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A Probabilistic approach for Detecting Node Failures in Mobile Wireless Networks

[1]Gajjela Srilatha, [2]Ms.Pokala Shailaja

[1]PG Scholar, Department of CSE, Vaagdevi College of Engineering, Bollikunta Warangal, Telangana, Mail id: gajjelasrilatha@gmail.com

[2]Assosciate Professor Department of CSE, Vaagdevi College of Engineering, Bollikunta Warangal, Telangana, Mail ID: pokalashylaja@gmail.com

ABSTRACT: Detecting node failures in mobile wireless networks is very difficult because the network topology can be highly dynamic, the network may not always be connected, and resources are limited. In this paper, we take a probabilistic approach and propose two node failure detection schemes that systematically associate localized monitoring, location estimation, and node collaboration. Extensive simulation results in connected and disconnected networks demonstrate that our schemes result in high failure detection rates (close to an upper limit) and false-positive rates, and low communication costs. overheads and only slightly lower detection rates and slightly higher false positive rates. In addition, our approach has the advantage that it can be applied to connected and disconnected networks while centralized monitoring is only applicable to connected networks. Compared to other approaches using localized monitoring, our approach has similar failure detection rates, up to 57% lower false positive rates.

I. INTRODUCTION

Mobile wireless networks have been used for many critical applications, including the search and rescue environment that monitors rescue operations and military operations. These mobile networks are usually trained in an ad hoc manner, with permanent or intermittent network connectivity. Nodes in such networks are vulnerable to failures due to battery drain, hardware defects, or a harsh environment. Detection of node failures is important for keeptabs on the network. It is even more important when mobile devices are worn by humans and are used as the main / sole communication mechanism. Detection of node failures in mobile wireless networks is very difficult because the network topology can be very dynamic. Therefore, techniques designed for static networks are not applicable. Second, the network may not always be connected.

Third, the limited resources (computing, communication, and battery life) require node failure detection to be performed in a manner that conserves resources. An approach adopted by many existing studies relies on centralized monitoring. It is necessary for each node to send periodic "heartbeat" messages to a central monitor, which uses the absence of heartbeat messages from a node (after a certain delay) as a node failure indicator [5], [12], [19]. there is always a path from a node to the central monitor, so it is only applicable to networks with persistent connectivity. In addition, since the anode can be several jumps from the central monitor, this approach can lead to a large amount of traffic on the network, in conflict with the resources constrained in wireless mobile networks. Another approach is based on localized monitoring, in which nodes broadcast heartbeat messages to their neighbors and nodes in a single hop in a neighborhood, monitoring each other by heartbeat messages. Localized monitoring generates only localized traffic and has been used successfully to detect node failures in static networks [15]. However, when applied to mobile networks, this approach suffers from inherent ambiguities - when node A stops hearing heartbeat messages from another node B, A can not conclude that B is failing because that message B can be caused by node B out of range. In this paper, we propose a new probabilistic approach that wisely combines localized monitoring, location estimation, and node collaboration to detect node failures in mobile wireless networks. More precisely, we propose two schemes. In the first schema, when an A node can not hear from a neighbor node B, it uses its own information about B and binaryfeedback from its neighbors to decide if B has failed or not. In the second diagram, A gathers information from his neighbors and uses the information together to make the decision. The first scheme implies a communication overhead that is lower than that of the second scheme. On the other hand, the second schema makes full use of information from neighbors and provides better detection of performance failures and false positive rates.

II. RELATED WORK

Most existing studies on node failure detection in mobilewireless networks assume network connectivity. Manyschemes adopt probe-and-ACK (i.e., ping)or heartbeat based techniques that are commonly used indistributed computing [9], [14]. Probe-and-ACK based techniquesrequire a central monitor to send probe messages toother nodes. When a node does not reply within a timeoutinterval, the central monitor regards the node as failed.Heartbeat based techniques differ from probe-and-ACK basedtechniques in that they eliminate the probing phase to reducethe amount of messages. Several existing studies [12], [24]adopt gossip based protocols, where a node, upon receivinga gossip message on node failure information, merges itsinformation with the information received, and then broadcaststhe combined information. A common drawback of probe-and-ACK, heartbeat and gossip based techniques is that they areonly applicable to networks that are connected. In addition,they lead to a large amount of network-wide monitoring traffic.In contrast, our approach only generates localized monitoringtraffic and is applicable to both connected and disconnectednetworks.The scheme in [15] uses localized monitoring. It is, however,not suitable for mobile networks since it does notconsider that failure to hear from a node might be due to nodemobility instead of node failure. Our approach takes account ofnode mobility. To the best of our knowledge, our approach isthe first that takes advantage of location information to detectnode failures in mobile networks.As other related work, the study of [2] detects pathologicalintermittence assuming that it follows a two-state Markovmodel, which may not hold in practice. The study of localizes network interface failures with a very high overhead:it uses periodic pings to obtain end-to-end failure informationbetween each pair of nodes, uses periodic traceroutes to obtainthe current network topology, and then transmits the failureand topology information to a central site for diagnosis.

III. PROBLEM SETTING

In this section, we first use several applications to motivateour study and illustrate the problem setting. We then describeour assumptions.

A. Motivating Applications

In the first application, a group of robotic sensor nodes [11], move in an area to detect hazardous materials. Each nodehas sensing, communication, computation and maneuveringcapabilities, as well as a GPS receiver for localization. Thesenodes form a mobile ad hoc network. In this application, it isimportant to detect node failures so that reactive actions canbe taken (e.g., have one node to replace a failed node).The second is a search-and-rescue application for hikers in wilderness areas . Each hiker wears a wireless device thathas a GPS receiver and RF transmitter. When two devicesmeet, they record the witness information of each other(i.e., when and where one node meets another node), andexchange the witness information recorded earlier. There arealso multiple sinks (e.g., access points) and a manager nodein the area; the sinks are connected to the manager node (e.g.,via satellite). The network is typically disconnected. When anode meets a sink, it dumps all the witness information tothe sink. The sink then relays the information to the managernode, which can be used for rescue purpose (e.g., determinethe last location of a missing person). In this application, it isalso valuable to keep track of node failures so that the managernode can take reactive actions (e.g., ask a hiker with a workingdevice to go with a hiker whose device has failed).Other applications using mobile wireless networks are in

disaster relief and military operations, where it is importantto know the status of the mobile devices and take reactiveactions when needed, since a mobile device is often the maincommunication mechanism for a human or a vehicle.

B. Assumptions

Consider a group of nodes moving in a 2D space. Anarbitrary node imay fail according to a prior failure (death)probability p(i)d . The failure probability depends on the nodeitself as well as the environment. We assume a rough estimate of p(i)d ;8i is known to all nodes in the network. Our approachis not sensitive to estimation errors in p(i)d .Once a node fails, it can no longer communicate with othernodes. For ease of exposition, we assume permanent failures,.e., a failed node does not recover from the failure. Thecase of non-permanent failures can be reduced to the caseof permanent failures by simply treating a recovered node asa new node.We consider a discrete-time system with the time unit of _seconds. Each node broadcasts heartbeat packets (containingthe node's ID and location estimate) to its neighbors. In practice,the heartbeat packets can be piggybacked with periodicrouting messages for route discovery without incurring extracommunication overhead.

IV NODE FAILURE DETECTION SCHEMES

Based on the presented building block, we design two schemes to detect node failures. The first schemeux binary while the second uses nonbinaryfeedback. We refer to them as binary and non-binary schemes, respectively. We then present these two models and then briefly compare their performance.

Binary feedback system

Suppose that a node, A, no longer hears from another node, B, at time t + 1. In the binary feedback scheme, A calculates the conditional probability p that B has failed (using (4)). Let2 (0; 1) indicates a predefined detection threshold (we define 0.7, 0.8 or 0.9 in our simulation parameter). If p is greater than the threshold _, then A has a high confidence that Bhas has failed. To reduce the risk of false alarms, A broadcasts in his vicinity a survey message on B (with its own calculated probability p). In order to avoid multiplying the broadcast request messages on B, we assume that A starts a delay with a random delay value, and only broadcasts

a request message about B when the timer expires and Ahas did not hear any request on B. In this case, only the node with the lowest random delay value will broadcast a request message about B; the other nodes refrain from sending a request on B.Supposes that A broadcasts a request message about B.Any neighbor, C, after receiving the request, makes a binary response: it responds with a single bit 0 if he heard B at time t + 1; it responds with a single bit 1 if its calculated failure probability for B is greater than _; otherwise, it remains stable. Then A generates a failure alarm for B and sends it to the manager node unless it receives a 0 (ie, a neighbor has heard B). Algorithm 1 summarizes the actions related to sending a request message and actions after receiving responses to the request. Algorithm 2 summarizes how a noder responds to a request message.

Algorithm 1 Binary feedback scheme (sending query)

1: suppose A hears from B at t but not t + 1

2: A calculates p, the probability that B fails, using (4)

3: if (p _ _) then

4: A starts a timer with a random timeout value

5: if A has not heard a query about B when the timer

times out then

6: A broadcasts an inquiry about B

7: if A receives at least one response of 0 then

8: A does nothing (B is alive)

9: else

10: A sends a failure alarm about B to the manager

node

11: end if

12: end if

13: end if

Algorithm 2 Binary feedback scheme (receiving query)

1: suppose C receives a query message about B
2: if C has just heard from B then
3: C responds with 0
4: else
5: C calculates p0, the probability that B fails using (4)
6: if (p0 _ _) then
7: C responds with 1
8: end if
9: end if

For the same reason as described in Section IV-B4, theabove scheme is insensitive to the choice of the threshold, which is confirmed by our simulation results .After A generates a failure alarm about B, in a connectednetwork, A will forward the alarm to the manager nodedirectly; in a disconnected network, A will opportunisticallyupload the alarm information to a sink, which will relay it tothe manager node. In the latter case, A can use existing DTN(delay/disruption tolerant network [13]) routing protocols, e.g.,multicopy forwarding, to speed up the dissemination of thealarm information

V PERFORMANCE EVALUATION

We evaluate the performance of our schemes through extensivesimulations using a purpose-built simulator. The simulatoris built using Matlab. The main reason for using the purposebuiltsimulator instead of other simulators (e.g., ns3 [1]) isbecause it provides much more flexibility in implementingthe node failure detection algorithms that are proposed in thepaper. Implementing location estimation (an important partof our algorithms) presented in Section IV-B3 is particularly

Simulation Setting

In all the simulations, the nodes move in a 500m _ 500msquare area. The total number of nodes, N, is varied from 20to 150. The initial locations of the nodes follow a 2D Poissondistribution. The transmission range of a node is circular withthe radius, r, varied from 30m to 130m (our schemes canbe applied to irregular transmission ranges; evaluation underthose settings is left as future work). The above combinationof parameters lead to a wide range of neighborhood densityfor evaluating our approach (see the range of neighborhooddensity in Section VI-B3).We evaluate our schemes with three mobility models: therandom waypoint model [8], the smooth random model [6]and the Levy walk model. The random waypoint model iswidely used in mobile network studies. We have applied the fix described in to overcome its limitations. The smoothrandom model is a variant of the random waypoint model inthat it changes the speed and direction of node movement

incrementally and smoothly. The Levy walk model is reportedto contain some statistical similarity to human walks where the travel distance (i.e., flight length) of each movementfollows a heavy-tail distribution.Each node sends a burst of K heartbeat messages in eachtime unit of _ seconds. We also refer to the time unit asthe heartbeat interval, and use the terms interchangeably.For simplicity, we assume independent node failures andpacket losses. In addition, we assume homogeneous nodefailure probability and packet loss probability. We remark thatour schemes do not have these assumption. Because of thehomogeneity assumption, we omit superscripts and use pdand pc to represent node failure probability and packet losprobability, respectively.

VI CONCLUSION

In this paper, we presented a probabilistic approach and designed two-node fault detection schemes that combine monitoring, location estimation, and node collaboration for mobile wireless networks. Extensive simulation results demonstrate that our schemes achieve high failure detection rates, low false positive rates, and low communication overhead. We have also demonstrated the tradeoffs of binary and non-binary feedback schemes..

REFERENCES

[1] ns-3. https://www.nsnam.org/.

[2] R. Badonnel, R. State, and O. Festor. Self-configurable fault monitoringin ad-hoc networks. Ad Hoc Networks, 6(3):458–473, May 2008.

[3] P. Bahl and V. N. Padmanabhan. RADAR: An in-building RF-baseduser location and tracking system. In Proc. of IEEE INFOCOM, 2000.

[4] Y. Bar-Shalom, T. Kirubarajan, and X.-R. Li. Estimation with Applicationsto Tracking and Navigation. John Wiley & Sons, Inc., 2002.

[5] D. Ben Khedher, R. Glitho, and R. Dssouli. A Novel Overlay-BasedFailure Detection Architecture for MANET Applications. In IEEEInternational Conference on Networks, pages 130–135, 2007.

[6] C. Bettstetter. Smooth is Better than Sharp: A Random Mobility Modelfor Simulation of Wireless Networks. In Proc. of ACM InternationalWorkshop on Modeling, Analysis and Simulation of Wireless and MobileSystems, pages 19–27, New York, NY, USA, 2001. ACM.

[7] C. Bettstetter. Topology Properties of Ad Hoc Networks with RandomWaypoint

Mobility. ACM SIGMOBILE Mobile Computing and CommunicationsReview, 7(3):50–52, 2003.

[8] J. Broch, D. A. Maltz, D. B. Johnson, Y.-C. Hu, and J. Jetcheva.A Performance Comparison of Multi-Hop Wireless Ad hoc NetworkRouting Protocols. In Proc. of MobiCom, pages 85–97, New York, NY,USA, 1998. ACM.

[9] T. D. Chandra and S. Toueg. Unreliable Failure Detectors for ReliableDistributed Systems. Journal of the ACM, 43:225–267, 1996.

[10] I. Constandache, R. R. Choudhury, and I. Rhee. Towards Mobile PhoneLocalization without War-Driving. In Proc. of IEEE INFOCOM, March2010.

[11] K. Dantu, M. H. Rahimi, H. Shah, S. Babel, A. Dhariwal, and G. S.Sukhatme. Robomote: enabling mobility in sensor networks. In Proc.of IEEE/ACM IPSN, 2005.

[12] M. Elhadef and A. Boukerche. A Failure Detection Service forLarge-Scale Dependable Wireless Ad-Hoc and Sensor Networks. InInternational Conference on Availability, Reliability and Security, pages182–189, 2007.

[13] K. Fall. A delay-tolerant network architecture for challenged internets.In Proc. of ACM SIGCOMM, pages 27–34. ACM, 2003.

[14] I. Gupta, T. D. Chandra, and G. S. Goldszmidt. On Scalable and EfficientDistributed Failure Detectors. In Proc. of ACM symposium on Principlesof distributed computing (PODC), pages 170–179, 2001.

[15] C.-F. Hsin and M. Liu. A Distributed Monitoring Mechanism forWireless Sensor Networks. In Proc. of ACM WiSe, December 2002.

[16] L. Hu and D. Evans. Localization for Mobile Sensor Networks. In Proc.of ACM MobiCom, 2004.

[17] J.-H. Huang, S. Amjad, and S. Mishra. CenWits: a Sensor-based LooselyCoupled Search and Rescue System using Witnesses. In Proc. of ACMSenSys, 2005.

[18] J. Jubin and J. Tornow. The DARPA Packet Radio Network Protocols.Proceedings of the IEEE, 75(1):21–32, January 1987.

[19] D. Liu and J. Payton. Adaptive Fault Detection Approaches for DynamicMobile Networks. In IEEE Consumer Communications and NetworkingConference (CCNC), pages 735–739, 2011.

[20] M. B. McMickell, B. Goodwine, and L. A. Montestruque. Micabot: Arobotic

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platform for large-scale distributed robotics. In Proc. of IEEEInternational Conference on Robotics and Automation (ICRA), 2003.

AUTHOR'S PROFILE:

GAJJELA SRILATHA,

PG Scholar, Department of CSE, Vaagdevi College of Engineering, Bollikunta Warangal, Telangana,

Mail id: gajjelasrilatha@gmail.com.

POKALA SHAILAJA,
Assosciate Professor Department of CSE,
Vaagdevi College of Engineering,
Bollikunta Warangal, Telangana,
Mail ID: pokalashylaja@gmail.com