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Development and Deployment of a Line of Sight Virtual Sensor for Heterogeneous Teams

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Abstract* — For a team of cooperating robots, geometry plays a vital role in operation. Knowledge of line of sight to local obstacles and adjacent teammates is critical in both the movement and planning stages to avoid collisions, maintain formation and localize the team. However, determining if other robots are within the line of sight of one another is difficult with existing sensor platforms – especially as the scale of the robot is reduced. We describe a method of exploiting collective team information to generate a virtual sensor that provides line of sight determination, greater range and resolution and the ability to generalize local sensing. We develop this sensor and apply it to the control of a tightly coupled, resource-limited robot team called Millibots.

Keywords-component; mobile robot teams; sensing; heterogeneous control

I. INTRODUCTION

Robots are versatile machines that can be programmed to react collectively to sensor information in a variety of tasks that range from surveillance and reconnaissance to rescue support. Despite this versatility, a single robot cannot always realize all applications. On the other hand, a team of robots can coordinate action and sensing to extend a collection of individual entities to a single, cohesive group. To facilitate this coordination, a robot team must be able to manage its formation to exchange information and leverage the proximity of the others.

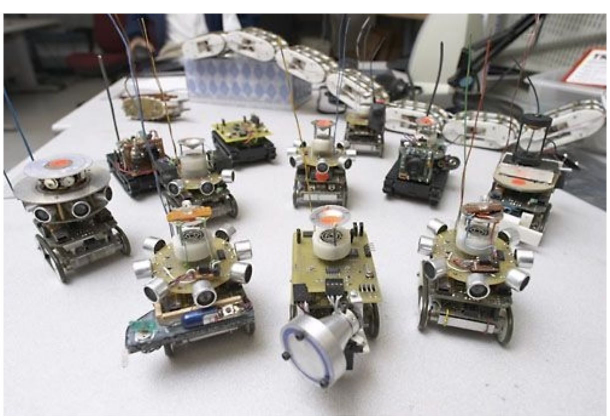

Figure 1. The Millibot Team – a heterogeneous collection of small-scale robots designed on the 5cm scale.

Formation control is essential in many aspects of team coordination from communications [1][2] to sensor coverage [7][11] to localization [4][9][12]. A critical component of formation control is line of sight. Line-of-sight is defined as an open, obstacle-free path between two points in space and must be wide enough to allow the passage of information signals such as light, video or ultrasonics. Unfortunately, local sensing is not always sufficient to directly determine the property of line of sight. Local sensors are often limited in their range and resolution and are incapable of discriminating between robot and obstacle. Even when a robot has access to a local map, it still may not have acquired sufficient information to make the determination on its own. This is especially true as the scale of the robot is decreased, the number of available sensors is restricted and the range of local sensing is reduced.

Coordinating multiple robots is a management issue as well. Conventional formation control is based on the idea that each robot is equipped with roughly the same sensing capabilities. Heterogeneous team control must take into account for the differences in the sensing and processing capabilities of each robot. In some cases, this sensing may be rudimentary and not able to provide the necessary local information needed to navigate on its own [7][11]. The problem becomes even more compounded when the composition and number of the team is dynamic.

Our work is primarily motivated by the control and coordination of a team of heterogeneous, resource-limited robots, called Millibots [7]. These are small-scale robots on the order of 5cm a side that are designed to operate in unknown or partially known environments. Their small size gives them access to tight, inaccessible areas while making them easier to conceal, deploy and manage. However, their small scale and dynamic heterogeneous composition makes conventional control strategies difficult to apply.

We address coordination of multiple, heterogeneous robots by developing the concept of a 'virtual' sensor. Robot teams have the advantage that they can collectively share information. They are able to fuse range information from a variety of different platforms to build a global occupancy map that represent a single collective view of the environment. A virtual sensor is simply an abstraction of the team's occupancy map. We call this a virtual sensor because it has all the properties of a real sensor with respect to that robot's navigation and planning but is derived from information already processed and not from the physical interaction of a sensor and its surroundings. However, when employed by the individual, the information derived from a virtual sensor can be treated in the same fashion as a real sensor.

In Section III, we develop the virtual sensor and show how it can provide essential line of sight information to obstacles, open space and other robots regardless of the platform being employed. In section IV, we show how this generalization aids in local, sensor-based planning by providing information with greater range and resolution than existing local sensors. We then show how it can be extended to the planning stage with respect to maintaining line of sight to multiple members during and after movement. Finally, in Section V, we show how the virtual sensor allows the generalization of existing sensors in such a way as to allow homogenous control laws to be applied to a heterogeneous team.

II. RELATED WORK

The concept of recasting local sensing is not new. Borenstein proposed recasting a robot's local map in terms of a polar sensor in the development of his Vector Field Histogram [5]. From the vector field, he is able to apply potential field methods for avoiding obstacles and navigating through open space. This method was designed primarily to support local, sensor-based navigation of a single robot and was not intended to support multiple robots.

Banos utilizes a high-resolution laser range sensor to express the robot's centric view as a collection of polylines by connecting the ends of each range measurement together into a contour [3]. As the robot generates new views, he combines polylines to form a composite representation of the environment. While a powerful geometrical means for combining robot views, this method lacks a means for separating other robots from the environment as well as a means for assessing new plans based on the line of sight to other robots. Moreover, it relies on high resolution sensing which becomes problematic for robot teams with more limited sensing modalities.

Nelson describes the generation of an enhanced range sensor by utilizing vision to evaluate the height information in a video image [10]. The relationship between range and image height is made possible by regulating the dimensions of the walls in the environment. Moreover, line of sight to other robots is obtained by assigning unique colors to each robot. While this method solves both the range and line of sight issue, it requires the construction of a controlled environment and is not suitable for applications in unknown environments.

III. THE VIRTUAL SENSOR

To develop the virtual sensor, we first recast the team occupancy map as a polar occupancy map with respect to robot. The polar map is constructed as a grid with the columns representing range and the rows representing bearing (Figure 2b). We make the transformation by mapping the value of the occupancy map cells to the corresponding polar occupancy cells for each cell in the polar map.

From the polar map, we generate a polar contour that records the closest features in the map with respect to the center of the robot. Features captured by the polar contour include the closest obstacle and the closest free space boundary. The polar contour is stored as a single linear array with the number of cells equal to the column width of polar map (Figure 2c). The indices of array correspond to the angle and their values are the range to the closest feature This reduced representation allows rapid calculation of line of sight as well as a compact representation for faster communications.

To determine the range to the closest features, we scan each of the columns of the polar map from bottom (closest to the robot) to the top (maximum range) until we detect a cell that transitions from open (low occupancy) to either closed (high occupancy) or unexplored. If a transition from open to high occupancy is detected, the scan is terminated and the range is

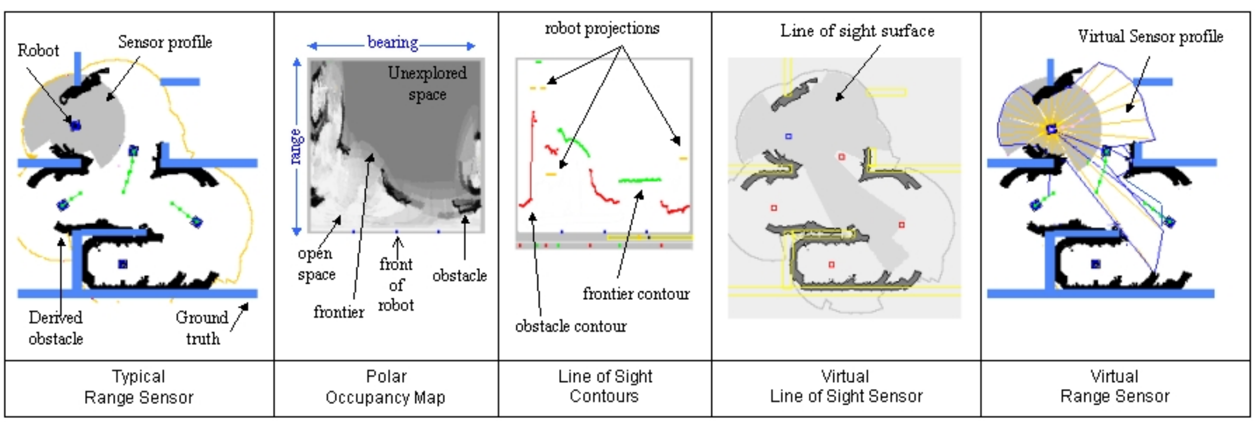

Figure 2. Generating the Virtual Sensor. - **a)** A robot's local sensors may not have the resolution to determine line of sight to other members (dark gray profile) **b)** First step is to map the team's occupancy map into the individual polar map with the target robot at the center - axes are range and bearing. **c)** We process the polar map to generate a polar contour - For a given bearing, we mark the closest transition from open space to form obstacle contours and frontier boundaries. Additionally, we project the profile of adjacent teammates onto the map **d)** We test each point in space against the contour map. All points within this region are within line of sight of the target robot. **e)** We utilize the values of a contour map to generate a virtual range sensor with greater range and resolution of the robot's individual sensor. This generalized profile is the same for any robot regardless of underlying sensor platform.

recorded in the array. These cells represent the closest obstacle points within the line of sight of the robot.

If a transition from open to unexplored is detected, the range to this feature is recorded. This transition represents the closest frontier point for that given angle. A frontier represents the boundary between known and unknown space and is used to guide exploration. To allow the storage of range information to two classes of features (frontier and obstacle points) in a single array, we store frontier points as negative values.

The polar contour stores the distance to the closest features within a robot's line of sight. However, its power comes from the ability to test line of sight to arbitrary points in space. We can readily establish whether a point in space is within line of sight of the robot by determining the angle and range to the point with respect to the robot. If the point is above the contour (range greater for a given bearing) it is beyond that robot's line of sight. If it is below the contour it is within line of sight.

Ironically, while robot range sensors, such as sonar, are good at detecting the distance to local obstacles, there are some cases where they are unable to detect the presence of other robots - even when they are within range. Such is the case of the Millibots where the sonar sensor platforms are mounted on top of the robot. These platforms present a small cross section (effective reflection area of the robot) to ultrasonic bursts and consequently do not always reflect sufficient energy to be detected. However, we can leverage team knowledge to account for undetected robots by artificially projecting their profile onto the polar contour. The positions of the robots are obtained from the team's localization solutions and mapped into the polar map.

Instead of simply treating these robots as a point source, we account for their size as well. We project these teammates onto an individual robot's polar map by generating a line whose width is a function of the size of the actual robot and the distance from the center of the target robot. Figure 2c shows the projection of team members onto the target robot's contour map. Where the robot's projection is closer than any other feature, it replaces that feature as the closest point. Now the team can move reliably even when it cannot directly detect its neighbors. Moreover, we have a method for determining the reliability of line of sight information. That is, we can assess whether a participating robot is partially obscured. This ability to account for the projected width of a robot (as opposed to a point source) is one of the advantages of utilizing a polar contour over determining line of sight by using simple ray tracing techniques.

IV. VIRTUAL SENSOR PLANNING

Line of sight is not just a detection issue; it must be considered during planning. Not only does a robot need to know which robots are within line of sight and which are not, it needs to make the same assessment for future cases in the planning stage. We can exploit the virtual sensor to aid in local robot planning as well as coordinated team planning. For example, localization effectiveness is often a property of the number of robots that participate. Therefore, planning must also account for the number of robots that will be within line of sight after the robot moves. If the new position cannot be adequately resolved due to lack of participation after such a move, the team may select an alternative move or opt to reposition others first.

A. *Local Planning*

Researchers are already exploiting the increased resolution of maps generated by fusing multiple robot sensors to aid in exploration and localization. However, this has traditionally been a one-way process. Few are exploiting this map information to augment an individual robot's perspective. Consequently, each robot is left to develop plans based primarily on local sensors. We approach information exchange from the other perspective. That is, we use the higher fidelity of the team map to support sensing and local planning.

In addition to line of sight determination, we can recast the virtual sensor in the form of an extended range sensor to aid in local robot planning. To accomplish this, we utilize the range values of a robot's polar contour as an element of a virtual sensor array (an imaginary range sensor) (Figure 2e). The angular and range resolution of the virtual sensor is a product of the number of rows and columns of the polar map and not the underlying sensor. Consequently, the range and resolution of the virtual sensor is generally greater than the underlying robot sensor.

One immediate advantage to this formulation is the ability to perform local sensor-based planning. With greater resolution provided by the virtual sensor, a robot is able to generate finer resolution plans than possible with its original sensors. Many techniques exist that allow a robot to reliably navigate through known spaces utilizing only local sensors [3][5][6]. However, the success of these methods is partially a function of the resolving ability of the sensors. For example, many robots have the luxury of supporting a high-resolution laser rangefinder or an array of 16 or more Polaroid sonar sensors. However, the typical Millibot sensor array utilizes only 8 sonar range sensors each with a range of 30cm. Consequently, it has a harder time applying local control laws to maintain a path or follow the contour of local obstacles. On the other hand, a virtual sensor has a derived range and resolution based on the resolution of the polar map and not the underlying sensor. Consequently, it can augment existing sensing to produce better motion plans for movement through the space.

Robots also utilize features, such as obstacle profiles and frontiers, extracted from the virtual sensor to navigate. One popular method in robot exploration is frontier expansion where the robot is directed towards existing boundaries between open and unexplored space. However, it has been shown that specular reflection and general sensor failure can complicate the proper generation of frontiers [8]. Instead of directing the robot to viable search areas, specular reflection produces erroneous frontiers resulting in plans that direct the robot through obstacles. If the obstacle cannot be traversed, the attempt fails wasting valuable time and resources. On the other hand, a virtual sensor identifies obstacle boundaries and frontiers with respect to the position of an individual robot. As such, it ignores potential erroneous information generated beyond the local line of sight of that robot. Consequently, it is not sensitive to the failures induced by specular reflection.

Obstacle profiles and frontier boundaries are extracted from the virtual sensor by clustering similar points along the polar contour into contiguous objects. Adjacent cells of positive values from the polar contour represent the profiles of obstacles while adjacent cells of negative values represent the profiles of frontiers. Consequently, exploration can be accomplished by directing the robot towards the center of clustered frontier points.

B. *Line of Sight Participation Planning*

Local control laws are useful for many aspects of robot navigation and planning. However, sometimes a robot has to coordinate its movements with respect to others in order to operate effectively. For example, Millibot requires that at least two other robots be within line of sight after any given move to generate a reliable position estimate. Before a Millibot moves to a new position, it must first assess its chances at localizing.

To support this planning, we first examine the line of sight region generated by a single robot. These are all the points directly viewable with respect to that robot (Figure 2d). Now, if we view the same line of sight region from the perspective of another robot, we have a way of predicting future line of sight constraints for the moving robot. Viewed in such a way, one robot's line of sight region represents all the places a second robot can move and still maintain a connection with the first. The same process can be applied to each of the robots in the team.

Consider the scenario given in Figure 3. Four robots have mapped a given space and have localized into the positions shown (Figure 3a). We now wish to move the robot under test to a new area in order to explore or provide mission specific sensing. The three remaining robots, denoted Ra, Rb, Rc, remain stationary to support localizing the robot after the move. For localization to be successful, the moved robot has to obtain valid range information from at least two of the other robots. The question is where can that robot move and still be in line of sight with respect to the remaining robots.

Again we answer this question by utilizing the virtual sensors of each of the stationary robots. Figure 3b shows the virtual sensor generated by each of these robots and their corresponding line of sight regions. Each reading provides local information about whether the new position will be within its line of sight (Figure 3c). However, we get a composite assessment by projecting each of these regions simultaneously onto a common map (Figure 3d). Points where the regions overlap once represent common areas that are within the line of sight of at least two robots. Regions that overlap twice represent places where all three robots will be within line of sight of the new position. Assessing regions in terms of multiple overlaps provides a basis for coordinating multiple robots. The same procedure can be applied for any operation that requires a robot to maintain line of sight to one or more robots including localization, communications or surveillance. In practice, every point in space does not have to be evaluated as in the way illustrated in Figure 3. Instead candidate movement points can be generated and evaluated by some other criteria.

C. *Combining with a Localization Metric*

Line of sight and the number of participants is not the only factor in achieving good localization. The geometry of the formation is also a critical factor. Some formations naturally

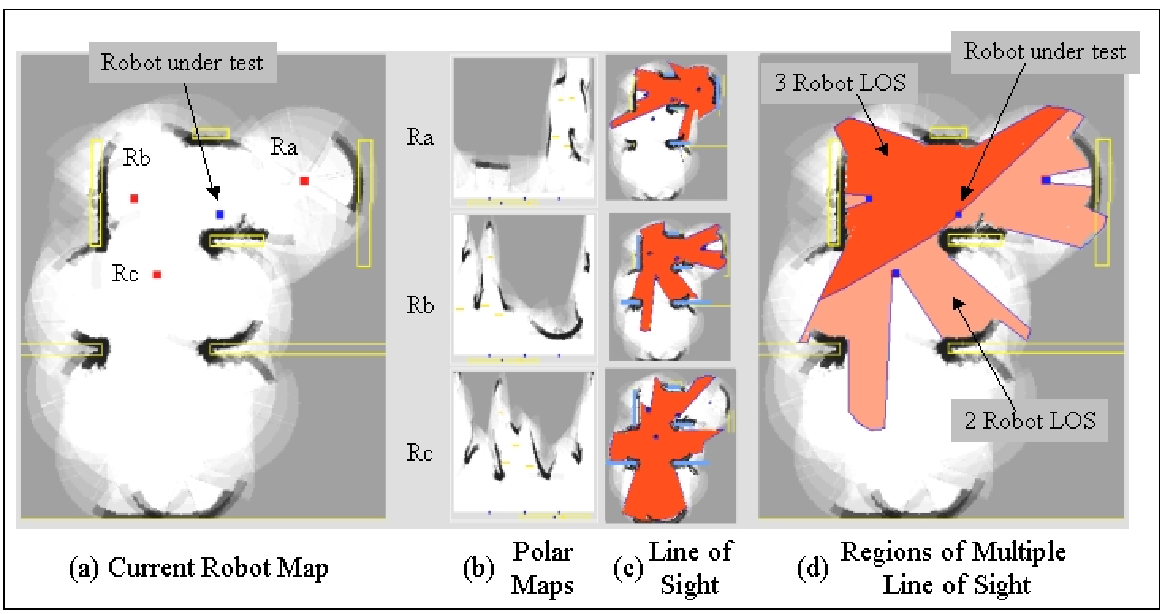

Figure 3. Line of Sight Participation - a) Given three participating robots, we want to find the places in the map where at least two are within line of sight. b) Each participating robot generates a polar plot by generating local polar map. c) Line of sight projected for each participating robot. d) Combine line of sight projections - the darker the overlay, the greater the number of participants. The robot under test can move anywhere within the shown projections and still be in line of sight of at least two robots.

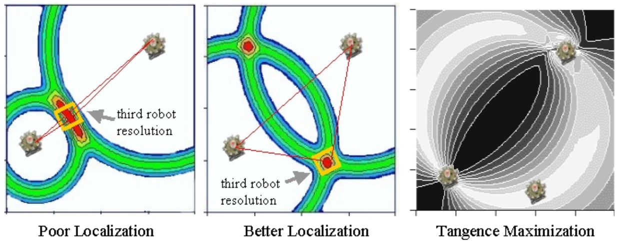

Figure 4. Localization Metric - a) Localization is poor when the team geometry approaches collinear. b) Localization is best when the angle between the two readings form a right angle. c) A metric plot showing utility of maximizing the angle between the tangents of intersecting measurements Lighter areas represent regions in space that generate better localization readings.

lend themselves to better position estimation than others. For example, in a three-robot system, resolution of a third robot is best if we maximize the angles between range measurement pairs of the participating robots. In localization, range measurement pairs can be visualized as an annulus with a center at the originating robot and a radius equal to the range measurement between the two robots. In a three-robot system, two range pairs are obtained to localize that robot. For the best localization, we maximize the angle between the tangents of the two intersecting range pairs so that their combined distributions lie in a confined region of space. If the placement of the third robot is poorly selected (for example if the three robots are collinear) the position estimate of the robot is also poor and spread over a large region of space (Figure 4a). However, if we maximize the angle between the tangents of the range measurements (Figure 4b), the same combined distribution is confined to a smaller region in space resulting in a better position estimate.

Given this knowledge, we can utilize geometry in the planning stage to guide robot movement as to best satisfy its line of sight constraints while taking into account the best location for maximizing its position estimate. To accomplish this, we develop a metric that maximizes the tangents of the range pairs. Figure 4c shows the application of this metric to the space around the set of robots. The lighter areas represent regions in space that generate well-localized position estimates while the darker areas generate poor estimates. Coupled with the line-of-sight assessment, candidates are selected that maximize localization resolution while ensuring an adequate number of robots remains within line-of-sight of each other.

A similar approach is applied to deal with the multitude of team constraints. For example, in the control of the Millibots, we cast a series of random points about a robot and pose each point as a candidate position for movement. From the list of candidates, we test each against conflicting constraints that include line of sight, obstacle clearance, travel distance, exploration gain etc. The point with the highest overall utility is then selected and the robot is directed to that point.

V. HETEROGENEOUS SENSING

As if reduced range and resolution were not enough of a handicap, some robot teams must contend with the composition of heterogeneous sensing. Such is the case for the Millibot team where the scale of the robots does not support a single robot type. Robots must distribute and coordinate sensing to achieve the necessary degree of perception. For example, some robots are equipped with sonar sensors that provide range information to obstacles while others are equipped with mission dependent sensing like heat detectors or video cameras.

Conventional team control is accomplished by treating each robot as if they were interchangeable. Control is a matter of managing the physical locations of the robots but not the individual resources of those robots. Heterogeneous composition complicates this methodology and introduces complexity in the control process. Uniformity of sensing on an individual robot is an issue as well. Local navigation strategies often assume a uniform sensor distribution about the robot. However, in some cases, a robot is equipped with a variety of sensors each with different sensing characteristics.

One example is the Dirrsbot (Figure 5a). This Millibot contains three forward-looking sonars similar to others in the group each with a range of 30cm. However, it gets its name from two side-looking, digital infrared range sensors (dirrs). These sensors have a range of 80cm but a narrow 5-degree field of view. Not only is the sensor profile for this robot non-uniform, it does not fully cover the area about the robot. Integrating this robot requires specialized routines for almost every aspect of operation. On the other hand a virtual sensor is posed as a uniform array with respect to the robot (Figure 5c). Moreover, since the virtual sensor for each robot is derived from the fusion of the same team map, each robot can utilize the same navigation strategies.

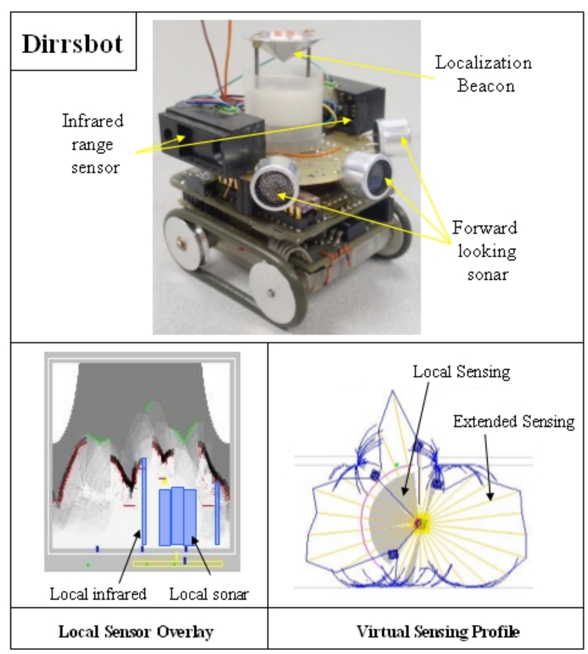

Figure 5. Supporting Heterogeneous Sensing – a) A heterogeneous Millibot equipped with forward-looking sonar and side-looking infrared. b) Correlation between local and virtual sensor. c) Comparison of non-uniform local sensor and uniform virtual range sensor.

Sensor failure also complicates reliable local navigation. Sensor failure and specular reflection often result in readings that indicate a clear path even when the path is obstructed. However, if we correlate the current sensor readings with the derived virtual sensor readings (Figure 5b), we have a means for putting local readings in context and rejecting suspect readings. This additional confidence in sensing equates directly to competence in moving through a desired space without incident.

In some cases, a robot simply does not have a means for sensing its own surroundings. One example is a Millibot equipped with only a video camera and localization beacon. Even when the robot needs to navigate in known space, it has no means for generating local plans without involving the operator. However, by utilizing the virtual sensor, the same robot can operate as if equipped with range sensors.

Virtual sensors provide an added benefit in that they allow the possibility of the generalization of local sensor platforms into a ubiquitous representation. Robots with long-range and short-range sensors generate similar virtual sensors as do robots with non-uniform sensor distribution or no sensors at all. This ability to generalize robot sensing is instrumental in applying generalized robotic algorithms to heterogeneous robot platforms.

VI. CONCLUSION

In this paper we have shown how to generate a virtual sensor for each robot that is an abstraction of an individual robots sensor and the team's occupancy map. The formulation of this sensor allows a local determination of line of sight local obstacles and frontiers as well as other robots in the team. This assessment is critical for establishing formation to support many aspects of team coordination including localization, communications and coverage. Equally important is the ability of determining when line of sight has been violated to reject potentially erroneous signals still present due to multipath reflections.

Line of sight assessment is facilitated by expressing the range and bearing to local features in the form of a polar contour. Line of sight to arbitrary points in space is determined by testing whether the desired point lies above or below this contour.

The utility of the virtual sensor moves from sensing to planning by viewing the contour of one robot with respect to the all the others. In this fashion, one robot's line of sight region represents all the areas a second robot can move and still remain within the line of sight of the first. The same process can be simultaneously applied to the other robots in the team to satisfy formations that require line of sight to multiple robots.

Finally we show the added utility of virtual sensing when applied to teams with heterogeneous sensor composition. The virtual sensor provides a means of recasting a robot's local sensing in terms of the collective sensing stored in the team's occupancy map. Consequently, the derived virtual sensor is the same for any robot regardless of the underlying sensor platform. This ubiquitous representation of sensing allows the application of conventional homogenous control techniques on heterogeneous teams.

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