www.ijecs.in
International Journal Of Engineering And Computer Science ISSN:2319-7242
Volume 4 Issue 4 April 2015, Page No. 11547-11552

Novel Approach for Localizing Jammers in wireless network.

Sundar.R[1], Mahesh.C[2]

[1]pg Student, Department Of M.C.A, Veltech Dr. Rr & Dr. Sr Technical University, Avadi.
[2]head Of The Department [M.C.A], Veltech Dr. Rr & Dr. Sr Technical University, Avadi.

ABSTRACT

Jammers can severely disrupt the communications in wireless networks, and jammers' position information allows the defender to actively eliminate the jamming attacks. Thus, in this paper, we aim to design a framework that can localize one or multiple jammers with a high accuracy. Most of existing jammer-localization schemes utilize indirect measurements (e.g., hearing ranges) affected by jamming attacks, which makes it difficult to localize jammers accurately. Instead, we exploit a direct measurement—the strength of jamming signals (JSS). Estimating JSS is challenging as jamming signals may be embedded in other signals. As such, we devise an estimation scheme based on ambient noise floor and validate it with real-world experiments. To further reduce estimation errors, we define an evaluation feedback metric to quantify the estimation errors and formulate jammer localization as a nonlinear optimization problem, whose global optimal solution is close to jammers' true positions. We explore several heuristic search algorithms for approaching the global optimal solution, and our simulation results show that our error-minimizing-based framework achieves better performance than the existing schemes. In addition, our error-minimizing framework can utilize indirect measurements to obtain a better location estimation compared with prior work.

I. INTRODUCTION:

THE increasing pervasiveness of wireless technologies, combined with the limited number of unlicensed bands, will continue to make the radio environment crowded, leading to unintentional radio interference across devices with different communication technologies yet sharing the
same spectrum, for example, cordless phones, Wi-Fi net-work adapters, Bluetooth headsets, microwave ovens, and ZigBee-enabled appliances. Meanwhile, the emergence of software-defined radios has enabled adversaries to build intentional jammers to disrupt network communication with little effort. Regardless of whether it is unintentional interference or malicious jamming, one or multiple jammers/interferers may coexist and have a detrimental impact on network performance—both can be referred as jamming. To ensure the successful deployment of pervasive wireless

networks, it is crucial to localize jammers, since the locations of jammers allow a better physical arrangement of wireless devices that cause unintentional radio interference, or enable a wide range of defense strategies for combating malicious jamming attackers.

II. LOCALIZATION FORMULATION:

Essentially, our jammer localization approach works as follows: Given a set of JSS, for every estimated location, we are able to provide a quantitative evaluation feedback indicating the distance between the estimated locations of jammers and their true locations. For example, a small value of evaluation feedback indicates that estimated locations are close to the true ones, and vice versa. Although unable to adjust the estimation directly, it is possible, from a few candidate locations, to select the ones that are closest to the true locations with high probability, making searching for the best estimate feasible. Leveraging this idea, our jammer localization approach comprises two steps: 1) JSS collection. Each boundary node locally obtains JSS.

2) Best estimation searching. Based on the collected JSS, a designated node will obtain a rough estimation of the jammers' positions. Then, it refines the estimation by searching for positions that minimize the evaluation feedback metric. The details are described in Algorithm 1. The search-based jammer localization approaches have a few challenging subtasks:

1. EvaluateMetric() has to define an appropriate metric to quantify the accuracy of estimated jammers' locations.
2. MeasureJSS() has to obtain JSS even if it may be embedded in regular transmission.
3. SearchForBetter() has to efficiently search for the best estimation.

Algorithm

1. Jammer Localization Framework

1: p ¼ MeasureJSS()
2: z ¼ Initial positions
3: while Terminating Condition True do
4: ez ¼ EvaluateMetricðz; pÞ
5: if NotSatisfy(ez) than
6: z ¼ SearchForBetter()
7: end if
8: end while

III. NOVEL APPROACH FOR LOCALIZING JAMMERS WITH GREEDY ALGORITHM:

The increasing pervasiveness of wireless technologies, combined with the limited number of unlicensed bands, will continue to make the radio environment crowded, leading to unintentional radio interference across devices with different communication technologies yet sharing the same spectrum, for example, cordless phones, Wi-Fi network adapters, Bluetooth headsets, microwave ovens, and ZigBee-enabled appliances. Meanwhile, the emergence of software defined radios has enabled adversaries to build intentional jammers to disrupt network communication with little effort. Regardless of whether it is unintentional interference or malicious jamming, one or multiple jammers/interferers may coexist and have a detrimental impact on network performance—both can be referred as jamming.

To ensure the successful deployment of pervasive wireless networks, it is crucial to localize jammers, since the locations of jammers allow a better physical arrangement of wireless devices that cause unintentional radio interference, or enable a wide range of defense strategies for combating malicious jamming attackers. In this work, we focus on localizing one or multiple stationary jammers. Our goal is to extensively improve the accuracy of jammer localization. Current jammer localization approaches mostly rely on parameters derived from the affected network topology, such as packet delivery ratios , neighbor lists , and nodes' hearing ranges . The use of these indirect measurements derived from jamming effects makes it difficult to accurately localize jammers' positions.

Furthermore, they mainly localize one jammer and cannot cope with the cases that multiple jammers are located close to each other and their jamming effects overlap. To address the limitation caused by indirect measurements of the jamming effect, we propose to use the direct measurement of the strength of jamming signal (JSS). Localizing jammers using JSS is appealing yet challenging. First, jamming signals are embedded in the regular network traffic. The commonly used received signal strength (RSS) measurement associated with a packet does not correspond to JSS. To overcome this challenge, we devise a scheme that can effectively estimate the JSS utilizing the measurement of the ambient noise floor (ANF), which is readily available from many commodity devices (e.g., MicaZ motes). Our experiments using MicaZmotes with multiple sender receiver pairs confirm the feasibility of estimating JSS under various network traffic conditions. With the ability to estimate JSS, it appears that one may leverage existing RSS-based localization algorithms designed for regular wireless devices to localize jammers.

However, we consider jamming localization different for the following reasons:

1) Most jammers start to disturb network communication after network deployment, which makes it infeasible to obtain a site survey of radio fingerprints around jammers beforehand, a commonly used method for localization in an indoor environment.

2) No detailed prior knowledge about the jammers' transmission power is available.

3) Multiple jammers with overlapped jamming areas may collude and disturb network communication together, while attempting to hide their true locations.

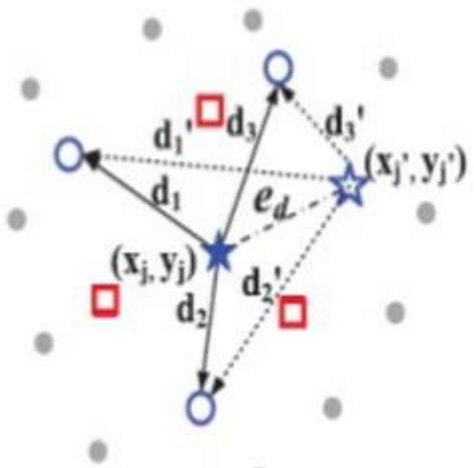
To overcome these challenges and increase the localization accuracy, we formulate the jammer localization problem as a nonlinear optimization problem and define an evaluation metric as its objective function. The value of evaluation metric reflects how close the estimated jammers' locations are to their true locations, and thus, we can search for the best estimations that minimize the evaluation metric. Because traditional gradient search methods may converge to a local minimum and may not necessarily yield the global minimum, we adopt several algorithms that involve stochastic processes to approach the global optimum.

In particular, we examined three algorithms: a genetic algorithm (GA), a generalized pattern search (GPS) algorithm, and a simulated annealing (SA) algorithm. Our extensive simulation\ results show that our localization error-minimizing framework not only can improve the estimation accuracy of localizing one jammer compared to prior work but also can estimate the positions of multiple jammers simultaneously, making it especially useful for identifying unintentional radio\ interference caused by multiple wireless devices or a few malicious and collaborative jammers. We summarize our main contributions as follows: . Estimating JSS is challenging because the jamming signals are embedded in the regular signals. To the best of our knowledge, our work is the first that directly utilizes the JSS to localize jammers. Our results using direct measurements (e.g., JSS) exhibit significant improvement compared with those using indirect measurements (e.g., hearing ranges). .

We exploited path loss and shadowing phenomena in radio propagation and defined an evaluation metric that can quantify the accuracy of the estimated locations. Leveraging such an evaluation metric, we formulated the jammer localization problem as an error-minimizing framework and studied several heuristic searching algorithms for finding the best solution. . Our error-minimizing-based algorithms can localize multiple jammers simultaneously, even if their jamming areas overlap. Localizing in such a scenario is known to be challenging.

GREEDY ALGOIRITM

1 $n \leftarrow length[s]$
2 $A \leftarrow \{1\}$
3 $j \leftarrow 1$
4 **for** $i \leftarrow 2$ **to** n
5 **do if** $s_i \geq \hat{a}_j$
6 **then** $A \leftarrow A \cup \{i\}$
7 $j \leftarrow i$
8 **return** A



IV. MEASURING JAMMING SIGNALS

RSS is one of the most widely used measurements in localization. For instance, a WiFi device can estimate its most likely location by matching the measured RSS vector of a set of WiFi APs with pretrained RF fingerprinting maps or with predicted RSS maps constructed based on RF propagation models. However, obtaining signal strength of jammers (JSS) is a challenging task mainly because jamming signals are embedded in signals transmitted by regular wireless devices. The situation is complicated because multiple wireless devices are likely to send packets at the same time, as jamming disturbs the regular operation of carrier sensing multiple accesses. For the rest of this paper, we refer the regular nodes' concurrent packet transmissions that could not be decoded as a collision. While it is difficult, if ever possible, to extract signal components contributed by jammers or collision sources, we discover that it is feasible to derive the JSS

based on periodic ambient noise measurement. In the following sections, we first present basics of ambient noise with regard to jamming signals and then introduce our scheme to estimate the JSS. Finally, we validate our estimation schemes via real-world experiments.

V. PERFORMANCE VALIDATION

In this section, we evaluated the performance of our jammer localization approaches that utilize the error-minimizing framework. Detailed evaluations are presented in the supplementary file, available online. We studied three heuristic search algorithms for finding the best estimation of jammers' position: a GA, a GPS algorithm, and an SA algorithm; and compared those three algorithms to the prior work by Liu et al. [3], i.e., the adaptive LSQ algorithm. We developed a simulator in Matlab. We simulated the underlying radio propagation according to the log-normal shadowing model and used GA, GPS, and SA functions provided in the global

optimization toolbox in Matlab. To make a fair comparison, we set the parameters of the shadowing model to the same values as the ones used in the prior work by Liu et al. We compared the algorithms in a variety of network configurations, including node densities, jammer's transmission power, the standard deviation of random attenuation, and the number of jammers. In addition, we examined our error-minimizing framework when indirect measurements(i.e., hearing ranges [15]) are used. A hearing range is the area within which a node can successfully receive and decode packets, and it is affected by the jammers' locationsand transmission power.

VI. CONCLUSION:

In this work, we addressed the problem of localizing jammers in wireless networks, aiming to extensively reduce estimation errors. The jammers could be several wireless devices causing unintentional radio interference or malicious colluding jamming devices who coexist and disturb the network together. Most of the existing schemes for localizing jammers rely on the indirect measurements of network parameters affected by jammers, for example, nodes' hearing ranges, which makes it difficult to accurately localize jammers. In this work, we localized jammers by exploiting directly the JSS.

Estimating JSS is considered challenging because they are usually embedded with other signals. Our estimation scheme smartly derives ANFs as the JSS utilizing the available signal strength measuring capability in wireless devices. The scheme samples signal strength regardless of whether the channel is busy or idle and estimates the ANF by filtering out regular transmission (if any) to obtain the JSS. We implemented an estimation scheme on MicaZ motes. Our experiment involving three jammers show that our estimation scheme can accurately derive the JSS from the measurements of ANF under various traffic scenarios.

REFERENCES:

[1] K. Pelechrinis, I. Koutsopoulos, I. Broustis, and S.V. Krishnamurthy, "Lightweight Jammer Localization in Wireless Networks: System Design and Implementation," Proc. IEEE GLOBECOM, 2009.

[2] H. Liu, Z. Liu, Y. Chen, and W. Xu, "Determining the Position of a Jammer Using a Virtual Force Iterative Approach," Wireless Networks, vol. 17, pp. 531-547, 2010.

[3] Z. Liu, H. Liu, W. Xu, and Y. Chen, "Exploiting Jamming-Caused Neighbor Changes for Jammer Localization," IEEE Trans. Parallel and Distributed Systems, vol. 23, no. 3, pp. 547-555, Mar. 2012.

[4] H. Liu, Z. Liu, Y. Chen, and W. Xu, "Localizing Multiple Jamming Attackers in Wireless Networks," Proc. 31st Int'l Conf. Distributed Computing Systems (ICDCS), 2011.

[5] T. Cheng, P. Li, and S. Zhu, "Multi-Jammer Localization in Wireless Sensor Networks," Proc. Seventh Int'l Conf. Computational Intelligence and Security (CIS), 2011.

[6] A. Wood, J. Stankovic, and S. Son, "JAM: A Jammed-Area Mapping Service for Sensor Networks," Proc. 24th IEEE Int'l Real-Time Systems Symp., 2003. 516 IEEE TRANSACTIONS ON PARALLEL AND DISTRIBUTED SYSTEMS, VOL. 25, NO. 2, FEBRUARY 2014 Fig. 8. Performance of all algorithms that use indirect measurements (e.g., hearing ranges).

[7] W. Xu, W. Trappe, Y. Zhang, and T. Wood, "The Feasibility of Launching and Detecting Jamming Attacks in Wireless Networks," Proc. ACM MobiHoc, 2005.

[8] A. Goldsmith, Wireless Communications. Cambridge Univ. Press, 2005.

[9] T. Rappaport, Wireless Communications—Principles and Practice. Prentice-Hall, 2001.

[10] P. Bahl and V.N. Padmanabhan, "RADAR: An In-Building RFBased User Location and Tracking System," Proc. IEEE INFOCOM, 2000.

[11] J. Yang, Y. Chen, and J. Cheng, "Improving Localization Accuracy of RSS-Based Lateration Methods in Indoor Environments," Ad Hoc and Sensor Wireless Networks, vol. 11, nos. 3/4, pp. 307-329, 2011.

[12] D. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning. Addison Wesley, 1989.

[13] E. Polak, Computational Methods in Optimization: A Unified Approach. Academic Press, 1971.