other vehicles - a fully connected communication network. Another method is to assume finite communication ranges and selectively communicate only self-gathered information, with no relaying allowed. Using a channel filter [2] or some other form of data tracking, previous data transmissions between vehicles can be recorded so only new information need be sent. A hybrid Information Filter/Covariance Intersect (CI) algorithm is applied on the communication links in [5]. Without the assumption of acyclic communication, the only other choice is to data tag every piece of information and its complete history to avoid double counting; a choice which would suffer severely from scaling issues in even moderate sized sensor networks.

In the case of connected acyclic networks all information received during a specific time step can be relayed to all other vehicles and fused so that all vehicles carry a current global map. It is not uncommon to assume an acyclic communication network [2], [6], but little is mentioned on how these communication networks are established and maintained, and limited measures are taken to optimize the integrity, efficiency and effectiveness of the information flow within the changing vehicle communication network.

In a synchronous communication mapping scenario vehicles are in a connected communication network during each communication/decision phase at $t = k$ and so share position estimate of all landmarks to be mapped. During this phase one landmark is then assigned for each vehicle to travel to and map during the subsequent gathering phase. At the next communication/decision phase $t = k+N$ the vehicles will again need to re-establish a connected communication network to fuse the newly mapped information on these landmarks. Since the vehicles will then be located at or near their assigned landmark, the landmark position topology can therefore be used at $t = k$ to plan a connected vehicle communication network at $t = k+N$.

Figure 1 is a graphical representation of a 4 UAV decentralized information gathering system communicating every N seconds. To maintain such a network in a limited communication range, the vehicles need only group together during the communication/decision phases, remaining autonomous during gathering phases. The more dispersed the assigned landmarks are the further the vehicle will have to travel to re-establish a connected network, which will reduce the time available for information gathering.

This paper outlines a protocol to dynamically re-establish a synchronous communication network while addressing the balance between vehicle dispersion for information gathering and vehicle grouping for communication connectivity. This problem is NP-hard and a graph theoretic heuristic solution is proposed.

II. Related Work

There is existing research that considers the communication network graph within a multi-sensor mapping context.

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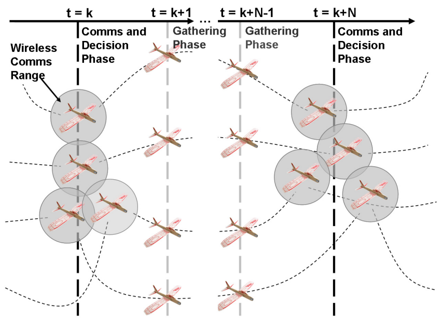

Figure 1. Communication and Decision Phase clustering and Gathering Phase separation.

Priyantha [7] designed a mobile-assisted localization (MAL) method to allow accurate localisation of wireless sensor nodes by a roving sensing vehicle. Priyantha designed movement strategies that produce a globally rigid wireless network of known distances among static sensor nodes. Stump *et al.* [8] applied communication network analysis to maintain a communication bridge between a base station and a roaming vehicle through mobile relay vehicles.

The idea of a mobile network building phase to acquire certain communication network characteristics for a completely mobile network is one of the innovations within this paper.

Research in the area of swarms [9] and the related field of consensus algorithms [10] and multi-agent networks [11] have placed strong importance on the role of communication network graph to the performance of a coordinated task.

III. THE DECENTRALIZED ARCHITECTURE

Figure 2 illustrates the structure of the decentralized multi-vehicle information fusion and decision phases. Vehicles are initialised with a common landmark map estimate. Local observation data is shared across all vehicles and fused using the Information Filter during the map update module, so that all vehicles share a common global map. The acyclic network is formed using Dijkstra's algorithm across the network of vehicle locations known to all vehicles using a suitable routing protocol [12]. The Utility and Communication Network Module (Section IV) calculates a recommendation of vehicle to landmark assignments based on the information benefit and communication network integrity and the Action Module (Section V) forms a viable action.

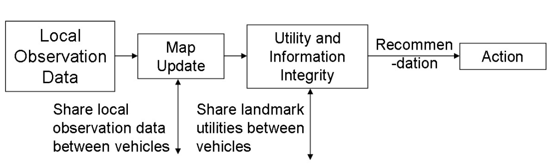

Figure 2. Decentralized multi-vehicle fusion and decision modules for a vehicle in the network.

The Information Filter [13] fuses data within the map update module. The Kalman Filter's representation of the belief as a mean μ and covariance Σ is replaced in the Information Filter with their canonical parametrization comprising an information vector y and information matrix Y. The parametrization is $Y = \Sigma^{-1}$ and $y = \Sigma^{-1}\mu$.

IV. RECOMMENDATION - UTILITY AND COMMUNICATION NETWORK MODULE

The Utility and Communication Network Module (Recommendation Phase) recommends a set of vehicle to landmark assignments following the stages outlined in figure 3. Each vehicle calculates the mutual information gain (utility) to go to each of the landmarks and shares these utilities with all other vehicles. Each vehicle independently selects the highest information landmarks by optimising over the combined utility matrix. Using Fine Dulmage-Mendolsohn Decomposition [14] these selected landmarks are broken into clusters of landmarks wherein vehicles and landmarks, when coincident, form a connected vehicle communication network. If the system cannot produce a connected communication network then outlying landmarks are removed and each vehicle recalculates the best landmark assignments over the remaining landmarks. The process repeats until a connected set of vehicle/landmarks is found or the set of possible landmarks are exhausted, in which case vehicles will be forced to rendezvous by the Action Module.

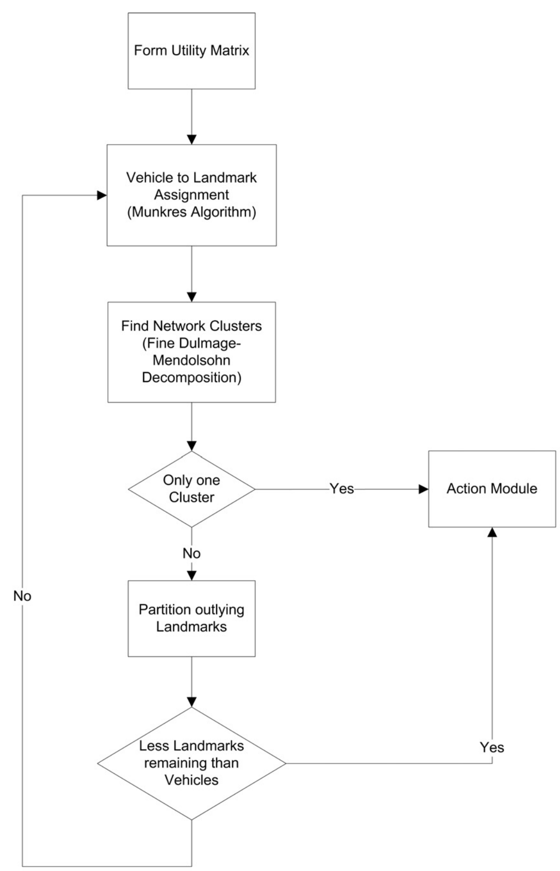

Figure 3. Stages of the Utility and Communication Network module (Recommendation Phase).

A. Utility Matrix Formation

The utility matrix $U = [U_{v=1}, \dots, U_{v=N_v}]$ is assembled at each of the N_v vehicles from communicated utility vectors U_v. The utility vector U_v is composed of the mutual information gain $U_v(l)$ of each vehicle v observing each of the N_l landmarks, where $Y_l(k-1)$ is the previous information matrix for landmark l and $I_{v,l}$ is the information gain when vehicle v observes landmark l:

$$U_v(l) \quad = \quad \frac{1}{2}\ln\frac{|I_{v,l}(k)+Y_l(k-1)|}{|Y_l(k-1)|}. \tag{1}$$

The information gained over a period of observations t_{obs} can be formed by integrating the information gain of time step k over time:

$$I_{v,l}|_0^{t_{obs}} = \int_0^{t_{obs}} I_{v,l}(k)dk. \tag{2}$$

$I_{v,l}|_0^{t_{obs}}$ will vary depending on the nature of the observation model . Let I_{obs} be an analytic approximation of the information gain per time then for $t_{obs}|_{v,l}$, the time vehicle v observes landmark l, the information gained is approximately:

$$I_{v,l}|_0^{t_{obs}} \quad \approx \quad t_{obs}|_{v,l}I_{obs}. \tag{3}$$

The protocol communicates and plans in constant information action gathering window of t_{window}, as such $t_{obs}|_{v,l} = t_{window} - t_{travel}|_{v,l}$ is the remaining time available after traveling to the landmark at position x_l from the original vehicle position x_v with velocity u where:

$$t_{travel}|_{v,l} = \frac{\|x_v - x_l\|_2}{u}. \tag{4}$$

If the landmark is unreachable in the given t_{window} then $t_{obs}|_{v,l}$ is assigned a small value $\varepsilon > 0$ to provide some incentive to travel towards a landmark. This allows for landmark assigned even in the event that the landmark is not reachable in the next planning window.

B. Landmark to Vehicle Assignment - Munkres Algorithm

Munkres Algorithm [15] is a combinatorial optimization algorithm which solves the assignment problem in polynomial time $\mathcal{O}(N^3)$. The algorithm models an assignment problem as a $N_v \times N_l$ cost matrix, where each element $U(v,l)$ represents the cost of assigning the vth vehicle to the lth landmark. The landmark index l of the highest utility assignment for each vehicle v is stored in a potential landmark vector l_p and a potential landmark matching 2-tuple $m_p = \{(v,l)\} \subseteq v \times l$.

C. Network Clusters - Fine Dulmage-Mendelsohn Decomposition

A communication landmark graph can be formed upon connection links between landmarks where Euclidean separation distance is less than the maximum communication distance d_{comms}.

The adjacency matrix for the potential landmark assignment $[A]_{lp\times lp}$ is formed from the full adjacency matrix of the communication landmark graph A by removing rows and columns not in l_p. The block triangular form of $[A]_{lp\times lp}$ is calculated using the Fine Dulmage-Mendelsohn Decomposition [14] and l_p is partitioned into disjoint vectors μ_i, where:

$$l_p = \bigcup_{i=1}^{N_\mu} \mu_i \,|\, \mu_i \bigcap \mu_j = \phi, \forall i,j = 1,\dots,N_\mu \tag{5}$$

The corresponding assignments of μ_i, similar to m_p are stored in the matching set $m_{\mu_i} \subseteq m_p$. If $N_\mu = 1$ there is one connected cluster, all landmarks are in communication range, and so the potential landmarks assignments are selected. Otherwise the value of each cluster is calculated from its members' utilities:

$$J(\mu_i) = \sum_{\{v,l\}\in m_{\mu i}} U(v,l). \tag{6}$$

The highest utility cluster of vehicles $\mu_{max} = \mathrm{argmax}_{\mu_i}(J(\mu_i))$ $\forall i$ is retained its adjacency matrix $[A]_{\mu max\times\mu max}$ formed from A. Using eigenvector centrality [16], where a_{max} is the eigenvector associated with the largest eigenvalue of $[A]_{\mu max\times\mu max}$. The most central landmark of this cluster is designated l_c corresponding to the largest magnitude element in a_{max}.

D. Partitioning

The outlying landmark l_o at position x_{lo} with the greatest squared Euclidean distance from l_c at position x_{lc} is selected from l_p that is not a member of μ_{max}:

$$l_o = argmax_l \|x_{lc} - x_l\|_2^2 \,|\, \forall l \in (l_p \backslash \mu_{max}). \tag{7}$$

The landmark space is partitioned by the line perpendicular to the vector $(x_{lo} - x_{lc})$ going through x_{lo}, whereby those landmarks in the half-plane containing x_{lc} are still considered in the working landmark set l_w:

$$l \in l_w \,|\, (x_{lo} - x_{lc})^T (x_{lo} - x_l) > 0. \tag{8}$$

Munkres Algorithm, Fine Dulmage-Mendelsohn Decomposition and Partitioning are reapplied over l_w until the set of l_p is fully connected or l_w has less elements than n_v whereby the last l_p is selected and marked as unconnected.

Figure 4 displays the partitioning protocol steps, for a ten vehicle scenario.

V. Action Module

The action module is delivered a recommended set of vehicle to landmark assignments together with a membership list of landmarks in the main connected cluster and the central landmark l_c of that cluster. A vehicle can follow one of three possible courses of action following from this set of recommendations to ensure the communication network will be connected at the next communication/decision phase. The set of possible actions are;

1) The vehicle v proceeds to and observes it's assigned landmark $l_p(v)$ if it falls within the main connected cluster until the next decision phase.

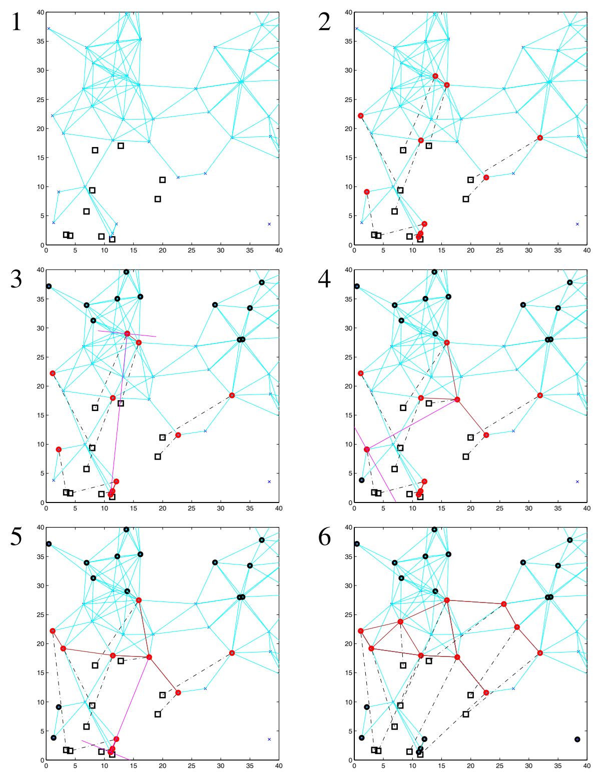

Figure 4. Plot 1 is the initial vehicle position (squares) and landmarks (crosses) joined by a graph. Plot 2 is the highest utility to vehicle assignment (dotted lines). Plot 3 the most central landmark l_c in the highest utility cluster μ_{max} is used for partitioning the outlying landmarks (circles). Plot 4-5 this process is repeated until the landmark network is connected in plot 6.

2) Where the landmark falls outside the main connected cluster, the vehicle v proceeds to and observes its assigned landmark $l_p(v)$ and then travels to the central rendezvous landmark l_c for the next decision phase.
3) Where there is no sufficient time to travel to perform the first two actions or the vehicle is not assigned to a landmark, the vehicle travels towards the central landmark l_c and waits at that landmark.

The stages within the Action module that govern which of these actions should be adopted is outlined in figure 5. The four parameters that are used to select which of the three actions is appropriate are;

1) The vehicle is assigned a landmark, $l_p(v) \notin \phi$. If there are less remaining landmarks than vehicles some vehicles will not be assigned a landmark.
2) The landmark is a member of the main cluster $l_p(v) \in V_m$ and not an outlying landmark that would require the vehicle to rendezvous at l_c.
3) The landmark is reachable in the time available, $\|x_{l p(v)} - x_v\|_2 < ut_{window}$.
4) The path from the landmark to the central landmark is achievable in the time available, $\|x_{l p(v)} - x_v\|_2 + \|x_{lc} - x_{l p(v)}\|_2 < ut_{window}$.

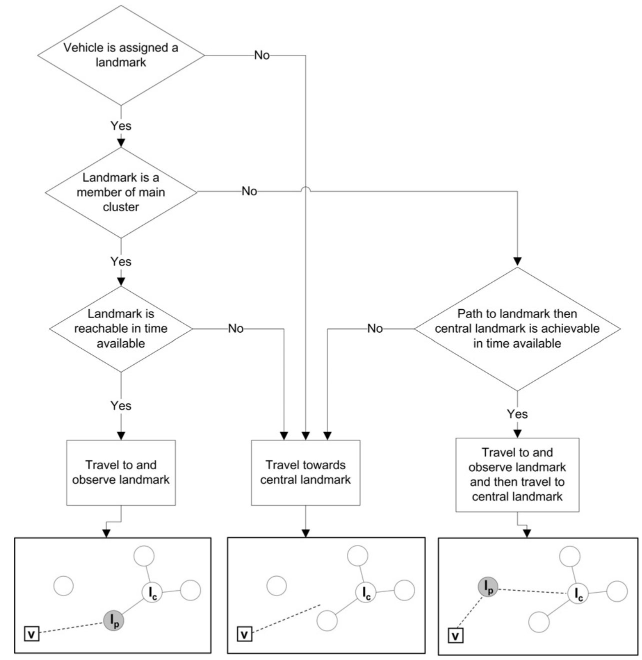

Figure 5. Stages of the Action module.

VI. Results

A. Sample Run

The results of this method for a system of 10 vehicles, 200 landmarks and mapping area of 10000 m^2 is displayed in the movie sample.mpg, and the normalised total information uncertainty over decision phase iterations in figure 6.

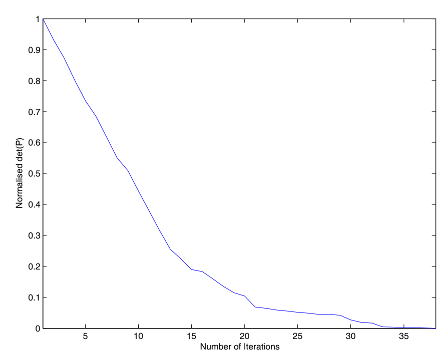

Figure 6. Partitioning protocol information uncertainty against number of decision phase iterations measured as the determinant of the covariance matrix normalised, $det(P)/det(P_0)$.

B. Performance Relationship to Landmark Distribution

The efficiency of the decision phase is tied to the maximum communication distance d_{comms}, within the recommendations phase (Utility and Communication Network module), and the planned maximum travel distance $d_{max} = ut_{window}$, within the action phase. Partitioning is required within the recommendation phase when landmarks fall outside d_{comms} and rendezvousing is called upon within the action phase when nominated landmarks fall outside d_{max}. Both reflect that further mission windows will be required to map these potentially lucrative excised landmarks.

Performance can thereby be examined with respect to the connection graphs defined with landmark connection distances of either d_{comms} or d_{max}.

In order to address the performance, the decision phase is assessed over three scenarios; infinite communications, near zero communications and a more conventional scenario with $d_{comms} \ll d_{max}$. The decision phase's performance under these scenario will be benchmarked against the number of iterations required to gather 50% of the information available in the system, for a random set of landmark distributions.

1) Landmark Distribution Manufacture: The decision phase predominantly selects locally clustered landmarks around the vehicles. The extent to which landmarks are clustered is therefore of importance to performance. The local graph measuring metric of the mean clustering coefficient C [17], is useful to quantify the extent of this clustering.

A property of a uniformly distributed grid is that it globally has good connectivity but locally has a mean clustering coefficient C of 0. This is because neighbors of any distinct landmark are unconnected from other neighbors of that landmark (plot 1 figure 7). On the other hand, a graph with landmarks randomly distributed over this area would globally have poor connectivity but, composed of many landmark clusters, have a high mean clustering coefficient (plot 4 figure 7).

To manufacture landmark distributions between these two extremes, landmarks of the uniform grid are shifted by δs_x and δs_y defined over a normal distribution $\delta s_x, \delta s_y \sim N(0, \sigma^2)$, while remaining within the area bounds. As σ^2 increases the graphs connections are re-routed and approach a random graph with a high C (figure 7).

The mean clustering coefficient C measured from these manufactured d_{comms} and d_{max} graphs provide a useful landmark distribution metric to assess the performance of the decision phase.

2) Infinite Communications - No Partitioning or Rendezvousing: The traditional case of infinite synchronous

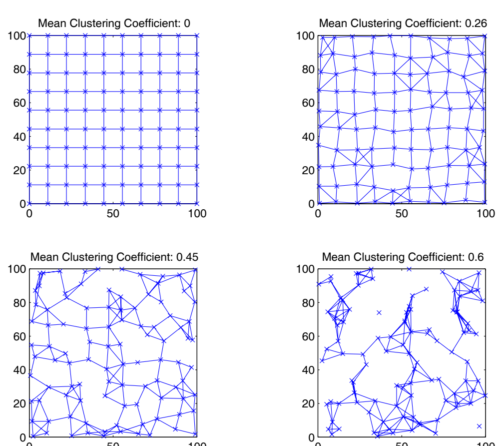

Figure 7. Manufactured graphs and associated mean clustering coefficient.

communication, commonly assumed in multi-vehicle information gathering is considered first. It assumes d_{comms} is much greater than the area dimensions in which case the Utility and Communication Network module (Recommendation Phase) is largely bypassed and no partitioning or rendezvousing occurs. The system parameters are $d_{comms} \sim \infty$ and $d_{max} = 15$ with the performance results over d_{max} graph C are presented in figure 8.

Under this scenario, the decision phase performance becomes less efficient as clustering increases because the non uniform distances between landmarks perform poorly against uniform vehicle steps. The efficiency is lost in vehicles loitering around landmarks that are much closer than d_{max} and once the observational information has been exhausted must wait for the next synchronized decision window.

The lack of influence of d_{max} clustering from $C = 0 \rightarrow 0.3$ on performance, in figure 8, can be accredited to poor $d_{max} = ut_{window}$ selection where t_{window} was designed too large and so the vehicles are loitering even when $C = 0$. With a smaller t_{window} and subsequently d_{max} the benefits of low C would appear at low C as well.

Overall a Utility and Communication Network module offers little to this scenario. A decision phase with variable t_{window} and no loitering time would offer a better solution.

3) Near Zero Communications - Continuous Rendezvousing: An alternative communication scenario is a fleet of vehicles with very poor communications coverage modeled as effective zero communications. The vehicles are therefore required to all rendezvous at every decision phase to maintain connectivity. The effect of varying d_{max} graph C with $d_{comms} = 0$, $d_{max} = 15$ is presented in figure 9.

The use of the Utility and Communication Network module shines in high d_{max} graph clustering because it allows the vehicles to be directed towards the high landmark density clusters. This promotes short distance rendezvousing for the decision phase and so more time can be spent observing and less traveling.

The horizontal line in these results can be accredited to a too low choice of d_{max}. To elaborate in the uniform grid all 10 vehicles do not have enough time to travel to their nominated landmarks, observe and rendezvous and some are forced to just rendezvous because d_{max} is too small. The landmark distribution does not become significantly clustered enough until at least $C = 0.3$ to take advantage of short rendezvousing distances.

This scenario is especially relevant to a multi-vehicle scenario where economics are such that low cost and less reliable communications are most likely in place.

4) $d_{max} \gg d_{comms}$ - Minimal Rendezvousing: A scenario where $d_{max} \gg d_{comms}$ vehicles have sufficient u or t_{window} to travel to neighboring landmarks, producing a relatively large $d_{max} = 30$. Therefore, landmark selection is predominantly based on the integrity of the information network with only minimal rendezvousing required and so is subject to the characteristics of the $d_{comms} = 10$ graph (figure 10).

The model improves vastly with increasing d_{comms} graph clustering as the decision phase is able to capture the high density information clusters in contrast to the poor communications and continuous rendezvousing of the previous case.

This is the more conventional scenario where communication range is limited compared to d_{max} and that clustering within the d_{comms} landmark distribution graph promotes decision phase performance.

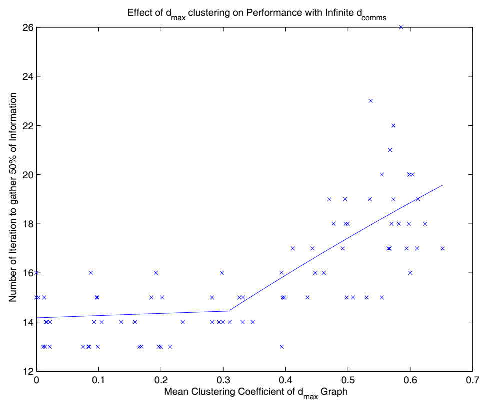

Figure 8. Performance effect of d_{max} graph clustering with infinite d_{comms}.

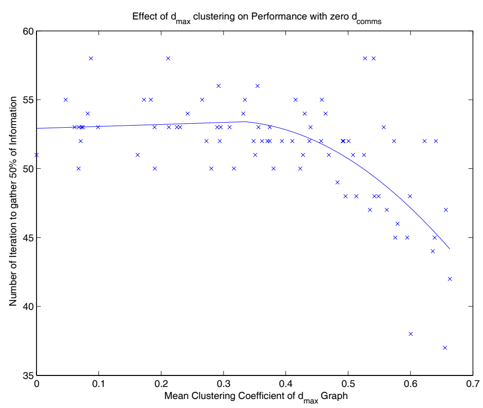

Figure 9. Performance effect of d_{max} graph clustering with near zero d_{comms}.

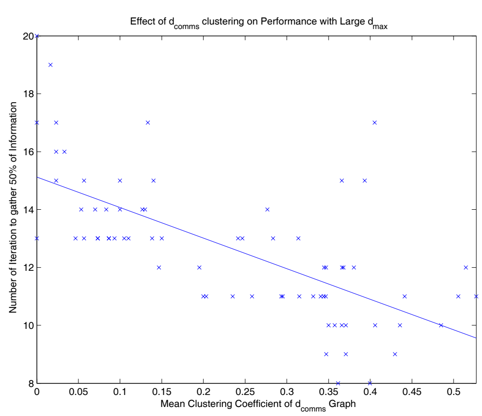

Figure 10. Performance effect of d_{comms} graph clustering with large d_{max}.

VII. Conclusion

The paper presented an integrated communication and planning protocol that supports the formation of an acyclic communication network for decentralized multi-vehicle mapping. Motivation for the work was to promote greater vehicle to vehicle information flow in multi-vehicle mapping in regions of poor communication by forcing an acyclic communication network while efficiently gathering information. The protocol uses graph theory tools to schedule landmark selection for forming a globally known connected communication topology to enable acyclic communication. The protocol is effective for situations where communication linkages may be weak and particularly in clustered landmark topologies.

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