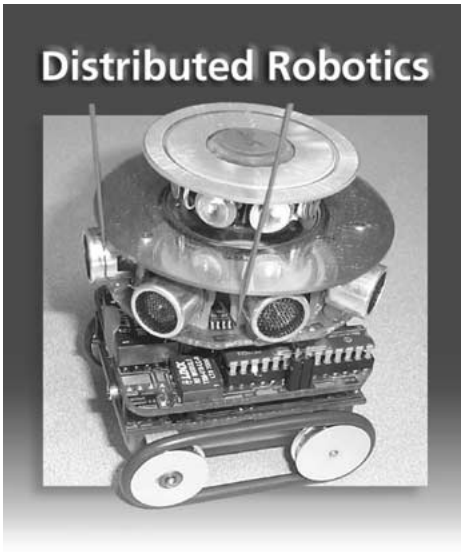


# Millibots

## *The Development of a Framework and Algorithms for a Distributed Heterogeneous Robot Team*

By LUIS E. NAVARRO-SERMENT, ROBERT GRABOWSKI, CHRISTIAAN J.J. PAREDIS, and PRADEEP K. KHOSLA

The value of a group of entities collaborating as a team has been proven many times in many domains. In the military, a team of men with specialized skills and limited resources coordinate to produce a combat unit with incredible force and range. Nature abounds with examples of predators who coordinate as a team to hunt prey that are stronger and swifter. These examples illustrate that the coordination of individuals with similar or disparate abilities can produce a team with abilities greater than the sum of its parts.

The same advantages can be extended to a group of robots coordinating as a team to share information and resources. In such a team, a task is not completed by a single robot but by the team of collaborating robots. Team members exchange sensor information, collaborate to track and identify targets, or even assist each other to scale obstacles. As for sensing, by coordinating its members a team can exploit information derived from multiple disparate viewpoints. Even a single robot, though equipped with a large array of different sensing modalities, is limited at any one time to a single viewpoint. Moreover, a team of robots can simultaneously collect information from multiple locations. There are many tasks for which distributed viewpoints can be exploited, such as surveillance, reconnaissance, and rescue.

One factor that determines team capability is the physical size of its members. A team composed by large-sized all-terrain vehicles (ATVs) would do very poorly mapping the inside of a building, whereas the same team would excel when exploring and surveying urban areas. Conversely, small robots—even in teams—are inappropriate in large, open spaces, such as fields or forests. However, small robots are more effective in other domains. Small robots can potentially crawl through pipes, access collapsed buildings, and hide in inconspicuous spaces. This increased accessibility dramatically impacts the effectiveness of the team in some surveillance and exploration tasks. However, with small size comes the disadvantages of limited mobility range, limited energy availability, and possibly reduced sensing, communication, and computation ability due to size and power constraints. Because limitations in size are immediately extended to power and processing capabilities, it was realized early that our robots would have to coordinate to achieve any useful tasks.

The main focus of our research is to develop a framework and algorithms for a group of small robots that can effectively achieve the functionality of a larger robot while retaining the ability to operate in new domains. This article describes the design and construction of a team of 7 × 7 × 7-cm robots called "millibots" (Fig. 1). We show how the team can exploit collaboration to perform missions such as mapping, exploration, surveillance, and eventually support rescue operations.

## The Millibot Team

To attain reasonable functionality for robots on a small scale requires careful attention to the development of the architecture of the team. As size is reduced, it becomes increasingly difficult to outfit a single robot with all the necessary sensors required to complete the mission. Furthermore, limitations in power and size further reduce the range and capabilities of these sensors. Our approach to overcoming the disadvantages imposed by small robot size is to exploit the properties of *specialization* and *collaboration*.

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Specialization is necessary to allow the team as a whole to optimize on size and resources—specifically power. For a robot to be mobile, it must carry its own power source. Considering that the battery volume for robots on the centimeter scale reaches upwards of one-third of its volume, it quickly becomes apparent that functionality must be spread among several members. Equipping each robot with only those sensors necessary to achieve a particular aspect of the task collectively conserves power.

In addition to specialized sensing, the same philosophy can be applied to processing. To perform some actions, an individual robot may require only limited processing capabilities. Conversely, other tasks may require more complicated calculations. Since computational ability and speed impact power, it is possible to extend the operational time of the team by matching processing to the required tasks. Discussion of the development of specialized sensing and processing will be continued later in the article.

Exploiting specialization comes at the cost of coordination and communication. Since the functionality of the team must be spread among several members, the distributed information must be collected and processed. Collaboration is necessary to coordinate and collect information so that the individual members of the team can act as a single logical entity. Coordination of team movement and data collection is also addressed later in this article.

### Modular Architecture

Through specialization, the composition of the team can be determined at run time. The choice of sensing and processing platforms for each robot and how the platforms are utilized depend on the needs of the mission. Some robots may be equipped with the specialized sensors necessary for team exploration. Other robots may be equipped with greater processing power to facilitate local map building and sensor data analysis. Other robots of the same team may be equipped with reduced sensing but extended actuation or mobility.

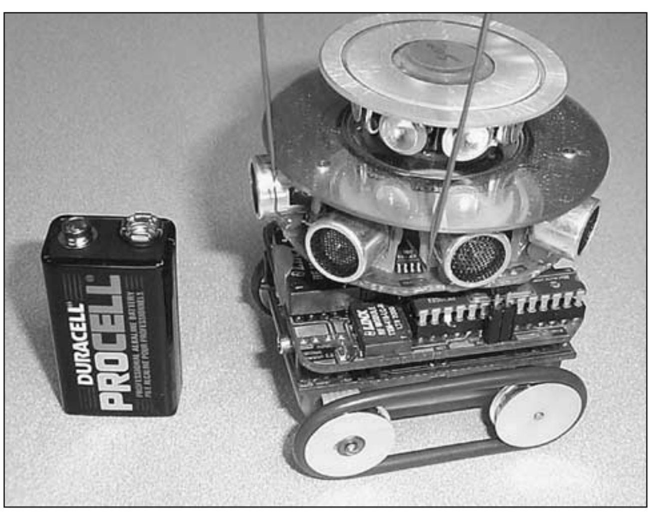


***Figure 1.*** *A millibot equipped with a long-range sonar module.*

To achieve this level of specialization without the need for a large repository of robots, the millibots have been designed in a modular fashion. A millibot is constructed by assembling a set of subsystems ranging from computation to communications to sensors. Even the mobility platform is modular and can be selected based on the terrain in which the team is deployed. Modularity is accomplished by implementing each subsection as a self-contained module complete with processor and interface circuitry.

Modularity also readily supports the integration of new sensing and processing modalities. As will be seen later in this article, a new module can be constructed and added to the team by implementing the defined module interfaces. This concept applies to processing as well; as advanced processing modules are developed and added, new modalities of existing sensing platforms can be extended. For example, greater processing power may be utilized to perform on-board filtering of sensor data, decentralized position estimation, or even the local generation of robot maps.

### The Localization System

Autonomous robots within distributed teams usually operate in three different sensing modes. One sensing mode measures internal parameters of the robot, e.g., the position of the driving motors, that provides the necessary information for operations, such as speed control and dead-reckoning. A second sensing mode perceives the environment in which the robot is operating, such as obstacle detection and identification. The third sensing mode provides information about the state of the *team*. For instance, localization sensors collect position data to determine the formation patterns of the group as a whole. It turns out that this sensing mode is the most critical for the team to operate as a cohesive unit.

The exploration and map-building capabilities of a robot team are strongly dependent on its sensory skills and capacity to determine group position. When the positions of all robots are known, the information extracted from their sensors can be related with their current viewpoint. A map is then constructed by creating a list of all these position-sensor relationships. Without knowing the position and orientation of the sensors in context with one another and the environment, it becomes impossible to interpret the sensor data in a global frame of reference. Moreover, position knowledge is critical to a distributed team during map construction in that the group must move to predetermined locations, avoid known obstacles, and be repositioned for maximum sensor efficiency.

There have been many proposed solutions to the localization problem. Many systems derive robot location based on dead-reckoning, that is, the position based on the extrapolation of a robot model [1]. Without some additional means, this method quickly accrues intractable errors due to wheel slippage and becomes ineffective for all but limited moves. The problem is compounded for systems that rely on skid steering. Some systems complement this mode by integrating knowledge of the environment, such as orthogonal walls. However, this knowledge may be difficult to obtain or quantify when operating in unknown environments. Some sensor-based solutions involve the use of a global positioning system (GPS) that derives the position by timing signals received from satellites. However, due to the relative large size of the receiver, limited accuracy, and satellite visibility requirements, GPS is not appropriate for small robot teams that operate mostly indoors. Higher performance systems have been designed that derive probabilistic models of the environment based on known information about the space and access to large amounts of data [2]. This method is less viable for small robot teams exploring relatively unknown spaces using low-resolution sensors. Along the same lines, other groups have developed localization methods based on the correlation of multiple video images [3]. However, though the size and power of the cameras continues to shrink, the computation complexity required to process the video signals remains. Moreover, the problem of integration of high-bandwidth video distributed among a group of robots is compounded by the additional problems of communications availability and scheduling.

To give the millibots the ability to maintain robot position as the team progresses, we have developed a custom solution that combines aspects of GPS, landmark-based localization, and dead reckoning while retaining a small form factor within a limited power budget. Each robot is capable of generating and detecting a set of synchronized ultrasound pulses used to determine the distance from itself to other robots in the team. These robot-to-robot ranges are used to compute the relative positions of team members using a process called trilateration, i.e., position determination based on distance measurements to known landmarks or beacons [4]. Similar ultrasonic beacon systems have been developed. However, they usually require carefully placed fixed beacons and carry a price tag in the tens of thousands of dollars. Unlike this fixed-beacon system, the millibot system is fully mobile and able to dynamically position itself during operation—a critical relaxation for the team's ability to explore unknown areas.

Each robot is equipped with a localization module. A typical localization module consists of a low-cost ultrasonic transceiver, circuitry, and a conic reflector. The reflector is a key component in the design of an effective beacon system in that it provides coverage of 360° in the horizontal plane. The localization transducer with reflector is about 2.5-cm tall. It can measure distances up to 3 m with a resolution of 8 mm while consuming only 25 mW. The design is constructed such that each robot can act as both emitter and receiver. This provides the team the greatest flexibility during group movement. A complete description of the coordination of timing signals and how they represent distance can be found in [5].

### *Modular Sensing Platforms*

Mobile robots require sensors to extract information from the environment in which they are operating. From a group perspective, sensors allow the team to learn and update its own model of the world. As the complexity of the system increases, so does the variety and number of sensors required to perceive the world effectively. To this end, we have developed several sensor modules for the millibot team. Depending on mission objectives, a millibot is retrofitted with an appropriate sensor modality. The selected sensor modules allow the robot to perform key functions ranging from localization, to mapping and exploration, to support for fire rescue.

***As size is reduced, it becomes increasingly difficult to outfit a single robot with all the necessary sensors required to complete the mission.***

#### SHORT-RANGE SONAR

Exploration is typically accomplished without previous knowledge of the environment. For this reason, the robot must be able to detect obstacles along its way in order to navigate safely through uncharted areas. To provide the robot with an efficient yet effective means of sensing, we designed a short-range sensor module capable of providing robot-to-obstacle ranging up to 50 cm [Fig. 2(a)]. However, instead of employing the traditional, high-power, electrostatic sonar elements, this module is designed with a set of piezoelectric transducers mounted in a ring about the outside of the module. Piezoelectric transducers are inexpensive, work at low voltages, and fit easily within the power and size budget of the millibots. To detect obstacles, each transducer in the array sequentially emits a set of ultrasonic pulses that propagates away from the transducer. If an object is within range, it is reflected back to the robot and captured by the center receiver. Distance is derived by measuring the time-of-flight between the emitted pulse and the detected echo. By employing the beacon receive circuitry as part of the sensing loop, circuit size is further reduced.

Another significant feature of our design is that sensing can be achieved for objects as close as the robot itself. This feature is critical for a small robot attempting to navigate in tight areas. Ultra-short range is accomplished by reducing the number of pulses sent by the transmitter. Reducing the count rate permits earlier reception of the echo but also reduces the energy transmitted and the range of detection. Longer ranges are recovered by increasing the pulse count at the expense of minimum range. The necessary number of pings is evaluated during operation based on the desired distances needed for sensing. A low ping count is used to verify and detect close objects, while higher counts achieve extended range sensing to maximize mapping.

#### LONG-RANGE SONAR

A team of robots equipped with short-range sonar modules can be coordinated to effectively map small spaces. However, when the team attempts to map larger open spaces, its performance decreases significantly. To increase the speed and performance of the team, we designed a module that extends the range of sensing for a single robot [Fig. 2(b)]. This long-range sonar operates under the same principle as the short-range module; however, the concept was turned inside out. This module emits a sonar pulse from its central composite transducer that radiates outward in all directions. Echoes are received simultaneously from an array of eight perimetric detectors. In this form, a single sonar pulse simultaneously returns information about the obstacles surrounding the robot, increasing sensing time by a factor of eight. Additionally, the same pulse used for sonar can also be utilized as a localization signal by other robots in the team. Sensitivity and range are further enhanced by integrating each transducer with its own custom, high-gain amplifier and detector mounted to the back of each transducer. Considering the fact that any movement comes at the additional cost of coordination and localization, the increased range and functionality of this module significantly improves the effectiveness of the team as a whole.

### INFRARED RANGE FINDER

Equipping a team with sensors derived from a common modality exposes it to complete failure under a single adverse condition. Potential complications with any ultrasonic-based sensor include the possibility of interference with similar modules on other robots or jamming from external ultrasonic noise sources. To increase system reliability, several sensing modalities have been added to the millibot team. For example, an alternate means of obstacle detection was produced by retrofitting a short-range sonar board with two digital infrared (IR) ranging modules mounted on each side of the robot [Fig. 2(c)]. Each module provides range information to objects up to 80-cm away within a detection cone of about 5°.

In addition to providing a different sensor modality, these units acquire information at higher rates than sonar modules, making them ideal for fast moving robots. By mounting them on the sides of the robots facing out, the digital IR modules are ideal for fast wall-following operations. Another advantage of employing mixed modality sensing, such as IR, sonar, and video is that multiple sensors can be utilized simultaneously without interfering with each other. Coordination is still re-

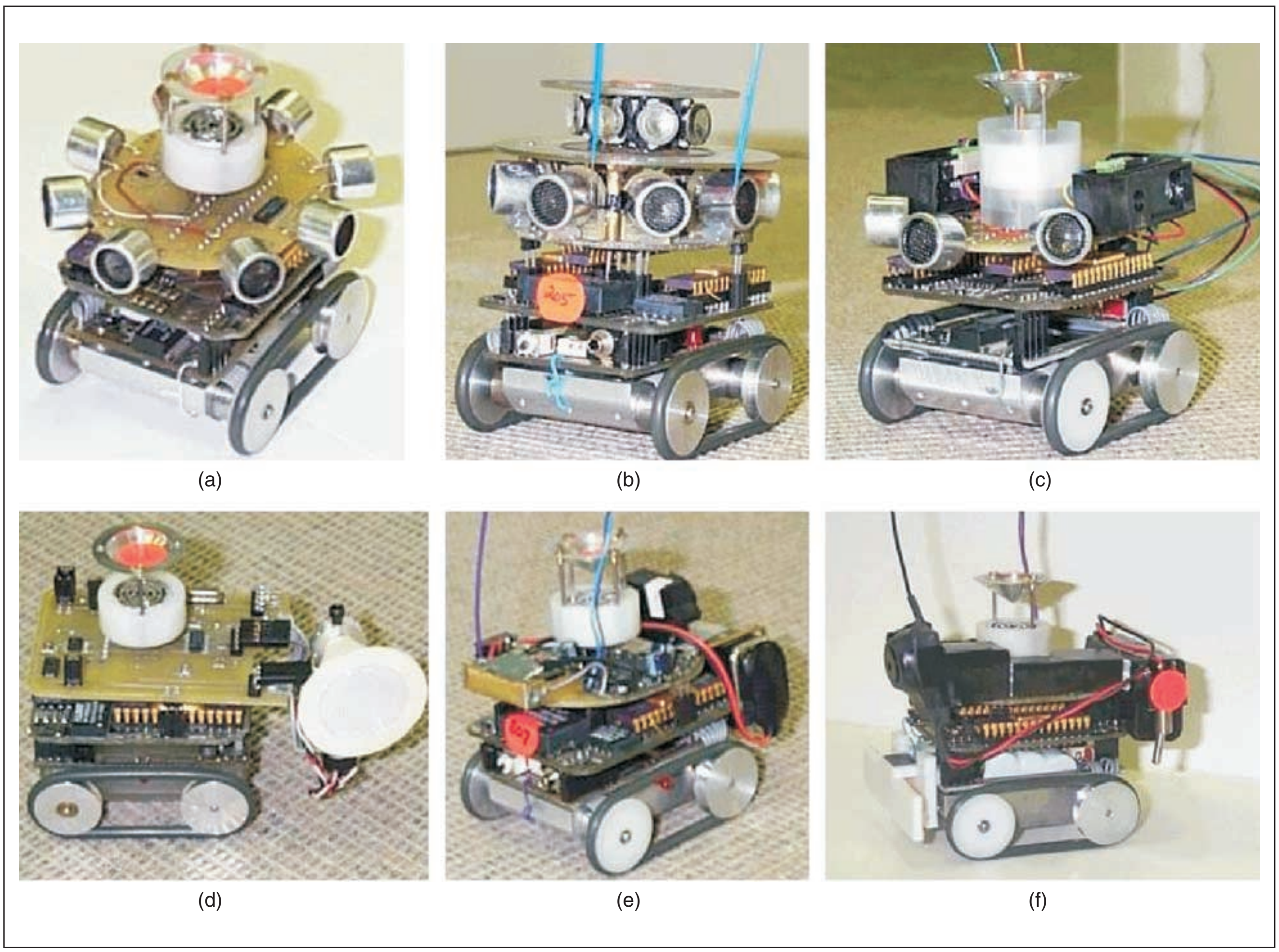


***Figure 2.*** *Hetergeneous team. (a) Short-range sonar. (b) Long-range sonar. (c) IR ranging. (d) Directional IR. (e) Camera. (f) Camera.*

quired to schedule sensing, but information can be more effectively interleaved, increasing information density.

### VIDEO CAMERAS

Another sensing modality developed for the millibot team is video. The sensors discussed so far generally cannot provide enough detail to resolve all of the problems facing a real robot. For example, if a robot is no longer able to determine its position in the group, video may be utilized to track and find the wayward robot. Video may also be employed to provide quick classification of obstacles identified by the group. We have developed two kinds of video modules for the millibots. The first type is a module equipped with a video camera, a radio-frequency (RF) video transmitter, and remote power-switching circuitry [Fig. 2(e)]. The ability to remotely power a camera provides two very important functions. The first is that the robot can optimize power by turning off the camera when video is not required. This power management can be critical for some types of cameras. For example, one of our camera modules dissipates up to 1.5 W during operation, which is right at the threshold of the millibot power budget. Scheduling camera operation significantly improves the team's runtime. The second feature of remote power operation is that the same team can utilize several camera modules while requiring only a single video channel. Interference is eliminated by only powering one device at a time.

A second type of video module that is designed to provide a continuous video signal was recently added [Fig. 2(f)]. New technologies have significantly reduced the size and power of remote video cameras to where continuous video is now feasible for small robots. Unlike switched video, continuous video allows the exploitation of video methods, such as motion detection, surveillance, docking, and visual servoing. The utility of switched and continuous video adds a great deal of flexibility and functionality to the team.

### DIRECTIONAL IR DETECTOR MODULE (DIRM)

Heat sources, such as open flames, hot zones, or unconscious people, are usually landmarks worth exploration. The detection of humans and/or human activity is particularly important. For this reason we designed a directional IR detector module (DIRM) that provides the millibots with a means of increasing their sphere of awareness when exploring an unknown space [Fig. 2(d)]. Objects that generate heat also generate IR radiation in direct proportion to the temperature, which can be easily detected.

The heart of the DIRM is a pyroelectric IR sensor. Pyroelectric sensors are made of ferroelectric crystals that generate a surface electric charge when exposed to IR. However, a pyroelectric sensor only produces an electrical output when the level of incident radiation changes. Electrical output is a function of the rate of change in detector temperature rather than temperature itself (this characteristic is one of the reasons why pyroelectric sensors are widely used as thermal motion detectors for detecting people). If the incident radiation changes slowly, the electrical output of the sensor will be small and may not be detected, regardless of the magnitude of the IR source.

**Specialization is necessary to allow the team as a whole to optimize on size and resources —specifically power.**

To enable the detection of immobile heat sources, we have designed a DIRM that is capable of detecting both mobile and immobile heat sources, such as warm bodies or flames. The sensor is mounted to a rotary platform that smoothly rotates and sweeps the sensor across an arc of about 170° in 5 s. If the sensor points towards a heat source while sweeping the area, it will produce an electrical output in response to the change of incident radiation.

The DIRM can only give a notion of the direction from which the heat originates, but not how far away. To find the location of the heat source, we have developed two different collaborative approaches. The first is to combine several readings of one DIRM taken from different viewpoints, using the rest of the team to determine the position of the measuring robot. The second approach is to combine the bearing information provided by the DIRM with range data collected from other millibots. In both cases, as described in [6], we build occupancy maps by combining information from different positions and time instances

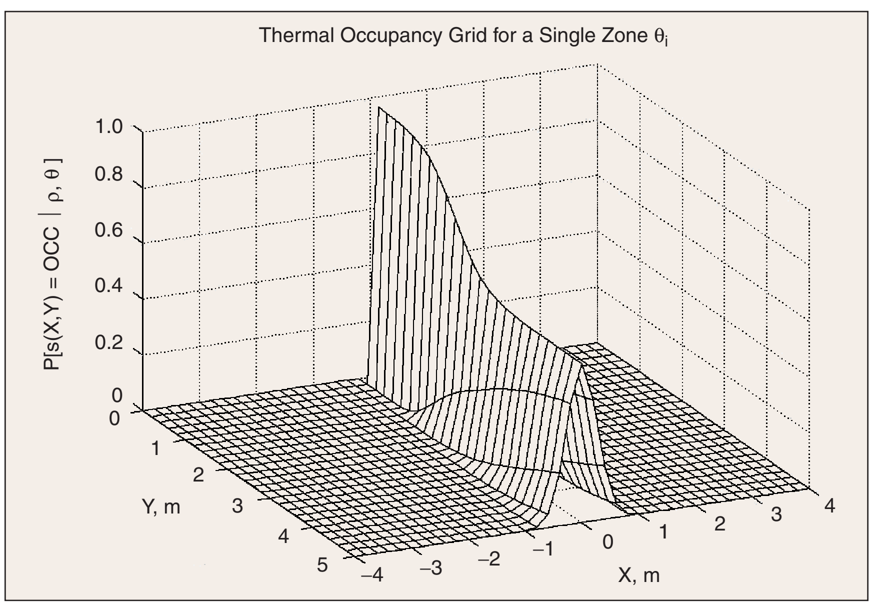


***Figure 3.*** *Occupancy update for DIRM.*

**Although millibots are small, they still collectively contain a full set of integrated capabilities, including sensing, computation, communication, localization, and mobility.**

within an occupancy grid. By merging thermal information taken from several different locations, we can construct an equivalent *thermal occupancy grid*. Each thermal grid cell stores the likelihood that a heat source is present at that location. An occupancy value near one corresponds to the likelihood that that position is occupied by a heat source. Similarly, a value near zero corresponds to the likelihood that the position is free of a heat source. Since nothing is initially assumed about the environment, all the cells are initially assigned a value of 0.5 (equally likely to contain or not contain a heat source). Following each measurement, the corresponding grid cells are adjusted using a Bayesian update rule based on a derived model of the sensor. A two-dimensional (2-D) occupancy model generated for the DIRM in a single zone is shown in Fig. 3. The sensor is modeled with Gaussian uncertainty in both range and angle. The profile shown corresponds to a DIRM positioned at the upper left and pointing to the lower right. The DIRM indicates a bearing in which a heat source is more likely to be found. With this information, since the position and orientation of the DIRM are known, the team leader can send other millibots equipped with different sensors to explore and pinpoint the location of the heat source.

## Team Collaboration

A direct consequence of distributing functionality and resources (i.e., specialization) among a group of robots is the need for collaboration. We define collaboration as the explicit exchange of information between members of a team. Individually, each robot can handle only small, well-defined tasks. However, by coordinating action and information, a collection of robots can pool resources to accomplish more complex tasks.

### *Collaborative Localization*

Millibots exploit collaboration to maintain global team position as they move through space. Each robot is equipped with a localization module that allows it to measure its distance to other members of the team. If all the distance measurements were perfectly accurate, a simple geometric trilateration algorithm would be sufficient to determine robot positions. However, measurements are often noisy, missing, or subject to unique failures. As a result, the set of equations resulting from a purely geometric approach is ill-conditioned and does not always yield a solution. Instead, we use a maximum-likelihood estimator that determines the most likely position and orientation of all the robots given their previous positions and orientations, their movements, and their sonar-based distance measurements. By verifying that both the dead-reckoning data and distance measurements are normally distributed, we can compute the likelihood of a particular set of measurements occurring for a given robot position:

- *Dead reckoning:* The likelihood that a robot moved over an angle, $\alpha \pm \sigma_\alpha$, and a distance, $d \pm \sigma_d$, given its initial position $(x^0, y^0, \varphi^0)$ and final position $(x^1, y^1, \varphi^1)$ is

$$P\left(\alpha, d \middle| x^0, y^0, \varphi^0, x^1, y^1, \varphi^1\right) = N\left(\frac{\alpha - \hat{\alpha}}{\sigma_\alpha}\right) N\left(\frac{\beta - \hat{\beta}}{\sigma_\beta}\right) N\left(\frac{d - \hat{d}}{\sigma_d}\right), \tag{1}$$

where $\beta$ is the angle over which the robot rotates while moving forward.

- *Distance measurements:* The likelihood that the measured distance between two robots, $i$ and $j$, is equal to $D_{ij}$ is

$$P\left(D_{ij} \middle| x_i^1, y_i^1, x_j^1, y_j^1\right) = N\left(\frac{D_{ij} - \sqrt{\left(x_i^1 - x_j^1\right)^2 + \left(y_i^1 - y_j^1\right)^2}}{\sigma_D}\right). \tag{2}$$

By fusing dead reckoning and distance information, the total conditional likelihood function $P_{tot}(\alpha i, d_i, \ldots, D_{ij}, \ldots \mid x_1^0, y_1^0, \varphi_1^0, \ldots, x_n^0, y_n^0, \varphi_n^0, x_1^1, y_1^1, \varphi_1^1, \ldots, x_n^1, y_n^1, \varphi_n^1)$ is the product of all the conditional likelihoods introduced above. The most likely robot positions are found by maximizing $P_{tot}$ with respect to the new robot positions

$$\left(x_1^1, y_1^1, \varphi_1^1, \ldots, x_n^1, y_n^1, \varphi_n^1\right).$$

The maximum likelihood estimator requires that the initial positions of the robots are known with respect to one another. This requires a slightly modified approach at start up. After collecting distance measurements between all possible robot pairs, a conditional probability density function is defined that only consists of distance measurement terms. In addition, one arbitrary robot is assigned the position (0,0), and a second robot is assigned a position on the X-axis. This defines a frame of reference in which the position of all other robots is determined by maximizing the conditional probability density function. However, based on distance measurements alone, there remains an ambiguity about the sign of the Y-coordinates of each robot. To resolve this ambiguity, the team leader commands one robot to follow a short L-shaped trajectory and recomputes its position. If the robot turned to the left, but the assigned coordinate system indicates a right turn, the signs of the Y-coordinates of all robots are reversed.

More importantly, the team is able to maintain global position during mission operation by carefully coordinating team movement. At any one time, a portion of the team remains stationary, providing a known reference point for the moving robots. Information is collected after the move and used to relocalize the team. Once relocalized, team members can exchange position, allowing the fixed robots a chance to move. Functionally, the movement of the team exhibits the behavior of leap-frogging, though strict formation is not necessary.

A description of the control algorithm and characterizations of the localization system can be found in [7]. In a more recent work [8], the problem of fault tolerance of the localization system is addressed, focusing on the detection and isolation of measurement faults that commonly occur. Such failures include dead-reckoning errors when the robots collide with undetected obstacles and distance measurement errors due to destructive interference between direct and multipath ultrasound wave fronts.

## Collaborative Mapping

One of the applications used to test the capabilities of the millibot team is the mapping and exploration of unknown environments. By coordinating movements, the team is able to collect and fuse sensor information from several robots into a composite map of the area [9]. It is difficult for a single robot to map a relatively large area, especially for robots of this scale. Even with its long-range sonar, a millibot is limited to a detection range of about 1 m. To cover any significant area would require extended and potentially inefficient movement. The size of the robot and the availability of power compounds the problem even further. More importantly, without the ability to maintain global position, a single robot would have difficulty in placing its sensor readings in the proper context to build effective maps. This dependence between map building and localization makes collaboration essential. By coordinating as a group, a team of millibots can cover more area in a shorter amount of time while also maintaining a sense of team position. Moreover, multiple robots allow the team to exploit parallel search algorithms, further increasing team speed.

In [7], we described a set of mapping experiments using a team of five robots. Each experiment mapped an area of about 1 $m^2$ in times ranging from 30-90 min depending on obstacle density. The results of five runs were merged to produce a composite map of the area (Fig. 4, left). High-level operation of the team was controlled by a remote operator viewing the team map. Speed was dictated by the time it took the operator to visually process the map and direct individual robot actions.

In the interim, we have added functionality that allows the team to close the loop. Collective team information has been exploited in the form of skills to automate low-level actions. In addition to providing methods for automating the synchronization and collection of sensor data, the composite map is exploited to generate team actions. Regions of the map are separated into explored, open, and unexplored. Open areas are exploited in path planning for team movement, especially for those robots without obstacle sensors. Clustering algorithms provide a means for converting the grid map into polygonal obstacles to facilitate path planning and formation control. Regions between open and explored are used to generate frontiers. These regions direct the team towards the most viable areas of exploration. The result of providing operational feedback is increased team speed and less operator involvement. Instead of spending time coordinating low-level actions, the operator can take on more of a supervisory role. As a result, by combining new sensor modalities with operational feedback, a similar team of five robots is now able to map an equivalent area in a fraction of the time. An area that originally took 30 min can now be accomplished in less than 10 min (Fig. 4, right).

## Rescue Support

When working as a coordinated, mobile sensing platform, a team of millibots can extract rich information from many new

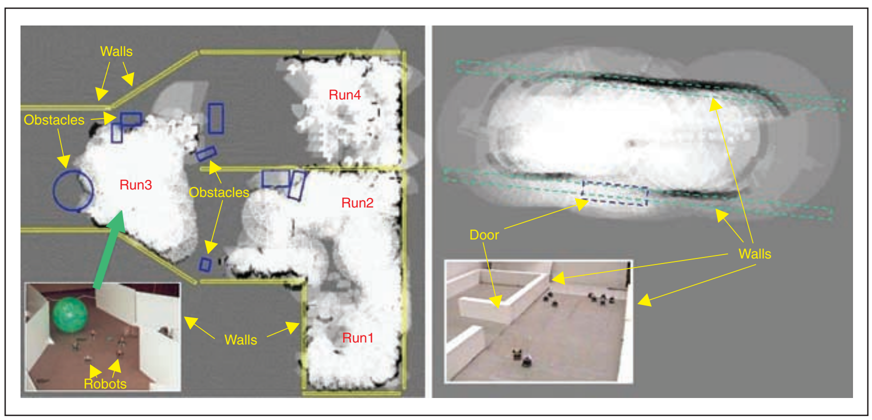


**Figure 4.**

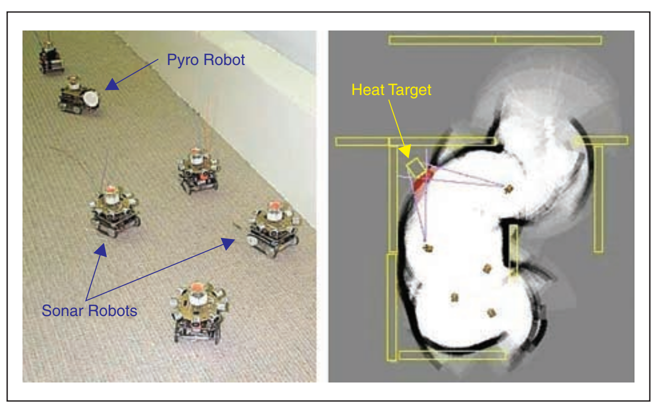


**Figure 5.** *Support for fire rescue.*

scenarios. Consider, for example, a rescue team working inside a burning building. While firefighters may easily spot open flames, some areas may be difficult to reach and inspect. Moreover, reduced visibility makes it difficult to detect and assist potential victims. This scenario presents a situation in which additional sensing provided by a team of roving robots can increase the effectiveness of the rescue effort. Fig. 5 illustrates a team of millibots exploring a space in the vicinity of a fallen victim. Several sonar robots have already explored the area and generated a map of the zone. The robots have passed a heat source but mapped it as another obstacle. Because of the poor angular resolution of the sonars, the corners are not clearly resolved in the map, so the free corners look the same as the corner in which the victim is located. Similarly, a thermal occupancy map would only indicate the direction of the heat source, providing no indication of the size or distance to the source. However, by fusing the information from both sensor types together, the team is able to assess that there is an object of interest located in the corner of the derived map. Furthermore, if properly equipped, the team can further exploit its heterogeneous nature by directing a robot with a video camera to return a snapshot of the area. By exploiting multiple sensor modalities, the sum of the team's combined experience can provide invaluable assistance in many areas.

***Figure 6.*** *Deployment in an air duct.*

### *Urban Reconnaissance*

Whereas heterogeneous teams allow the exploration of new sensor modalities, small size allows the deployment of the team in many new domains. One potentially fruitful application for small robot teams is surveillance. By their very nature, small robots are less conspicuous, can access tighter spaces, and are more likely to go unnoticed. An extension of this idea is to deploy a team of millibots in the ventilation ducts of a building (Fig. 6). Whereas access to multiple rooms might be restricted by locked or guarded doors, air ducts tend to extend throughout a building without major interruption. Moreover, since air ducts are generally low-flow systems, they tend to be flat, smooth, and regular, making them ideal highways for a team of small robots.

An example of the utility of a team of robots high in the air ducts of a building is in hostage situations. During a hostage scenario, the team can be deployed into the ventilation system from an adjacent room. Quietly, the team moves towards the critical area while building a map of the system. Once positioned, selected millibots equipped with microphone sensors can then return audio information from the room undetected.

However, achieving functionality in a series of air ducts requires a second look at conventional robotic sensing and communications. First, the robot team cannot rely on traditional sonar as its main sensing source. The smooth, tight aspects of an air duct amplify the errors associated with specular reflection and poor angular resolution. However, other modes of sensing, such as IR and video, do not suffer from the same problem in this domain. Similarly, communications—usually a transparent resource in robot operations—are potentially reduced to line of sight by the shielding effect of the metal in most air ducts. To overcome this problem, the robot team must geographically place members at key positions to relay messages around corners and down the ducts. Fortunately, the modular nature of the millibot team easily supports the development of new sensing and operational modalities to support operation in new domains.

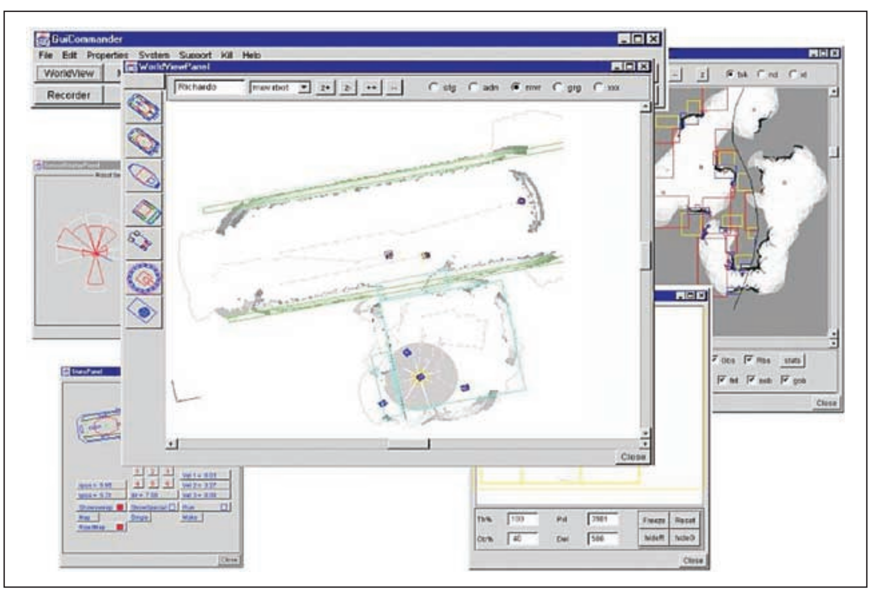


***Figure 7.*** *Graphical user interface.*

## Graphical User Interface

Tasking of the team is accomplished through a distributed control system called CyberRAVE. CyberRAVE is a client-server architecture that allows multiple, heterogeneous teams to coordinate operation and share data via a central control server and a set of distributed graphical user interfaces (GUIs). Through a designated control GUI (Fig. 7), an operator is able to direct a team by setting goals, querying maps, and viewing live sensor data. Additional interfaces can be launched to remotely observe team operation. In addition, the distributed nature of the architecture allows computation to be spread among several machines, allowing efficient and speedy operation.

To increase mission flexibility, CyberRAVE architecture supports hierarchical control as well. Robots may be grouped and controlled as individuals, groups, or subgroups in order to perform specific tasks. In this way, low-level coordination of the subgroup can be abstracted away from the user.

Team functionality is obtained through the composition of skills. Skills are control algorithms that are designed to perform specific actions or tasks using one or more robots. A skill can range from simple, reactive atoonomous actions, such as motor commands or sweeping sensors, to higher level functions, such as sensor-based wall-following or coordinated, incremental map-building. Additionally, skills are composable and recursive. A high-level skill can be the composition of many low-level skills arbitrated by a state machine or any other user-defined mission planner.

One of the unique features of this architecture is the close interaction with the operator. In most cases, the millibot team will be providing a support role for missions, such as reconnaissance, exploration of unknown spaces, and surveillance. The inclusion of the operator in the processing loop helps to bridge the gap between totally reactive systems and proactive autonomy in a continuous fashion. In many domains, the operator is already interactively a part of the team. To facilitate operator feedback, a scripting language and skill composition dialog has been included to provide quick access and composition of team skills. In essence, the operator becomes the highest level decision maker for the group. Based on feedback from the robot team and intrinsic knowledge of the mission, the operator can quickly select and launch appropriate team skills.

## Summary

In this article, we have presented the design of a distributed robotic team consisting of small mobile robots called millibots. Although millibots are small, they still collectively contain a full set of integrated capabilities, including sensing, computation, communication, localization, and mobility. To expand the capabilities even further, the millibots have been designed in a modular fashion, allowing a user to easily create specialized robots with particular sensing and processing configurations. By combining several such specialized robots, a team can be created with a broad range of capabilities while still maintaining a small form factor.

An important component of the millibots is the ultrasound-based localization system. This system has an important advantage over currently existing systems in that it does not require any fixed beacons. By using the millibots alternately as beacons and localization receivers, the team as a whole can move and reposition while maintaining accurate localization estimates. Tracking robot positions accurately is especially important for tasks that involve mapping and exploration. Each robot explores the unknown environment with various sensing modalities. The team leader collects the sensor information and integrates it into a global view of the environment, utilizing multiple-occupancy grid representations. Finally, we presented a few applications that exploit the nature of a small, heterogeneous team.

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## Keywords

Collaborative, heterogeneous, modular, distributed, semi-autonomous, sensor fusion.

## References


[1] J. Borenstein, H. R. Everett, and L. Feng, *Navigating Mobile Robots: Sensors and Techniques*. Wellesley, MA: A.K. Peters, Ltd., 1996.

[2] S. Thrun, "Learning maps for indoors mobile robot navigation," *AI Mag.*, vol. 99, no. 1, pp. 21-71, 1997.

[3] A. Soto, M. Saptharishi, J. Dolan, A. Trebi-Ollennu, and P.K. Khosla, "CyberATVs: Dynamic and distributed reconnaissance and surveillance using all terrain UGVs," in *Proc. Int. Conf. Field and Service Robotics*, Pittsburgh, PA, 1999, pp. 329-334.

[4] L. Kleeman, "Optimal estimation of position and heading for mobile robots using ultrasonic beacons and dead-reckoning," in *Proc. IEEE Int. Conf. Robotics and Automation*, Niece, France, 1992, pp.2582-2587.

[5] L.E. Navarro-Serment, C.J.J. Paredis, and P.K. Khosla, "A beacon system for the localization of distributed robotic teams," in *Proc. Int. Conf. Field and Service Robotics*, Pittsburgh, PA, 1999, pp. 29-31.

[6] A. Elfes, "Using occupancy grids for mobile robot perception and navigation," *Computer*, vol. 22, no. 6, pp. 46-57, June 1989.

[7] R.J. Grabowski, L.E. Navarro-Serment, C.J.J. Paredis, and P.K. Khosla, "Heterogeneous teams of modular robots for mapping and exploration," *Autonomous Robots*, vol. 8, no. 3, pp. 293-308, June 2000.

[8] R. Tinós, L.E. Navarro-Serment, and C.J.J. Paredis, "Fault tolerant localization of teams of distributed robots," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems*, 2001, vol. 2, pp. 1061-1066.

[9] H.P. Moravec, "Sensor fusion in evidence grids for mobile robots," *AI Mag.*, vol. 9, no. 2. pp. 61-74, 1988.


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