<u>**โครงร่างวิทยานิพนธ์**</u>

ชื่อเรื่อง (ภาษาไทย)	การร่วมกันระบุตำแหน่งโดยใช้ข้อมูลเชิงมุม
ชื่อเรื่อง (ภาษาอังกฤษ)	Cooperative Localization Using Angular Measures
เสนอโดย	นายสรวิชญ์ ธนพานิชกูล
รหัสประจำตัว	487 05066 21
สาขาวิชา	สาขาวิศวกรรมคอมพิวเตอร์
คณะ	คณะวิศวกรรมศาสตร์
สถานที่ติดต่อ	Intelligence System Lab2 ภาควิชาวิศวกรรมคอมพิวเตอร์ ชั้น 20 อาคารวิศวกรรมศาสตร์หลังที่ 4 จุฬาลงกรณ์มหาวิทยาลัย
โทรศัพท์	081-243-5448
E-mail	sorawish@gmail.com
อาจารย์ที่ปรึกษาวิทยานิพนธ์	ดร. อรรถวิทย์ สุดแสง
คำสำคัญ(ภาษาไทย)	การระบุตำแหน่ง, การทำงานร่วมกัน, ข้อมูลเชิงมุม
คำสำคัญ(ภาษาอังกฤษ)	Localization, Cooperative, Angular measures

Thesis Proposal
Cooperative Localization Using Angular Measures

1 Introduction

To work autonomously, a mobile robot usually need to know where it is located in its working environment. Ability to determine one's own location is known in robotics literature as localization. Localization, undoubtedly, plays an important role in many recent robotic applications. A robot tour guide [34] leads a group of visitors through several halls of a museum giving proper narration of artifacts on its path while avoiding collision with the visitors and exhibition in the museum. A nurse robot [9] automatically and safely cruises to patient rooms making delivery of medicine and supply. A robot vacuum cleaner [2] autonomously manages to sweep the entire house and recharge its own battery. As the single robot localization begins to function sufficiently well for real-world applications, a new challenging variation of the problem emerges: how to localize multiple robots in a multi-robot platform.

A multi-robot platform provides many advantages over a single robot operation. Multiple robots are necessary for some tasks such as cooperative object manipulation. Multi-robot platforms are obviously more efficient than a single robot for several parallelizable tasks such as search and rescue, map making, and de-mining operation. Since it is now possible in terms of hardware to deploy a large team of robots (over hundred), multi-robot research is quickly gaining tremendous attention; the future of multi-robot system is very promising. One of the most challenging problems in multi-robot research is how to efficiently localize multiple robots. Although it might be feasible to apply single robot localization techniques, the cost of installing localization devices on every robot would be prohibitively high. One solution to this problem is to allow only few special robots to completely localize themselves relative to the environment while the remaining robots only have to localize with the special robots. This strategy is known as cooperative localization (CL).

Nevertheless, there are many challenges in CL, particularly on how to efficiently and cost-effectively localize with the special robots. Common problems include noise and resolution limitation of sensors. Most CL systems use radio signal as a communication channel and as a localizing medium. Radio signal propagation however cannot be modelled easily due to its characteristics such as as multi-path interference, radio-signal attenuation and environmental disturbance. Undoubtedly, calculating the distance from signal-strength usually results in large error. Some CL techniques rely on cameras for localizing the robots. Typically, feature

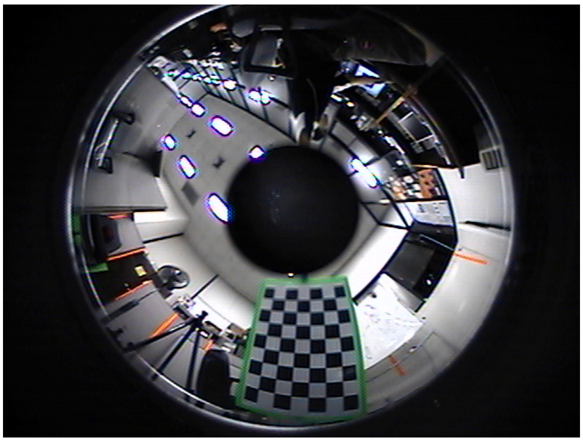


Figure 1: An image retrieved from omni-directional camera.

detection is applied to give relative location of the robots in its environment. For each robot to be detected and identified, it must possess a distinct feature, e.g., different color for each robot. Thus, a large group of robots needs many unique features. In addition, the distance between each of them can be computed, if the actual size of the features are known. An accuracy of computed position and ability to distinguish among large group of robots depend heavily on the image's quality which relies on many factors such as the environmental condition and the construction of camera. In [31], their robots are attached with colored cylindrical collar. The image's color can be suffered from the multiple light source. Moreover, it is hard to distinguish among many colors.

In this thesis, we investigate a new way to localize the robots relative to one another. Our proposed approach requires each robot to be equipped with a compass and an omni-directional camera. This type of camera produces a 360-degree panoramic view of the environment. A sample image from an omni-directional camera is shown in Figure 1. Using omni-directional input image, each robot computes angular measures of the other robots. Angular measures from every robot are then collected and processed to construct a positional pattern of all the robots. Although the distance to the detected robots can also be extracted, it is not used in our method because its accuracy is insufficient to be useful in practice. To clearly understand the process, let us consider the scenario where five robots are located as shown in Figure 2(a). The angular measures from each robot is shown in Figure 2(b)-2(f). The measure is taken under the same reference from the equipped compass. Observe that angular measures from a robot only tell the angles of the other robots around it. Information describing which angle is for which robot is not required. As a consequence, our method does not need each robot to compute correspondence between a robot and its image; it only needs to detect which regions of the input image contain an image of a robot. Once all angular measures from every robot are collected, a positional pattern of the robots can be computed. The result of the computation is a relative arrangement of the robots in the 2D workspace. This arrangement is exact up to a scale factor.

The remainder of this proposal is organized as follows. In Section 2, brief explaination

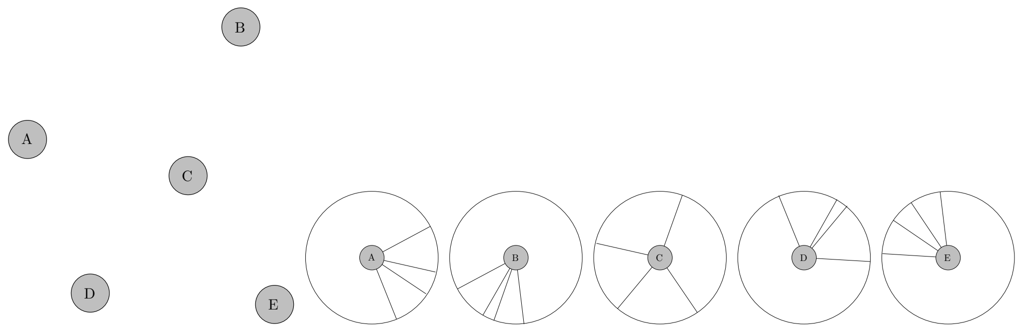


Figure 2: (a)shows the configuration of robots. Each line indicates sensing measures. (b),(c),(d),(e)and(f) depict the perceived measures of each robot.

on several localization techniques is presented. In Section 3, the problem of this thesis is formally stated. The following Section 4 describes the concept used in prior localization experiments. This concept establishes the framework to be applied in the problem of this thesis. On the last two sections, Section 5 and Section 6, our results from prior experiment, the ongoing works and the scope of this thesis are described respectively.

2 Related Works

CL have been studied more extensively by many researchers in broad areas, such as multi-robot systems and wireless sensor networks. In this section, we will breifly describe the related works of CL. This section are split into three subsection. In Section 2.1, we talk about the localization of mobile robot. Section 2.2 is about localization in wireless sensor networks area. Lastly, this Section 2.3 is one kind of mobile robot localization but they use different approach to deal with the problem.

2.1 Mobile robot cooperative localization

Recently, Cooperative localization of mobile robots has been studied by many researchers due to the flexibility of sensor and actuator sharing which is provided when designing heterogeneous robot teams that communicate through wireless networks. The first system that introduced relative position measurements is in [18]. A group of robots is divided into two separate teams with alternating roles. At each time instant, one team is in motion while the other remains stationary and acts as a set of landmarks. The team then exchange roles and this process continues until both reach their goals. Improvements over this system and optimal motion strategies are discussed in [17],[16]. Similarly, in [26] only one robot moves, while the rest forms an equilateral triangle of localization beacons in order to update their pose estimates. Another implementation of this type of cooperative localization is described in [24] and [25], where a team of robots moves through the open space and systematically map the environment. In [28], the authors present a cooperative localization technique based on virtual links between robots which remain within the field of view of their teammates.

All the aforementioned approaches which rely on robots acting as portable landmarks have the following limitations: 1) only one robot (or team) is allowed to move at any given time; and 2) the two robots (or teams) must maintain line-of-sight contact at all times. In addition to the use of robots as portable landmarks, static landmarks have also been employed for facilitating the localization of robot teams, in the context of cooperative simultaneous localization and mapping (C-SLAM). Since this study focuses on the localization only, we will not discuss this case further. For a thorough presentation of the related literature, the interested reader is referred to [3], where the Riccati recursion is employed for the study of the positioning accuracy of C-SLAM. Besides [3], [20] are similar to [3], the distinguishable difference between them is that in the latter case, a number of static landmarks are assumed to be always visible, which results in bounded uncertainty for the robots' position estimates at all times.

A different collaborative multirobot localization scheme is presented in [11] and [12]. The authors have extended the Monte Carlo localization algorithm [35] to the case of two robots that both possess a map of the area. When these robots detect each other, the combination of their belief functions improves the accuracy and convergence speed of global localization. The main limitation of this approach is that it can be applied only within a known indoor environment. In addition, since information interdependencies are being ignored every time the two robots meet, this method can lead to overly optimistic position estimates. At the cost of increased computational requirement, [14] treats the problem of not considering the correlation terms in Monte Carlo-based cooperative localization by introducing a dependency tree.

In [15], a maximum likelihood estimator is employed to process relative pose and odometric measurements recorded by the robots, and a solution for the robots' pose is derived by invoking numerical optimization. In contrast to this batch approach, a recursive estimator design is more often employed for cooperative localization, due to its lower computational complexity. In [27] and [33] a distributed Kalman filter pose estimator is presented. Every robot collects sensor data regarding its motion continuously and measures the relative pose of the other robots intermittently. Positioning information is propagated through the team only during the update cycles, allowing Kalman filter to be decomposed into a number of smaller communicating filters, one for each robot.

Spletzer and Taylor propose a new multi-robot localization approach [32]. Their sensor error model is unknown-but-bounded. Both angular and distant measures are bounded with maximum error threshold assumed to be homogeneous. They use linear programming to calculate the polytope which represent the configuration of all robots and approximately project this polytope into desired subspace. They showed that their approximation can result in the upperbound of the actual result.

2.2 Wireless sensor networks localization

In the field of wireless sensor networks, self-position awareness is also important, since many applications such as environment monitoring, vehicle tracking and mapping depend on knowing the location of sensor nodes. Furthermore, location-based routing protocols can save significant energy by eliminating the need for route discovery and improve caching behavior for applications where requests may be location dependent. Security can also been enhanced by location awareness(for example, preventing wormhole attacks). The approaches taken to achieve localization in sensor networks differ in their assumptions about the network deployment and their hardware capabilities. Localization in wireless sensor networks area can be categorized into two main types, centralized and decentralized localization.

2.2.1 Centralized localization

Centralized localization techniques depend on sensor nodes transmitting data to a central location, where computation is performed to determine the location of each node. Doherty, Pister and Ghaoui developed a centralized technique using convex optimization to estimate positions based only on connectivity constraints given some nodes with known positions [8]. MDS-MAP [30] improves on these results by using a multidimensional scaling approach.

2.2.2 Distributed localization

Distributed localization methods require no centralized computation, and rely on each node to determining its location using only limited communication with nearby nodes. These methods can be classified as range-based and range-free. Range-based techniques use distance estimates or angle estimates in location calculations, while a range-free solution depends only on the contents of received messages.

In range-based approaches, the distance or angle estimates may be obtained from:

Received signal strength (RSSI) measurements: where knowledge of the transmitter power, the path loss model, and the power of the received signal are used to determine the distance of the receiver from the transmitter. A sensor node estimates the distances from three or more beacon nodes to compute its location. The major drawback of this method is that multi-path reflections, non line-of-sight conditions, and other shadowing effects might lead to erroneous distance estimates. Techniques using a combination of RSSI and other measurements may lead to reliable location estimates, as proposed in [5]. However, nonuniform propagation environments make RSSI methods unreliable and inaccurate.

Time-of-arrival and time-difference-of-arrival (TOA,TDOA) measurements: which may be used to estimate the distance from a set of reference points by measuring the propagation times (or differences thereof) of the signals. However, due to the high propagation speed of wireless signals, a small measurement error causes a large error in the distance estimate. Hence, when a dense network is involved, such as a sensor networks, localization techniques using TOA or TDOA measurements need to use a signal that has a smaller propagation speed than wireless, such as ultrasound [29]. Though this gives fairly accurate results, it requires additional hardware at the sensor nodes to receive the ultrasound signals.

Angle of arrival (AOA) measurements: where special antenna configurations are used to estimate the angle of arrival of the received signal from a beacon node. This concept is used in the VOR/VORTAC system for aircraft navigation, where the VORTAC stations act as beacon nodes, which transmit special omnidirectional signals that allow a receiver to determine its bearings with respect to the station [1]. A prototype navigation system described in [19] is also based on a similar concept but uses a set of optical sources and a rotating optical sensor for obtaining the angular measurements. The main drawback of this technique for terrestrial systems is the possibility of error in estimating the directions caused by multipath reflections.

Because of the limitations of sensor devices, range-free localization algorithms are a cost effective alternative to more expensive range-based approaches [13]. There are two main types of range-free localization algorithms that have been proposed for sensor networks.

Local techniques: In centroid method [7], each node estimates its location by calculating the center of the locations of all seeds it hears. If seeds are well positioned, location error can be reduced [6], but this is not possible in ad hoc deployments. The APIT method [13] isolates the environment into triangular regions between beaconing nodes, and uses a grid algorithm to calculate the maximum area in which a node will likely reside. APIT typically assumes a larger radio range for seed nodes and hence has high seed density.

Hop counting techniques: To provide localization in networks where seed density is low, hop-counting techniques propagate location announcements throughout the network. DV-HOP [22] uses a technique based on distance vector routing. Each node maintains a counter denoting the minimum number of hops to each seed, and updates that counter based on messages received. Seed location announcements propagate throught the network. When a node receives a new seed announcement, if its hop count is lower than the stored hop count for that seed, the recipient updates it hop count to the new value and retransmits the announcement with an incremented hop count value. The Amorphous localization algorithm [21] uses a similar approach. The coordinates of seeds are flooded throughout the network so each node can maintain a hop-count to that seed. Nodes calculate their position based on the received seed locations and corresponding hop count.

None of these schemes target the case where nodes or seeds can move. They can be adapted for mobile networks by refreshing location estimates frequently, but are not designed with any consideration for how mobility can be exploited to achieve localization.

2.3 Structure and Motion from 1D Retinal Vision

In a special case of affine cameras, the structure and motion problem using line features can be reduced to the structure and motion problem for points in one dimension less, i.e. one-dimensional cameras [23]. Same as vision for planar motion, it can be proved that ordinary vision(2D retina) can be reduced to one-dimensional cameras if the motion is planar, i.e. if the camera is rotating and translating in one specific plane only [10].

Astrom and Magnus propose a solution in [4]. In their works, they use an autonomous guided vehicles(AGV) attached with laser scanner, called a laser guided vehicle(LGV). They use strips of inexpensive reflector type as a beacon and these beacons are put on wall or objects along the route of the vehicle. The laser scanner measures the direction from the vehicle to the beacons, but not the distance. A laser beam generated by a vertical laser in the scanner, is deflected by a rotating mirror. When the laser beam hits a beacon, a large part of the light is reflected back to the scanner. Thus, all beacons are identical. This means that the identity of a beacon cannot be determined from a single measurement. They introduce the minimal conditions for solving the structure and motion problem for 1D retinal camera. These conditions are three images with five points and four images with four points and they are solved by different approaches, the calibrated trilinear tensor and the dual calibrated quadrillinear tensor consecutively.

3 Propose of the Thesis

This thesis focuses on the Cooperative Localization of a robot's team. In this work, we investigate a CL technique based on geometrical constraints in a planar workspace. The correspondence between angular measures and robots is not required. This is of great advantage since it is in practice not simple to always obtain the correct correspondence due to various problems regarding sensors. A group of homogeneous mobile robots, attached with a compass and a sensor for determining the angular positions of the others, is deployed in the workspace to perform some cooperative tasks. Each robot transmits the data, the angular measures of the others and self-orientation, to the leader. The group leader then computes the positional pattern and broadcast this pattern. After receiving the broadcast, each robot compares its measures with the received configuration to estimate its own position. We assume that all angular measures have the same bounded uncertainty and all of the other robots can be detected. Note that the resulting positional pattern is only accurate upto a scale factor; absolute positions of all robots can be computed with the additional knowledge of at least two absolute positions.

4 Concept

A team of robots are spreaded over the planar workspace to perform some cooperative tasks. Figure 2 shows an example of the robots' configuration. If we scale up this figure, distances between each pair of them will be farther. Still, each of them will perceived the same measures. This means that we can scale up the result from localization with only angular measures by any scale factor. Each measure can be represented by a unit vector. Obviously, each of them must have at least one measure(of another robot) which has the opposite direction. By searching for all correspondence, we are able to compute the robots' configuration. However, its complexity is high due to the exhaustive search. For each measure, we have to find the set of all matching measures and recursively search for all correspondence until all measures know their corresponce. We propose a new approach with lower complexity. Our method relies on geometrical constraints of the plane. We need only two correspondece to compute the solution. Knowing one correspondence gives us two robots and one connecting line. We triangulate all pair of measures which are selected from these two robots. The result is the set of possible locations which may be positions of the other robots. Next, we use the other correspondence (one robot from this correspondence must be in the previous correspondence) to verify previous result. Algorithm 1 describes the overall process. Firstly, each robot retrieves the data from sensors, positional angles and its self orientation. Secondly, the robots which are located at the extreme points will be selected. One of them will served as a reference point. After the selection, the two robots which are located on the left and on the right extreme points of the reference will be identified. The robot on the left is then chosen to be the second reference. The next process is the triangulation of all measures from the first and the second reference. The result is the set of all possible locations. From these locations, we identify the real locations by using the measures from the robot on the right extreme point of the first references. We can discover the points which exist in the real configuration. The entire process will give the positional pattern. It can be scaled up by a scale factor. If we know two absolute position of any robots, then the real configuration can be computed.

Algorithm 1 Computing group's pattern

for $i \leftarrow 1$ to $nRobot$ **do** ▷ Rotate each robot's measures by self orientation
  adjustReferenceFrame($Robot_i$,$rOrientation_i$)
  if isExtremePoint($Robot_i$) **then**
    putIntoList(EPL,i)
    $leftmostAngleList[i]$ ←findLeftmostAngle($Robot_i$)
    $rightmostAngleList[i]$ ←findRightmostAngle($Robot_i$)
    if isSuitableForReference($leftmostAngleList[i]$,$rightmostAngleList[i]$) **then**
      $iRef \leftarrow i$
    end if
  end if
end for
$Ir \leftarrow$ findSetofRight($Robot, EPL, iRef$)
$il \leftarrow$ chooseLeft-reference($Robot, EPL, iRef$)
$T \leftarrow triangulateAllMeasures(Robot, iL)$
$ir \leftarrow chooseRight - reference(Robot, Ir, il)$
identifyRealConfiguration($Robot, T, ir$)

By assuming that all robots are percevable, we can draw a convex graph which each edge represents a correspondence between each pair of robot(see Figure 3).

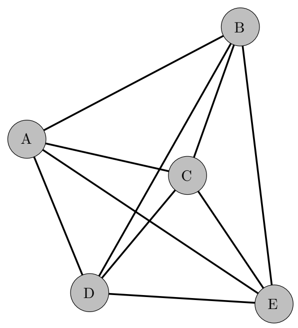
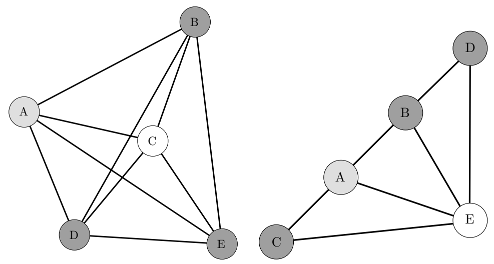


Figure 3: Graph represent angular informations and configuration of each robots.



(a) (b)

Figure 4: In 4(a), the grey points are the extreme points. In 4(b), the darker one is the reference point.

Finding extreme points

Given a number of all robots ($nRobot$), a set of angular measures (A^i) of the $Robot_i$ and each angular measure ($a^i_j; a^i_j \in A^i$ and $0 \leq j \leq nRobot - 1$), we will find a set of extreme points ($E; e_i \in E$ and $0 \leq i \leq N_e$). In Figure 3, the extreme points are the outmost vertices. For each extreme point, it must have two outmost neighbors. We define these two measures as a leftmost measure and a rightmost measure. In some cases where the robots are collinear, there are more than one leftmost or rightmost measures. Therefore, $Robot_i$ which is extreme point will have a set of leftmost measures (L_i) and a set of rightmost measures(R_i). Considering each measure as a unit vector, each of leftmost(l_i) and rightmost(r_i) measures must meet the following condition; $r_i \times l_i \geq 0; a^i_j \times l_i \geq 0$ and $r_i \times a^i_j \geq 0$. E will be chose by the previous condition and one of them will be selected as the reference point. The result is shown in Figure 4(a)

Finding reference point

We use reference point and one of its leftmost measures,called Left-reference, to compute an all possible configuration and use another one of its rightmost measures,called Right-reference, to identify the real configuration. If all reference, Left-reference and Right-reference are collinear, it is not possible to find the correspondence (see Figure 4(b)). On the Left-reference's view, distinguishing between reference point and its rightmost is impossible. Thus, we must choose the reference point which is not collinear to its outmost measures. After

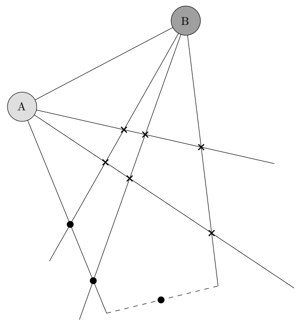


Figure 5: Triangulation resulted from measures of A and B. Crosses and discs represent the point which are generated. One of the discs is the rightmost point.

choosing the reference point, we triangulate all measures from both reference and Left-reference. Before triangulation can be occurred, we must identify the robot which will be used as Left-reference.

Finding a leftmost point

Obviously, Left-reference must be an extreme point and must has the measure which correspond with the leftmost measure of reference point. There may be more than one robot which satisfy this condition. So, we will choose one them to be a Left-reference.

Triangulation

All measures from reference and Left-reference will be triangulated. Since this calculation needs to know where exactly both of them are, we assume the position of the reference and the position of Left-reference. T is a set of position resulted from this calculation. From the Figure 4(a), all measures from point A and B are triangulated and the result are shown in Figure 5. Obviously, only some of triangulated points correspond with the real configuration. We need to use another point to identify this.

Searching for rightmost point

We choose one measure from reference's rightmost set to be Right-reference. Since there is no identification of each measure, we must find a Left-reference's measure which corresponds with Right-reference. After knowing the correspondence, the position of Right-reference in T can be calculated. This position will be used for verification of the real configuration.

Verifying the triangulated points

By using the Right-reference's location and measures, we can find the real configuration. The point in T which is the real configuration must be observed by the Right-reference as well. Thus, some points in T which correspond with Right-reference's measure are the real configuration.

Still, this concept needs to be further studied due to correspondent problem. In this concept, finding the correspondence between Right-reference and Left-reference is not shown yet. It can be done by using exhaustive search but its complexity is too high. The result of this process is the team's configuration. This result can be scaled up to the actual size, if we know at least one distance between any of them. In addition, knowing of one position and one distance, we can calculate all real coordinates.

5 Research Methodology

Our preliminary works incorporate simulating localization of robots' team by using only angular measures. In many real situations, the angular measures are corrupted by environment noise. By assuming that the noise will not exceed some boundary, we are developing the algorithm which can tolerate to boundary uncertainty.

5.1 Preliminary Work

1. Literature review
2. Study basic localization approach
3. Develop an algorithm for localization of a team
4. Conduct experiment on simulation platform

5.2 Ongoing Work

1. Study probabilistic localization approach
2. Develop an algorithm for localization of a robot's team capable of handling measurement errors
3. Conduct experiment on a simulation platform

6 Scope of the work

- The workspace is planar.
- Each robot can sense all of the others.
- Bounded uncertainty of measurement is given.

References

[1] *http://en.wikipedia.org/wiki/Vortac.*

[2] *http://www.irobot.com/.*

[3] I. M. Anastasios and I. R. Stergios. Performance bounds for cooperative simultaneous localization and mapping (c-slam). In *Robot. Sci. Syst. Conf., Cambridge, MA, Jun. 2005*, 2005.

[4] Kalle Astrom, Anders Heyden, Fredrik Kahl, and Magnus Oskarsson. Structure and motion from lines under affine projections. In *The Proceedings of the Seventh IEEE International Conference on Computer Vision*, 1999.

[5] Paramvir Bahl and Venkata N. Padmanabhan. Radar: An in-building rf-based user location and tracking system. In *In Proceedings of INFOCOM*, 2000.

[6] Nirupama Bulusu, Deborah Estrin, Lewis Girod, and John Heidemann. Density adaptive algorithms for beacon placement in wireless sensor networks. In *Proceedings of the Sixth International Symposium on Communication Theory and Applications (ISCTA '01)*, 2001.

[7] Nirupama Bulusu, John Heidemann, and Deborah Estrin. Gps-less low cost outdoor localization for very small devices. Technical report, IEEE Personal Communications Magazine, 2000.

[8] Lance Doherty, Kristofer Pister, and Laurent El Ghaoui. Convex position estimation in wireless sensor networks. In *IEEE InfoCom 2001*, 2001.

[9] J. Evans, B. Krishnamurthy, B. Barrows, T. Skewis, and V. Lumelsky. Handling real-world motion planning: a hospital transport robot. *IEEE Control Systems Magazine*, 12:15–19, 1992.

[10] Olivier Faugeras, Long Quan, and Peter Strum. Self-calibration of a 1d projective camera and its application to the self-calibration of a 2d projective camera. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22:1179–1185, 2000.

[11] Dieter Fox, Wolfram Burgard, Hannes Kruppa, and Sebastian Thrun. Collaborative multi-robot localization. In *in Proc. 23rd Annu. German Conf. Artif. Intell.*, 1999.

[12] Dieter Fox, Wolfram Burgard, Hannes Kruppa, and Sebastian Thrun. A probabilistic approach to collaborative multi-robot localization. *Autonomous Robot*, 8:325–344, 2000.

[13] Tian He, Chengdu Huang, Brian M. Blum, John A. Stankovic, and Tarek Abdelzaher. Range-free localization schemes for large scale sensor networks. In *MobiCom*, 2003.

[14] A. Howard, M.J. Mataric, and Sukhatme G.S. Putting the 'i' in 'team': an ego-centric approach to cooperative localization. In *Robotics and Automation, 2003. Proceedings. ICRA '03. IEEE International Conference on*, 2003.

[15] A. Howard, M.J. Matark, and G.S. Sukhatme. Localization for mobile robot teams using maximum likelihood estimation. In *Intelligent Robots and System, 2002. IEEE/RSJ International Conference on*, 2002.

[16] R. Kurazume and S. Hirose. Study on cooperative positioning system: optimum moving strategies for cps-iii. In *Robotics and Automation, 1998. Proceedings. 1998 IEEE International Conference on*, 1998.

[17] R. Kurazume, S. Hirose, S. Nagata, and N. Sashida. Study on cooperative positioning system (basic principle and measurement experiment). In *Robotics and Automation, 1996. Proceedings., 1996 IEEE International Conference on*, 1996.

[18] R. Kurazume, S. Nagata, and S. Hirose. Cooperative positioning with multiple robots. In *Robotics and Automation, 1994. Proceedings., 1994 IEEE International Conference on*, 1994.

[19] Clare D. Mcgillem and Theodore S. Rappaport. A beacon navigation method for autonomous vehicles. *IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY*, 38:132–139, 1989.

[20] A.I. Mourikis and S.I. Roumeliotis. Performance analysis of multirobot cooperative localization. *Robotics, IEEE Transactions on [see also Robotics and Automation, IEEE Transactions on]*, 22:666 – 681, August 2006.

[21] Radhika Nagpal, Howard Shrobe, , and Jonathan Bachrach. Organizing a global coordinate system from local information on an ad hoc sensor network. In *International Workshop on Information Processing in Sensor Networks (IPSN).*, 2003.

[22] Dragos Niculescu and Badri Nath. Dv based positioning in ad hoc networks. *Journal of Telecommunication Systems*, 22:267–280, 2003.

[23] Long Quan and Takeo Kanade. Affine structure from line correspondences with uncalibrated affine cameras. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 19(8):834–845, 1997.

[24] I.M. Rekleitis, G. Dudek, and E.E. Milios. Multi-robot collaboration for robust exploration. In *Robotics and Automation, 2000. Proceedings. ICRA '00. IEEE International Conference on*, 2000.

[25] I.M. Rekleitis, G. Dudek, and E.E. Milios. Multi-robot cooperative localization: a study of trade-offs between efficiency and accuracy. In *Intelligent Robots and System, 2002. IEEE/RSJ International Conference on*, 2002.

[26] G. Robert and L. E. Navarro-Serment. Heterogeneous teams of modular robots for mapping and exploration. *Autonomous Robots*, 8:293–308, 2000.

[27] S.I. Roumeliotis and G.A. Bekey. Collective localization: a distributed kalman filter approach to localization of groups of mobile robots. In *Robotics and Automation, 2000. Proceedings. ICRA '00. IEEE International Conference on*, 2000.

[28] W. Rynn, W.A. Malik, and Sooyong Lee. Sensor based localization for multiple mobile robots using virtual link. In *Intelligent Robots and Systems, 2003. (IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on*, 2003.

[29] Andreas Savvides, ChihChieh Han, and Mani B. Strivastava. Dynamic finegrained localization in adhoc networks of sensors. In *In ACM/IEEE International Conference on Mobile Computing and Networking (MOBICOM)*, 2001.

[30] Yi Shang, Wheeler Ruml, Ying Zhang, and Markus Fromherz. Localization from mere connectivity. In *MobiHoc 2003*, 2003.

[31] J. Spletzer, A.K. Das, R. Fierro, C.J. Taylor, V. Kumar, and J.P. Ostrowski. Cooperative localization and control for multi-robot manipulation. In *Intelligent Robots and Systems, 2001. Proceedings. 2001 IEEE/RSJ International Conference on Volume 2*, volume 2, 2001.

[32] J.R. Spletzer and C.J. Taylor. A bounded uncertainty approach to multi-robot localization. In *Intelligent Robots and Systems, 2003. (IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on*, 2003.

[33] I. Roumeliotis Stergios and A. Bekey George. Distributed multirobot localization. *IEEE TRANSACTIONS ON ROBOTICS AND AUTOMATION*, 18(5):781–795, 2002.

[34] Sebastian Thrun, Maren Bennewitz, Wolfram Burgard, Armin B. Cremers, Frank Dellaert, and Dieter Fox. Minerva: a second-generation museum tour-guide robot. In *IEEE International Conference on Robotics and Automation, 1999*, 1999.

[35] Sebastian Thrun, Dieter Fox, and Wolfram Burgard. Monte carlo localization with mixture proposal distribution. In *AAAI National. Conf. Artificial Intelligent*, 2000.