WiFi Based Communication and Localization of an Autonomous Mobile Robot for Refinery Inspection

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***Abstract*— Oil and gas refineries can be a dangerous environment for numerous reasons, including heat, toxic gasses, and unexpected catastrophic failures. In order to augment how human operators interact with this environment, a mobile robotic platform is developed. This paper focuses on the use of WiFi for communicating with and localizing the robot. More specifically, algorithms are developed and tested to minimize the total number of WiFi access points (APs) and their locations in any given environment while taking into consideration the throughput requirements and the need to ensure every location in the region can reach at least k APs. When multiple WiFi APs are close together, there is a potential for interference. A graph-coloring heuristic is used to determine AP channel allocation. In addition, WiFi fingerprinting based localization is developed. All the algorithms implemented are tested in real world scenarios with the robot developed and results are promising.**

I. INTRODUCTION

Removing humans from inhospitable environments is often desirable. For instance, in the oil and gas industry, during inspection, maintenance, or repair of facilities in a refinery, people may be exposed to severely high temperatures (+50°C) for an extended period of time, to toxic gasses including methane and H2S, and to unexpected catastrophic failures. One way to remove human exposure from these types of situations is to instrument an oil refinery with a wireless sensor network [1], which attaches a wireless sensor on every gauge and valve. Unfortunately, this approach is expensive and labor-intensive, let alone wireless sensors are failure prone. Hence, maintenance of the network and reliably collecting data from the network are extremely challenging. We, therefore, resort to a different approach that aims to augment how the human operators interface with the physical world. A mobile robotic platform is a rational analog to a physical human - it can move through an environment either autonomously or through tele-operation while sensing its surroundings with an array of sensors. However, further constraints are applied when introducing physical systems into an oil and gas environment. All devices deployed must meet the specified standards set by the industry. A detailed explanation of these standards applied to a mobile robot are stated in [2].

In our interdisciplinary project that aims to automate oil and gas processes using a mobile robot, we have built Blaster (Fig. 1), a mobile robot capable of both tele-operation and autonomous control. Blaster is capable of path planning, path tracking, obstacle avoidance, and auto inspection autonomously. A network camera, a thermal imaging camera, an acoustic sensor for leak detection, and a methane gas sniffer are mounted on the end of Blaster's 5 degree-of-freedom arm. It is capable of reaching a height of 2m when fully extended. Communication between Blaster and the control station occurs over WiFi. For more details on the design of the system, interested readers may refer to our paper [3].

Fig. 1. A refinery inspection mobile robot

Using an autonomous robotic system for an offshore oil and gas refinery has been proposed before [2], [4]. However, no detailed studies on WiFi communication and localization issues have been reported. In this paper, we focus on the WiFi aspects when using a mobile robotic platform in an oil refinery. More specifically, we consider the two problems: WiFi communication and localization. First, while the robot is mobile, an operator must be able to communicate with it to receive sensor data collected from the refinery

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(e.g., images and acoustic data) as well as send it various commands that either manipulate the robot or the arm, request certain specific information, or ask it to move in a certain way; however, most refineries lack a wireless network infrastructure. Therefore, WiFi access points (APs) must be strategically placed throughout an environment to minimize the number of units required to achieve full coverage needed for communication. Second, in order for a robotic system to be autonomous, it must have an accurate understanding of its location. Since an oil refinery often is comprised of tall structures made of steel, GPS may not always be available, WiFi based localization becomes essential. It complements localization methods using other sensors built in a robotic system.

The work presented in this paper makes the following contributions.

- We have conducted thorough studies of WiFi signal propagation properties in both indoor and outdoor environments, which forms the basis for WiFi AP deployment and communication.
- We have implemented an AP placement algorithm to achieve single coverage (i.e., every point in a site can communicate with at least one WiFi AP).
- For better reliability and localization, we have implemented a k-coverage AP placement algorithm (i.e., every point in a site can communicate with at least k WiFi APs), where $k > 1$.
- We have implemented a channel allocation algorithm to minimize interference from neighboring APs.
- We have implemented a WiFi localization technique and tested it on the mobile robotic platform in both indoor and outdoor environments.

The rest of the paper is organized as follows. Section II discusses related work regarding wireless communication in an oil refinery. A WiFi AP placement technique is discussed in Section III. A WiFi localization technique is discussed in Section IV and implemented and tested on an autonomous robotic system. Finally, Section V presents concluding remarks.

II. Related Work

In this section, we only discuss related work in providing wireless communication in an oil refinery. We defer the discussion of the work related to specific aspects of WiFi communication and localization to later sections. Previous work [1] proposes to use wireless sensor networks (WSNs) for remote monitoring to detect leaks of harmful by-products of oil refineries. While WSNs are capable of being equipped with an array of sensors, the major deficiency of WSNs is battery life as well as their failure prone nature. A robotic mobile platform is developed [4], [2] to provide secure and reliable two-way wireless communication at a lower cost and less maintenance than a WSN. In [4], localization is performed through a form of Simultaneous Localization and Mapping (SLAM). In [2], localization is performed through fusing the inertial navigation system (INS) and infrared sensor (IR) with reflective tapes to characterize specific shaped objects. Communication is established through WiFi to an operator control station or through Bluetooth to a nearby handheld device. While both systems use WiFi for communication and localization, none of them provide any details. In contrast, our work introduces an autonomous system capable of localizing to a sub-meter level in indoor or outdoor environments. We provide detailed discussion of the technical details and extensive performance studies.

III. WiFi Communication

Two types of data are communicated between the robot and the control station. Control information has the higher priority as it informs the robot how to act and react, i.e.: whether it is direct movement commands through tele-operation or more general commands such as informing the robot of a new destination for inspection. Tele-operation and emergency stop are two operations that require real-time communication and must be executed by the robot regardless of the state of sensor information. For example, if the operator receives a report describing low pressure in a tank, the robot should be able to drive upstream of the tank, begin to transmit acoustic information, and then drive along the pipe to determine if there is a visible leak. If the communication between the robot and control station times out, the robot halts - this is to ensure safety of the surrounding environment and of the robot itself. Therefore, communication between the systems must be reliable.

Since an oil refinery typically does not have WiFi infrastructure available, we need to determine the minimum number of WiFi APs needed and where to deploy them so that the entire region is covered. When multiple APs are located close to each other, we need to determine how different channels should be used by each AP to avoid interference. The following subsections describe the algorithms used for these purposes.

A. AP Placement

When determining placement of APs in a given environment, the required minimum throughput that supports both control information and sensor information must be maintained in order to ensure communication at every location in the environment. This requires that at any time, the mobile robot be in communication range of at least one AP. While a dense network dispersed through an environment can achieve this, it is costly. Therefore, the single-coverage WiFi AP placement problem is to determine the minimum number of APs and their locations so that each location in the environment can reach at least one AP, given a region and throughput needs specified by the application.

The single-coverage WiFi placement problem is NP-hard [5] and belongs to a large class of problems known as "Coverage Problems". A classical example of which is the "Art Gallery Problem" [6]. Several heuristics have been proposed before [7], [8]. We have implemented an algorithm based on [7]. Fig. 2 shows the algorithm flow. Environment information, consisting of the dimensions of a given area and a list of object locations, and a minimum throughput requirement are passed into the algorithm. A 2D grid-system map is then generated consisting of object and non-object nodes, where an object node is defined as a node whose location correlates to an occupied space such as a wall. Each non-object node is considered a candidate location for AP placement. The algorithm considers every candidate location during each iteration by mapping the coverage of the APs already chosen as well as the propagation of the new AP. The signal of the new AP is propagated until it reaches the cut-off distance or an object-node is encountered. This hard encounter cut-off is used because in an oil and gas refinery, the objects that are encountered are typically large and made of steel. The best AP for that iteration is then chosen as the one that provides the minimum average distance between all uncovered nodes. That AP is then added to the list of best APs. Once all nodes have been covered, the list of best AP locations is returned.

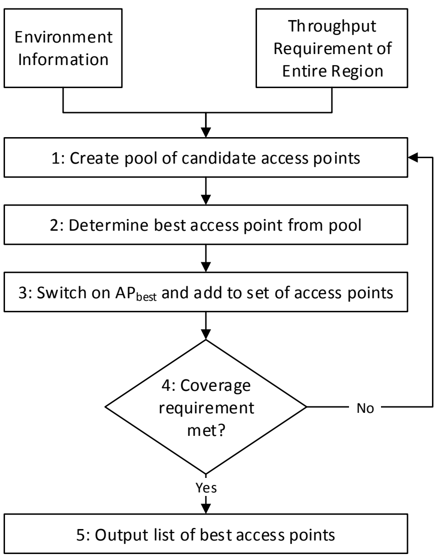
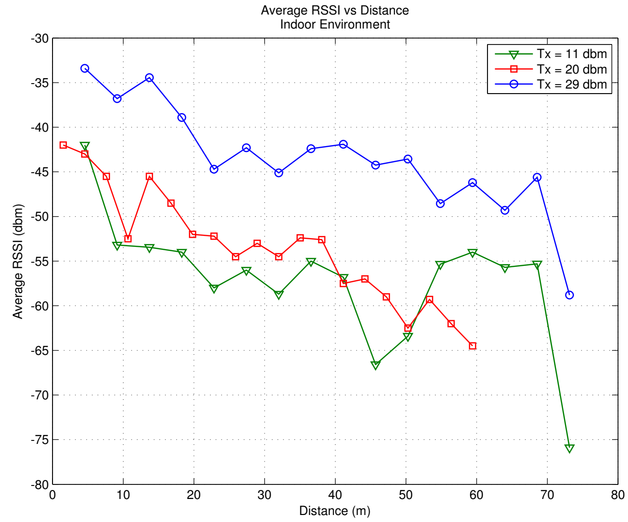


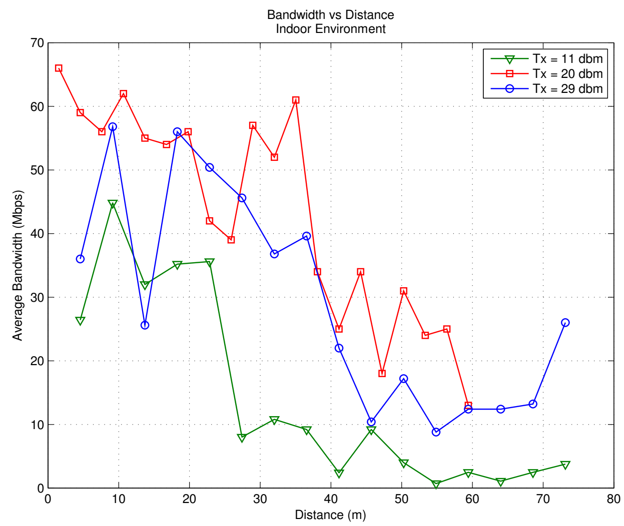
Fig. 2. Algorithm flow of access point placement algorithm

In this algorithm, a key step is to predict the signal propagation of a potential AP. In order to have a clear picture on how WiFi signal propagates in a specific environment, we have conducted thorough studies in both indoor and outdoor environments. Note that, similar studies need to be conducted in a target environment. In the following, we discuss the methodologies taken and results obtained in our studies.

An oil and gas refinery can be thought of as a combination of both an indoor and an outdoor environment due to the nature of the layout, so a series of studies were conducted to understand how WiFi signals propagate in both indoor and outdoor environments. Specifically, we study the impact of distance, transmission power, or speed of the mobile robot on the upper and lower bounds of received signal strength indicator (RSSI), bandwidth, and packet delivery ratio. Fig. 3 depicts the impact of distance and transmission power on the received signal strength and bandwidth in the Brown Hall



(a) Average RSSI at three transmission powers in an indoor environment.



(b) Average bandwidth at three transmission powers in an indoor environment.

Fig. 3. Received signal strength and bandwidth vs distance at three transmission powers in an indoor environment

of the Colorado School of Mines (CSM) campus. Similar trends are observed in an outdoor environment: a soccer field at CSM. Figures are omitted due to page limitations. These results show that in order to provide a network that is capable of supporting a 10 Mbps throughput, a RSSI of -70 dbm (80 m) must be used. We will use this as the cut-off distance.

We have tuned the classic Log-Distance Path-Loss Model (1) to fit our experimental data (Fig. 4).

$$PL_d[dbm] = PL_0[dbm] + 10 * n * log(d/d_0), \qquad (1)$$

where $PL[dbm]$ is the calculated signal strength, $PL_0[dbm]$ is the relative signal strength at a distance of d_0 (4.572 m or 15 ft), n is the log-loss exponent (1.8), and d is the given distance. Therefore, in the AP placement algorithm, we use this propagation model to determine signal propagation of each potential AP.

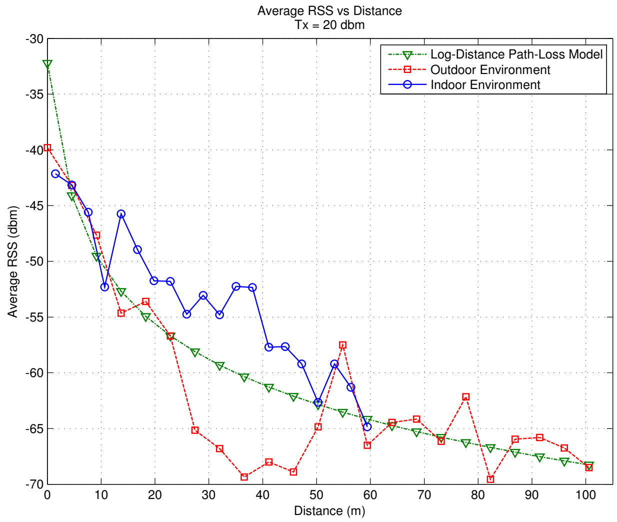


Fig. 4. Received signal strength vs distance for both indoor and outdoor environments with the log-distance path-loss propagation model results.

We have tested the single-coverage AP placement algorithm at Colorado School of Mines 3^{rd} floor Brown Building (Fig. 5(a & b)). The building consists of a large hallway, approximately 3 m by 45 m with numerous classrooms and an open area in the center. The building material is mostly sheetrock. The algorithm created a 72 by 10 grid-point map using a grid-length of 0.9144 m (3 ft), which resulted in the requirement of 6 APs Table I. Fig. 5(a) shows the position of AP placement (X_i), where i is the placement order.

This single-coverage deployment ensure that at any location in the given environment, communication between the robotic mobile system and the operator control station is possible. In order to better support WiFi localization, a coverage greater than one is required. In other words, we need to determine how to cover an area with minimal number of APs so that each point in the area is covered by at least k APs, where $k > 1$.

This is a very different problem from existing work on placement of multiple WiFi APs whose focus is typically for handling a large number of mobile clients or nonuniform client load. Techniques such as cell dimensioning and dynamic load balancing are developed [9]. However, the k-coverage AP placement problem bears certain similarity with k-coverage sensor deployment in WSNs, which has been studied extensively in the community [10]. The difference between the two problems is that in WSNs, multi-hop communication is often needed and also sensors may have different sleep schedule. We, hence, adapted a greedy approach from [11] and [12] that attempts to maximize the net coverage (also called K-benefit) introduced by the new AP or sensor. The K-Benefit of a new AP P is defined as: $(V(M \cup P, K) - V(M, K)) / (|M \cup P| - |M|)$, where M is the existing AP set.

$$V(S, K) = \sum_{e \epsilon E} \left(max \left(K, \sum_{s \epsilon S} (\delta(e, s)) \right) \right), \qquad (2)$$

where S is the set of AP candidate locations, K is the required k-value, E is the region of interest, and $\delta(e, s)$ is 1 if node e is covered by AP s. The algorithm shown in Fig. 2 for single coverage is modified in the following ways:

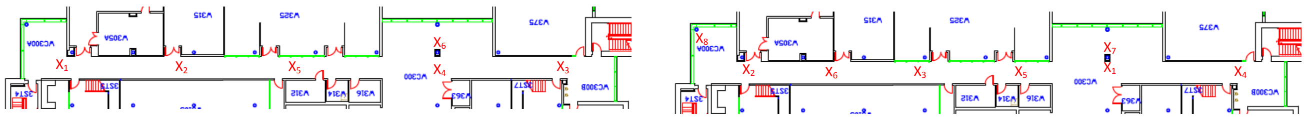
1) Step 2: the algorithm instead distributes the signal of the candidate AP and maximizes the count of the newly covered nodes that are under the k-covered requirement for every candidate location as seen in (2).
2) Step 3: The candidate AP that produces the largest K-Benefit is then added to the set of APs that cover the region - its coverage is added to the final map.
3) Step 4: The algorithm continues to iterate until all locations have been at least k-covered.

Fig. 5(b) shows the coverage count for $k = 2$, where X_i marks the location of an AP and i is the placement order. This configuration is repeated k times.

B. Channel Allocation

In the previous section, we defined a heuristic to determine the placement of APs for single coverage as well as k-coverage. Because of the nature of wireless signal propagation, APs will interfere with other neighboring APs. In order to prevent them from interfering, neighboring APs must be assigned to different channels. WiFi operates in the frequency range of 2.4 GHz to 2.485 GHz. Within this 85 MHz band, WiFi defines 11 partially overlapping channels. Any two channels are non-overlapping if and only if they are separated by four or more channels. In particular, the set of channels 1, 6, and 11 is the only set of three non-overlapping channels [13]. Therefore, we need to assign the minimum number of channels for all the APs deployed while making sure no two nearby APs (i.e., potentially may interfere with each other) are assigned to the same channel.

The channel allocation problem can be formulated into the classic NP-hard graph coloring problem: each AP represents a node in an interference graph and if the coverage of two APs overlap, a bi-directional edge is added between the two nodes. We borrow a heuristic from [14] that attempts to color the most nodes in one iteration before considering the next color. During each iteration, the uncolored node with the smallest index is chosen and colored with the current iteration color. Interference is then calculated for all 2+ hop nodes of the current node, where if a 2+ hop node is a child of another 2+ hop node, the interference count of those nodes are increased by one. Once the interference for every 2+ hop node has been calculated, the node with the smallest interference count is colored the current iteration color and children of the newly colored node are removed from the 2+ hop list. Once this list is empty, the heuristic moves onto the next color iteration. The heuristic continues to iterate until all nodes have been colored.



(a) single coverage placement

(b) k-coverage placement, $k = 2$

Fig. 5. AP placement results for CSM's West Brown Building 3^{rd} floor

We have tested the channel allocation algorithm on the AP placement determined in Fig. 5(a), 4 channels are allocated as seen in Table I.

TABLE I

CHANNEL ALLOCATION RESULTS FOR CSM BROWN BUILDING, 3^{rd} FLOOR HALLWAY.

AP	0	1	2	3	4	5
Location (x, y)	$(5, 5)$	$(24, 6)$	$(67, 6)$	$(52, 5)$	$(36, 6)$	$(52, 5)$
Color	0	1	0	2	1	3

IV. WiFi Localization

Now that the WiFi infrastructure has been deployed, we can use it for localization. Indoor WiFi localization has been studied extensively - [15] provides a survey of wireless indoor positioning techniques. When performing localization through a WiFi network, two approaches are generally taken: signal propagation modeling and WiFi fingerprinting [16]. Research shows that the signal propagation model requires a very accurate model tuned to a specific environment and tends to result in a lower localization accuracy than the fingerprinting method [17]. Therefore, we have chosen to use the WiFi fingerprinting method. WiFi fingerprinting has also been studied for outdoor localization, in particular in urban canyons. Due to the impact of pedestrian and car traffic, the accuracy drops significantly in outdoor environments [18]. The process of WiFi fingerprinting can be very tedious, so [19] presents an autonomous mobile robot approach for indoor localization where Simultaneous Localization and Mapping (SLAM) is used to create and update the positions in the WiFi fingerprint database for geo-locating people. Visual localization through SLAM has also been studied extensively - [20] presents a survey of SLAM for urban ground vehicles.

WiFi fingerprinting based localization consists of two phases: offline and online. In the offline phase, a collection of fingerprints is taken at unique locations and stored in a database. A fingerprint is comprised of each surrounding AP's BSSID and RSSI. In our work, the fingerprint database was constructed in the following way. We have chosen to use a spacing of 1.5m in between fingerprint locations in order to ensure that each unique location of the robotic platform has a corresponding fingerprint in the database, considering that the size of the robotic platform is about 1.2m by 0.8m. To increase the accuracy of WiFi fingerprinting, [16] states that a reading in each orientation at every location must be taken. However, in an oil and gas facility, we can assume that the robot will never drive perpendicular to a path, so we have only taken fingerprints in two orientations along defined paths and then four orientations at corners. WiFi signal propagation becomes very unstable at larger distances in terms of the reliability of the RSSI as determined from our experiments. To address this, we have chosen to only include APs whose RSSI is greater than -70 dbm.

In the online phase, the fingerprint database is used to determine location of the robot by finding the best matching of current visible APs along with their RSSI. More specifically, the robot polls the surrounding WiFi APs in order to create its current fingerprint, only considering APs with an RSSI better than -70 dbm. These values are then compared to the fingerprint database using the averaged Euclidean distance in signal space (3).

$$d(Z, Z_i) = \frac{1}{N} \times \sqrt{\sum_{j=1}^{N} (RSSI_j(x, y) - RSSI_j(x_i, y_i))^2}, \tag{3}$$

where Z is the fingerprint currently observed by the robot composed of L APs at an unknown position (x, y), and Z_i is the fingerprint from the database for position (x_i, y_i) composed of M APs. N is the total number of APs in $Z \cup Z_i$. $RSS_j(x_i, y_i)$ is the mean RSSI value of location (x_i, y_i) for AP "j". Our approach is modified from [17], where the entire set $(Z \cup Z_i)$ is considered when determining the Euclidean distance in signal space instead of only using the APs in Z, which allows for a more accurate fingerprint match as Z might be a subset of numerous Z_is. If an AP exists only in one list, its value is compared against the cut-off value of -70 dbm. The averages of the number of comparisons between the current fingerprint and the database fingerprints are sorted in non-decreasing order. The K closest neighbors' locations are then averaged to determine the location of the robot.

We deployed the system at the Petroleum Institute in Abu Dhabi, UAE. The robot drove through a 12 m by 46 m rectangular path on the third floor of Ruwais Building - a sheetrock academic building. This test was performed over two days. In order to determine the ground truth location of the robot, physical markers were manually placed at the robot's location every 5 seconds. Fig. 6 shows the resulting absolute position error for each location across the 7 cycles. We achieved an average accuracy of 2.30 m across 7 loops (cycles) with remote control of the robot. Due to a mismatch in fingerprinting, some locations (e.g., Location 3), have a high position error. The error in location 8 is due to a physical change in environment during testing, i.e.: cabinets from classrooms were moved into the hallway in between the offline and online phases.

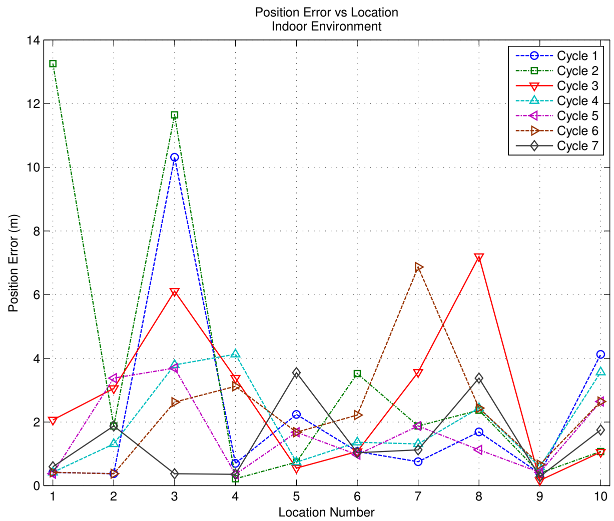


Fig. 6. Absolute position estimation error using WiFi fingerprinting methods across 7 cycles

WiFi was never intended to be the only source of localization, instead it should be fused with other localization sensors available on the robot. We have implemented an Extended Kalman Filter to fuse results from the Inertial Navigation System (INS), compass, GPS, WiFi, and a fiducial marker system. A validation gate is applied to each localization sensor to help reject outlier measurements. For a detailed explanation of this implementation, interested readers may refer to [21].

Table II shows the results of fusing different sets of localization sensors. By fusing INS with the WiFi, we were able to achieve an absolute position error of 1.02 m using a WiFi validation gate value of 0.5. Accuracy was further increased by fusing INS, WiFi, and the fiducial marker system (discussed in [21]) to achieve an absolute position error of 0.43 m using a WiFi validation gate value of 0.1 for WiFi.

TABLE II
INDOOR LOCALIZATION RESULTS

Localization Method	WiFi Only	INS Only	INS+ WiFi	INS+ WiFi+ Fiducial
Mean Error (m)	2.30	2.88	1.02	0.43

V. CONCLUSIONS

For a robotic system to autonomously navigate in an oil and gas refinery, it must be able to communicate with the control room and also localize itself. In this work we define the kinds of communication required to deploy an autonomous robot. We study WiFi signal propagation characteristics and apply the findings to determine WiFi AP placement. We also assign channels to interfering APs. WiFi fingerprinting based localization was implemented that achieves a reasonable accuracy when used alone and achieves desired accuracy (less than 1m) when combined with INS and fiducial marker based approach.

REFERENCES

[1] M. R. Akhondi, A. Talevski, S. Carlsen, and S. Petersen, "Applications of wireless sensor networks in the oil, gas and resources industries," in *Advanced Information Networking and Applications (AINA), 2010 24th IEEE International Conference on*. IEEE, 2010, pp. 941–948.

[2] B. Graf and K. Pfeiffer, "Mobile robotics for offshore automation," *Proceedings of the EURON/IARP International Workshop on Robotics for Risky Interventions and Surveillance of the Environment, Benicassim, Spain*, 2008.

[3] J. P. H. Steele, Q. Han, A. A. Ayoade, M. R. Sweatt, W. A. Yearsley, and D. P. Albert, "Development of an oil and gas refinery inspection robot," *ASME*, pp. 1–10, 2014.

[4] M. Bengel, "Mobile Robots for Offshore Inspection and Manipulation," in *Intelligent Robots and Systems*, 2009.

[5] E. Malaguti and P. Toth, "A survey on vertex coloring problems," *International Transactions in Operational Research*, vol. 17, no. 1, pp. 1–34, Jan. 2010.

[6] A. Aggarwal, "The art gallery theorem: Its variations, applications, and algorithmic aspects," *Ph.D thesis, Johns Hopkins University*, 1984.

[7] D. Plets, W. Joseph, K. Vanhecke, E. Tanghe, and L. Martens, "On Coverage Prediction and Optimization Algorithms for Indoor Environments," *EURASIP Journal on Wireless Communications and Networking*, vol. 2012, no. 123, 2012.

[8] J.-m. Gorce, "On predicting in-building WiFi coverage with a fast discrete approach Guillaume de la Roche , * Katia Jaffrès-Runser and," vol. 2, no. 1, 2007.

[9] A. R. T.-c. Chiueh, "Deployment issues in enterprise wireless lans," 2003.

[10] J. Yick, B. Mukherjee, and D. Ghosal, "Wireless sensor network survey," *Computer Networks*, vol. 52, no. 12, pp. 2292–2330, Aug. 2008.

[11] Gupta, Zhou, Das, and Gu, "Connected Sesnor Cover: Self-Organization of Sensor Networks for Efficient Query Execution," *Networking, IEEE/ACM*, vol. 14.1.

[12] Z. Zhou, S. Das, and H. Gupta, "Connected K-Coverage Problem in Sensor Networks," in *Computer Communications and Networks*, 2004.

[13] J. Kurose and K. Ross, *Computer Networking: a Top-Down Approach*. Addison-Wesley, 2009.

[14] W. Wang and X. Liu, "List-coloring based channel allocation for open-spectrum wireless networks," *VTC-2005-Fall. 2005 IEEE 62nd Vehicular Technology Conference, 2005.*, vol. 1, pp. 690–694.

[15] H. Liu, S. Member, H. Darabi, P. Banerjee, and J. Liu, "Survey of Wireless Indoor Positioning Techniques and Systems," vol. 37, no. 6, pp. 1067–1080, 2007.

[16] P. Bahl and V. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE. Vol. 2. Ieee*, 2000.

[17] F. Evennou and F. Marx, "Advanced Integration of WiFi and Inertial Navigation Systems for Indoor Mobile Positioning," *EURASIP Journal on Advances in Signal Processing*, vol. 2006, pp. 1–12, 2006.

[18] Y. Chen, Y. Chawathe, A. LaMarca, and J. Krumm, "Accuracy characterization for metropolitan-scale wi-fi localization," *ACM Mobisys*, 2005.

[19] R. Palaniappan, P. Mirowski, T. K. Ho, H. Steck, P. Whiting, M. Macdonald, A.-l. B. Labs, M. Avenue, and M. Hill, "Autonomous rf surveying robot for indoor localization and tracking," *International Conference on Indoor Positioning and Indoor Naviation (IPIN)*, September 2011.

[20] G. Ros, A. D. Sappa, D. Ponsa, and A. M. Lopez, "Visual slam for driverless cars : A brief survey," *Intelligent Vehicles Symposium Workshops*, 2012.

[21] A. Ayoade, M. Sweatt, J. Steele, Q. Han, K. Al-wahedi, H. Karki, and W. Yearsley, "Integration of multisensor data for indoor-outdoor robot localization," Department of Electrical Engineering and Computer Science, Colorado School of Mines, Tech. Rep., September 2014.