Value-Based Communication Preservation for Mobile Robots

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Summary. Value-Based Communication Preservation (VBCP) is a behavior-based, computationally efficient approach to maintaining line-of-sight RF communication between members of robot teams in the context of other tasks. The goal of VBCP is, at each time step, to reactively choose a direction in which to move that provides the best communication quality of service with the rest of the team. VBCP uses information about other robots, real-time quality of service measurements and an a priori map of the environment to approximate an optimal direction in an efficient manner. Here, VBCP maintains communication between members of a robotic team while traversing an urban environment in formation. Quantitative and qualitative results are demonstrated in simulation and physical robot teams.

1 Introduction

This work addresses the task of maintaining line-of-sight RF communication between the members of a team of robots in the context of other tasks. Exact requirements vary from mission to mission, but systems dealing with issues of coordinated group behavior often must maintain communication between team members [3]. In the context of a multi-robot surveillance mission, it might be required that all members of the team share information, throughout the mission in a dynamic and noisy environment. The members must react to their teammates' actions in order to maintain a signal in an urban or otherwise RF-unfriendly environment. Simultaneously, each robot must also go about its surveillance mission. This work uses motor schemas, a behavior-based architecture, to preserve line-of-sight communication between members of a team of robots.

Value-Based Communication Preservation (VBCP) is a navigation behavior that takes into account shared locations of its teammates, measured communications signal quality and map-based predictions of communications signal quality to calculate movement vectors. These movement vectors serve to direct the robot along paths that tend to conserve communication between teammates. This behavior can be used in conjunction with other behaviors, in the context of a motor schema based architecture, to create complex, behavior-based robotic team behavior.

While the VBCP behavior takes into account the current position of all the robot's teammates, it does not use multi-agent planning to calculate movement vectors. It does use map information to estimate communication quality one step, or a short distance, away. The computational complexity of calculating the communication quality at a point one step away is kept to a minimum by assuming that all the robot's teammates remain in the same position one step into the future. By estimating the communication quality at several positions a short distance away in several directions, an estimation of a communications quality gradient can be calculated for the current position. This work is based on the hypothesis that following this gradient will tend to preserve communication quality within the team.

Current applications of VBCP are based around military surveillance or terrain coverage missions. This work is funded under the DARPA MARS Vision 2020 program. Simulation tests were run on models of the Military Operations in Urban Terrain (MOUT) facility at Marine Corps Base Quantico, in Quantico, Virginia. Hardware tests were run at the U.S. Army's McKenna MOUT site at Ft. Benning, Georgia. These tests showed promising results for the utility of this behavior in military applications. While the emphasis of this research is of a military nature, it is expected that this behavior be found to be of use in a wide variety of multi-robot applications.

2 Related Work

This work is based on the motor schema approach to reactive robotics presented by Arkin [1]. Arkin presents an architecture for choosing mobile robotic actions. In this architecture, behaviors are defined for every sub-goal of the mission. These vectors are then combined to create a movement vector that the robot then acts on.

In [2], Balch and Arkin present a motor schema approach to multi-robot formation maintenance. Balch and Arkin defined several formations, including line, column, wedge, and diamond. Building on their work on formations, Balch and Arkin presented a study on the effect of formations on line-of-sight communication in a cluttered environment [3]. Balch and Arkin concluded that column formations allow teams to maintain communication more easily than line formations.

In 2003, Redi and Bers presented a hardware platform for mobile ad-hoc networks [4]. This platform, besides routing data between nodes, provides a user at a particular node with real-time quality of service metrics, including measures of signal strength to neighboring nodes, the number of hops required to reach nodes in the network and the identities of other nodes in the network. The algorithm explained below relies on this type of information.

Finally, in 2003, Stroupe and Balch presented Value-Based Observation for Robot Teams (VBORT) [5]. In this work, a team of robots use a one-step lookahead heuristic to maximize certainty of a group of targets' locations. VBCP should be viewed as an evolution of VBORT, using a similar approach applied to the communication realm.

3 Approach

VBCP is a behavior-based approach to communication preservation. At every time step, each robot in the team chooses its next action according to its current state and several predicted states, based on current observations and rules based on an a priori map of the environment. In order to choose an optimal next action with respect to communication preservation, it would be necessary to evaluate all possible next steps in combination with all possible next steps for each teammate. In order to remain computationally tractable for large robot teams, the VBCP behavior approximates the optimal next action.

VBCP reduces computational complexity on two fronts. First, rather than predicting every possible next step, VBCP predicts just a small set of possible next steps. Each next step is equally spaced around a radius representing the distance to be traveled in the next time-step. An approximated best next step is calculated by summing vectors in the direction of each candidate next step, respectively scaled with respect to their predicted communication quality. This is equivalent to approximating the predicted gradient of communication quality at the robot's current position. It is possible to make this approximation if quality of communication is assumed to be relatively smooth. The line-of-sight pathloss model used in this work is discontinuous when obstructions block the signal between two robots. However, in this case the model of communication quality can simply be assumed to decline steeply between regions of continuous communication quality.

VBCP further reduces complexity by approximating the future positions of a robot's teammates. When predicting the quality of communication at each next step, all teammates are assumed to remain still in the next step. Thus, computation of the behavior reduces from exponential to linear complexity, with respect to the number of robots in the team. Stroupe and Balch point out that, given no information about the teammates' intentions, their current positions represent an average predicted next position [5].

Communication quality between multiple teammates is evaluated according to a value function that can be crafted to reward behaviors defined in the mission specification. For this work, it was assumed that each robot must maintain connectivity with at least two teammates. Additionally, it was considered advantageous to maintain two signals with similar quality over two signals with disparate quality. A continuous function provides smoother behavior with respect to changes in communication quality, and relatively large "dead zone", in the range of communication quality considered to be adequate, allows robots to move relatively independently when communication quality is good enough.

The following function satisfies all the above constraints:

$$v = \frac{1}{(1 + e^{-C_1(\frac{r_1+r_2}{100} - C_2)})(1 + e^{C_3(\frac{r_1-r_2}{100} - C_4)})} \tag{1}$$

where r_1 and r_2 are the strongest and second strongest predicted or measured signals with teammates. (In the case of two-robot teams, r_2 is set equal to r_1.) C_1, C_2, C_3 and C_4 are positive constants. Increasing C_1 decreases the dead zone with respect to the added strength of r_1 and r_2. Increasing C_3 decreases the dead zone with respect to the difference of r_1 and r_2. C_3 and C_4 affect the steepness of the function. Figure 1 is a plot of v where r_1 and r_2 range between 0 and 100 and $C_1 = 9$ and $C_2 = 4$. There are undoubtedly many ways to evaluate communication quality according to the above specifications. The above function falls under no claims of being the best. It does, however, provide reasonable behavior in the context for which it was designed.

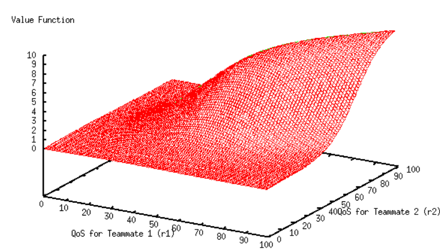

Fig. 1. Equation 1 plotted as r_1 and r_2 vary between 0 and 100.

The full algorithm VBCP uses to calculate a movement vector at each time-step follows:

1. The current signal strength with each teammate is measured. The current overall communication quality is calculated using Equation 1 , where r_1 and r_2 are respectively the two strongest measured signals.
2. The predicted signal strength at possible next steps evenly distributed around a radius representing the distance to be traveled in the next time-step. The overall communication quality is calculated at each next step using Equation 1, where r_1 and r_2 are the two strongest respective predicted signals at each next step. (Figure 2a)

3. A unit vector a_i in the direction of each next step is created and scaled by the overall communication quality at the respective next steps. (Figure 2b)
4. A unit vector b is created in the direction of the sum of the a_i's and scaled by the current overall communication quality. (Figure 2c)
5. Vector b is returned as the best next movement with respect to communication preservation.

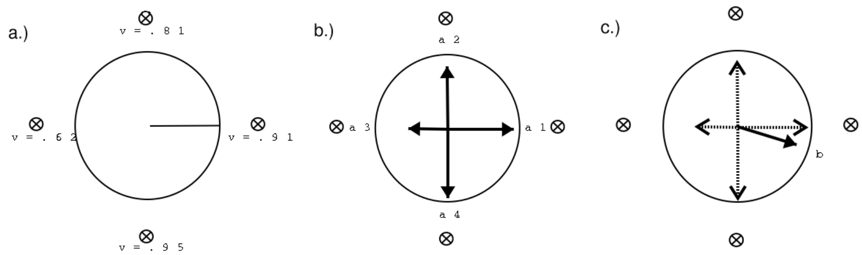

Fig. 2. A graphical representation of the VBCP algorithm. This figure represents steps 2-4 as explained in Section 3.

Measured and predicted values of communication quality are never compared in the computation of a movement vector. Predicted communication quality is used only in computing the direction of the movement vector. Measured communication quality is used only in computing the magnitude of the movement vector. Therefore, the scales of the predicted communication quality and measured communication quality need not match. This makes the task of modeling communication quality easier, as only general trends must be accurately modeled.

4 Experimental Approach

A series of experiments was run to evaluate the effect VBCP has on communication preservation in the context of an overall mission. Simulation experiments were run using the MissionLab [6] behavior specification software. Quantitative statistics were measured and compiled from these simulations. The simulated environment was modeled after the MOUT facility at Marine Corps Base Quantico in Quantico, Virginia. (Figure 3) This environment was chosen because it met the description of the target environment in the mission specification. Communication between robots was modeled using a line-of-sight pathloss model.

These experiments were compared using five metrics:

- Time to Complete Mission - measures the number of simulation cycles required to complete the mission. Real time was not used as simulation cycles take longer to compute as more robots are added to the team.

- Percent of Time as One Network - measures the percent of time every robot in the team has a network route to every other robot. Multi-hop routes are considered equal to one-hop routes in this metric.
- Percent of Time as Fully Connected Network - measures the percent of time every robot in the team has a one-hop network route to every other robot in the team.
- Percent of Time at Least One Robot Alone - measures the percent of time at least one robot from the team has no network routes to any other robot.

The one-network, full-network and lone-robot metrics prove to be trivial for the one-robot case. They are calculated, however, as the one-robot case provides a baseline for all the metrics.

The motor schema used consisted of 4 behaviors, summed proportional to their respective gains. The behaviors and respective gains used follow:

- **preserve-communication** – gain = 1.0
- **move-to-goal** - gain = .4
- **avoid-static-obstacles** - gain = .6
- **maintain-formation** - gain = .4

The move-to-goal, maintain-formation and preserve-communication gains were chosen so that the move-to-goal and maintain-formation behaviors would never force a robot into a position that would compromise its communication quality of service. The avoid-static-obstacles gain was chosen to provide an adequate margin of safety from any obstacles that might pose a danger to the robots, given the gains of other behaviors in use.

Proof-of-concept hardware experiments were run on two laboratory robots in both relatively controlled and uncontrolled environments. The robots used are iRobot ATRV-jr robots. They are equipped with differential GPS receiver, digital compass and gyroscopic accelerometer for localization. An industrial-grade laser scanner provides perception for obstacle detection. As the networking hardware as presented in [4] was not yet available at the time of testing, an IEEE 802.11b bridge on each robot provided the infrastructure for a simple mobile ad-hoc network. Because the target hardware was not available, real-time network quality of service measurements had to be replaced by calculations from the line-of-sight pathloss model. It was at least possible to measure a binary connected/not connected metric to make a coarse judgment about the quality of the network between the robots.

The first set of experiments took place on the intramural athletic fields on the Georgia Tech campus. These large, flat artificial turf fields provide a relatively clean environment, similar to that of the simulations in the preceding section. Temporary obstacles were constructed on field to create a very simple urban environment. These obstacles were visible to the robots' laser scanners and were modeled in the a priori map as communication-obstructing obstacles.

The second set of experiments took place at the McKenna MOUT site at Fort Benning, GA. This urban testing ground provided an experimental environment very close to the target environment. Large cinder block buildings made up the set of modeled communication obstacles. The cinder block walls were a closer fit to the line-of-sight pathloss model than the temporary obstacles on the athletic fields. In addition to modeled communication obstacles, the environment was full of unmapped physical obstacles, such as fire hydrants, cars and trees. While these obstacles pose no serious threat to communication quality, they demonstrate the advantages of a reactive approach.

5 Results

Simulation experiments were run comparing a variety of robot team configurations. Each experimental run consisted of running a team of one, two, three or four robots in a terrain-coverage formation either with or without VBCP across the experimental environment. Three formation configurations were tested: line formation, column formation and no formation. Each unique robot team configuration ran twenty missions from unique starting points in each cardinal direction. (i.e., twenty starting points were evenly distributed on the west side of the environment, moving toward a goal on the east side; likewise on the north, east and south sides.)

Figure 4 shows the effect of number of robots on the communication quality of service in line and column formations, both with and without the VBCP behavior, according to the above metrics. Without VBCP, communication quality of service according to all metrics declines as the number of robots is increased. However, with VBCP, the mean percent of time in one network is greater than 98% for all cases. The percent of time in fully-connected network declines as robots are added to the team, but does not decline as rapidly as without VBCP.

Fig. 3. Experiments being run in the simulated MOUT site, the Georgia Tech intramural athletic fields and the McKenna MOUT site.

In the athletic field environment, teams of two robots were started at one side of the obstacle field and tasked with moving in formation to a point on the other side of the field while maintaining communication quality of service.

Although the temporary obstacles did not necessarily break the robots' communication link according to the line-of-sight pathloss model, they were considered adequate for a qualitative demonstration of a robotic behavior. Because the obstacles were modeled in the a priori map as opaque to the robots' communication signal, and the line-of-sight pathloss model was being used, line-of-sight and a maximum separation should be maintained by the robots at all times. (i.e., because the obstacles were modeled as serious communication barriers, the robots should behave as if they are.)

As the robots moved through the obstacle field, they could, qualitatively, be seen to be maintaining line-of-sight throughout the mission. Qualitative demonstrations of this behavior include robots passing an obstacle on the same side, so as not to allow and obstacle to come between them, and swinging wide around corners, so as not to allow the corner of an obstacle come between the robots. Figure 3 shows two robots swinging wide around a corner to maintain line-of-sight communication.

The experiments at the McKenna MOUT site resembled the athletic field experiments, in an environment that more closely resembles the target environment. As in the experiments on the athletic fields, teams of two robots were tasked with moving in formation across a subset of the environment while maintaining communication quality of service. Again, the robots should maintain line-of-sight and a maximum separation to maintain communication quality. Qualitative results were easier to demonstrate in these experiments over the athletic field experiments since a loss of line-of-sight was likely to cause a real communication failure.

As the robots moved through the urban environment, they could again qualitatively be seen to be preserving line-of-sight communication. Additionally, the robots maintained actual communication throughout the mission. Figures 3 shows two robots finding their way around a building without breaking communication. If the same mission is run without VBCP, the robots will move around opposite sides of the building.

6 Discussion

Overall, VBCP improves communication quality of service within a team of robots, especially as the number of robots in the team is increased. The performance of team configurations without VBCP declines in one-network and full-network metrics as the number of robots in the team is increased. This indicates that the problem of communication preservation gets harder as the number of robots increases. VBCP markedly improves performance in these metrics. The full-network metric declines slightly for the four-robot case with VBCP. However, the value function used in this work rewarded states where robots had double-connectivity. In the four-robot case, all robots can achieve double-connectivity without a fully-connected network. The time required to

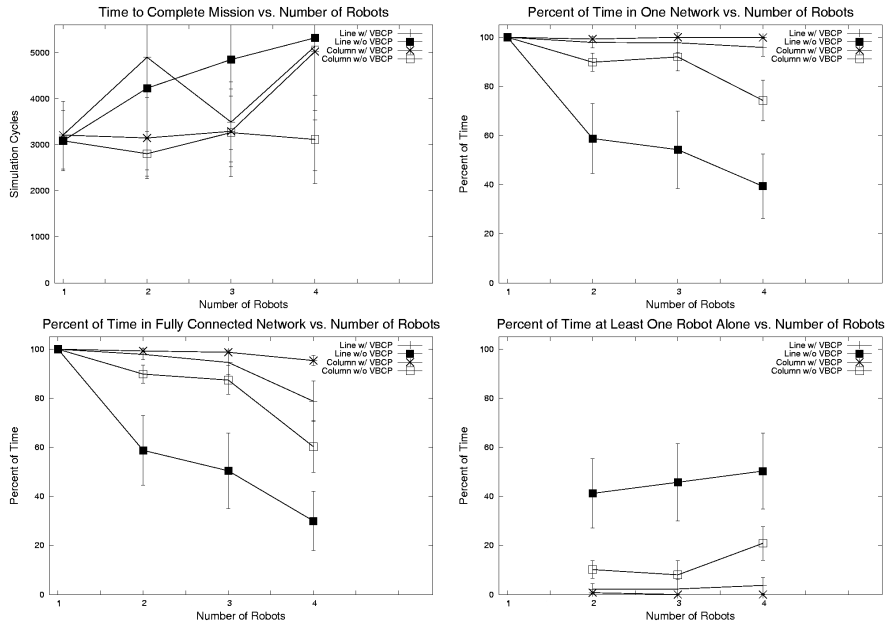

Fig. 4. The effect of the number of robots on the time required to complete a mission, the percent of time the team spends as one network, the percent of time the team is in a fully connected network and the percent of time at least one robot is disconnected from all other robots, both with and without VBCP. Errorbars indicate 95% confidence intervals.

complete a mission increased slightly when VBCP was used. This is both expected and acceptable. Teams using VBCP are likely to take the same path as teams not using VBCP, until this path takes them into a situation that causes a loss of line-of-sight communication. At this point, teams using VBCP will find a different, often longer, path to the goal. However, since the goal of this research is to maintain communication quality of service, an increase in running time is considered acceptable, providing the problem remains tractable.

The percent of missions completed declined slightly when VBCP was used. Of missions that were not completed, with or without VBCP, most were not completed because one or more robots became stuck in local minima. The use of VBCP made robot teams more likely to become stuck in local minima. This is not of major concern, since strategies for keeping reactive systems out of local minima exist [7, 8]. None of these strategies were used in the above experiments, as they do not take into account communication-sensitive strategies. At least one of these strategies will have to be adapted to communication-sensitive missions before this work is deployed into the target environment.

In simulation, the cause of failure of VBCP seems to be incorrect evaluation of possible next steps. This stems from the inherent loss of information in estimating that a robot's teammates will remain still during the next time step. In practice, the effect of this misestimation can be mitigated by increasing the distance the robots look ahead at each step, the trade-off being a loss of responsiveness to smaller fluctuations in communication quality.

In practice, an inherent weakness of VBCP is its reliance on map-accuracy. While a conservative signal strength model can make up for some of a map's shortcomings, at some level, the behavior is only as good as the map provided. Work is currently underway to relieve some of this reliance on an a priori map by learning and/or updating the map as the mission is run.

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