An Exclusive Faulty Node Detection in Mobile Wireless Network

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Abstract: In this paper, we propose a novel probabilistic approach that judiciously combines localized monitoring, location estimation and node collaboration to detect node failures in mobile wireless networks. Specifically, we propose two schemes. In the first scheme, when a node A cannot hear from a neighboring node B, it uses its own information about B and binary feedback from its neighbors to decide whether B has failed or not. In the second scheme, A gathers information from its neighbors, and uses the information jointly to make the decision. The first scheme incurs lower communication overhead than the second scheme. On the other hand, the second scheme fully utilizes information from the neighbors and can achieve better performance in failure detection and false positive rates and incur low communication overhead.

Keywords: Mobile Wireless Networks, Node Failure, Node Failure Detection, Network Management, Fault Management.

I. INTRODUCTION

Mobile wireless networks have been used for many mission critical applications, including search and rescue, environment monitoring, disaster relief, and military operations. Such mobile networks are typically formed in an ad-hoc manner, with either persistent or intermittent network connectivity. Nodes in such networks are vulnerable to failures due to battery drainage, hardware defects or a harsh environment. Node failure detection in mobile wireless networks is very challenging because the network topology can be highly dynamic due to node movements. Therefore, techniques that are designed for static networks are not applicable. Secondly, the network may not always be connected. Therefore, approaches that rely on network connectivity have limited applicability. Thirdly, the limited resources (computation, communication and battery life) demand that node failure detection must be performed in a resource conserving manner. Node failure detection in mobile wireless networks assumes network connectivity. Many schemes adopt probe-and-ACK (i.e., ping) or heartbeat based techniques that are commonly used in distributed computing. Probe-and-ACK based techniques require a central monitor to send probe messages to other nodes. When a node does not reply within a timeout interval, the central monitor regards the node as failed. Heartbeat based techniques differ from probe-and-ACK based techniques in that they eliminate the probing phase to reduce the amount of messages. Several existing studies adopt gossip based protocols, where a node, upon receiving a gossip message on node failure information, merges its information with the information received, and then broadcasts the combined information. A common drawback of probe-and-ACK, heartbeat and gossip based techniques is that they are only 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 monitoring traffic and is applicable to both connected and disconnected networks.

II. EXISTING AND PROPOSED SYSTEMS

A. Existing System

One approach adopted by many existing studies is based on centralized monitoring. It requires that each node send periodic "heartbeat" messages to a central monitor, which uses the lack of heartbeat messages from a node (after a certain timeout) as an indicator of node failure. This approach assumes that there always exists a path from a node to the central monitor, and hence is only applicable to networks with persistent connectivity. Another approach is based on localized monitoring, where nodes broadcast heartbeat messages to their one-hop neighbors and nodes in a neighborhood monitor each other through heartbeat messages. Localized monitoring only generates localized traffic and has been used successfully for node failure detection in static networks.

B. Proposed System

In this paper, we propose a novel probabilistic approach that judiciously combines localized monitoring, location estimation and node collaboration to detect node failures in mobile wireless networks. Specifically, we propose two schemes. In the first scheme, when a node A cannot hear from a neighboring node B, it uses its own information about B and binary feedback from its neighbors to decide whether B has failed or not. In the second scheme, A gathers information from its neighbors, and uses the information jointly to make the decision. The first scheme incurs lower communication overhead than the second scheme. On the other hand, the second scheme fully utilizes information from the neighbors and can achieve better performance in failure detection and false positive rates.

1. Advantages of Proposed System

- Simulation results demonstrate that both schemes achieve high failure detection rates, low false positive rates, and incur low communication overhead.
- Our approach has the advantage that it is applicable to both connected and disconnected networks.

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- Compared to other approaches that use localized monitoring, our approach has similar failure detection rates, lower communication overhead and much lower false positive rate.

  Our approach only generates localized monitoring traffic and is applicable to both connected and disconnected networks.

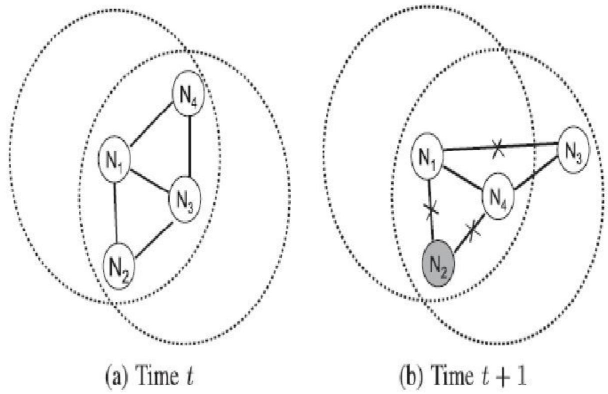

Fig.1. System Architecture

C. Modules

We have 3 main Modules.

- Localized Monitoring Module
- Location Estimation Module
- Node Collaboration Module

1. Module Description

- **Localized Monitoring:** Localized monitoring only generates localized traffic and has been used successfully for node failure detection in static networks.
- **Location Estimation:** By localized monitoring, Node only knows that it can no longer hear from other neighbor nodes, but does not know whether the lack of messages is due to node failure or node moving out of the transmission range. Location estimation is helpful to resolve this ambiguity.
- **Node Collaboration:** Through this module, we can improve the decisions which are taken during Location estimation module.

III. PERFORMANCE EVALUATION

We evaluate the performance of our schemes through extensive simulations using a purpose-built simulator. The simulator is built using Matlab. The main reason for using the purpose built simulator instead of other simulators (e.g., ns3 [2]) is because it provides much more flexibility in implementing the node failure detection algorithms that are proposed in the paper. Implementing location estimation (an important part of our algorithms) presented-B3 is particularly convenient in Matlab (because of many readily available mathematical libraries) than that in other network simulators. In the following, we first describe the simulation setting, and then describe the evaluation results.

Algorithm1 Non-binary feedback scheme (sending query)

suppose A hears from B at t but not $t+1$
A calculates p, the probability that B fails, using (4)
if $(p \geq \theta)$ **then**
  A starts a timer with a random timeout value
  if A has not heard a query about B when the timer times out **then**
    A broadcasts an inquiry about B
    if A receives at least one response of 0 **then**
      A does nothing (B is alive)
    else
      A updates p based on the feedbacks using (17)
      if $(p \geq \theta)$ **then**
        A sends a failure alarm about B to the manager node
      end if
    end if
  end if
end if

Algorithm2 Non-binary feedback scheme (receiving query)

suppose C receives a query message about B
if C has just heard from B **then**
  C responds with 0
else
  C responds with the probability that all K messages from B to C are lost and the probability that C is in B's transmission range
end if

A. Simulation Setting

In all the simulations, the nodes move in a 500m × 500m square area. The total number of nodes, N, is varied from 20 to 150. The initial locations of the nodes follow a 2D Poisson distribution. The transmission range of a node is circular with the radius, r, varied from 30m to 130m (our schemes can be applied to irregular transmission ranges; evaluation under those settings is left as future work). The above combination of parameters leads to a wide range of neighborhood density for evaluating our approach (see the range of neighborhood density). We evaluate our schemes with three mobility models: the random waypoint model [9], the smooth random model [7] and the Levy walk model. The random waypoint model is widely used in mobile network studies. We have applied the fix described to overcome its limitations. The smooth random model is a variant of the random waypoint model in that it changes the speed and direction of node movement incrementally and smoothly. The Levy walk model is reported to contain some statistical similarity to human walks, where the travel distance (i.e., flight length) of each movement follows a heavy-tail distribution. Each node sends a burst of K heartbeat messages in each time unit of δ seconds. We also refer to the time unit as the heartbeat interval, and use the terms interchangeably. For simplicity, we assume independent node failures and packet losses. In addition, we assume homogeneous node failure probability and packet loss probability. We remark that our schemes do not have these assumptions.

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... the homogeneity assumption, we omit superscripts and use p_d and pc to represent node failure probability and packet loss probability, respectively. In our simulations, p_d is varied from 0.01 to 0.05; p_c is varied from 0.001 to 0.1. The above choices of p_d and p_c cover a wide range of settings. Our scheme also works for higher or lower p_d, we briefly describe the cases of larger p_c (larger pc can lead to lower confidence in detecting failures). We assume that p_d and p_c are not known, but can be estimated. The maximum relative estimation error is denoted as *err*. The location measurement error is assumed to be zero mean Gaussian white noise with the standard deviation, σ_W (refer to), varied from 1m to 10m. There is no interference model in the simulator. Adding an interference model will lead to different characteristics of packet losses, which is left as future work. In each simulation run, we start with a warm-up phase of 20 seconds and then simulate node failures. For simplicity, node failures are simulated at each time unit, and we stop the simulation when at least one node fails. For each setting, we repeat the simulation at least 100 times, and present the average results; the confidence intervals are tight and hence omitted for clarity. The performance metrics are (1) detection rate, defined as the number of failures that are detected successfully divided by the actual number of failures, (2) false positive rate, defined as the number of false alarms (i.e., a node is considered to be failed but actually it is not) divided by the number of alarms that are raised, and (3) communication overhead, defined as the average number of messages sent per second during the entire detection period. We evaluate the performance of both of our schemes. In the following, we mainly report the performance of the binary feedback scheme, and "our scheme" henceforth refers to this scheme. The non-binary scheme mainly differs from the binary scheme in the minimum required K for effective failure node detection and communication overhead, simulation results on these two aspects are, respectively. In the following, we present evaluation results under the random waypoint model and the smooth random model, first in connected networks and then in disconnected networks. At the end, we briefly present the results under the Levy walk model.

B. Evaluation Results for Connected Networks

The evaluation setting for connected networks is motivated by the robotic sensor network application. The network is connected at every point of time. A manager node is in the central region of the area. Node failure alarms are sent to the manager node. We consider three node movement speed ranges: low speed range of [1; 5]m/s, medium speed range of [5; 10]m/s, and high speed range of [10; 15]m/s. We compare our scheme to two schemes, referred to as centralized and localized schemes, motivated by the schemes in [6], and the scheme, respectively. In the centralized scheme, each node sends periodic heartbeat messages to the manager node, which decides that a node has failed when not hearing from the node. The localized scheme differs from our scheme only in that it does not calculate the probability of node failure. Specifically, when node A no longer hears from node B, instead of calculating the probability that B has failed, A simply suspects that B has failed and sends an inquiry to its neighbors. If none of A's neighbors reply that B is alive, then A sends a message to the manager node that B has failed. In the following, we first report the results when the heartbeat interval is one second (i.e., $\delta = 1$ sec), assuming the failure and packet loss probabilities are known and the standard deviation of the location measurement error is 1m. We then investigate the impact of probability estimation errors, location measurement errors, and heartbeat interval. We only report the results under random waypoint model; the results under the smooth random model are similar.

- **Choice of Threshold θ:** We set the detection threshold, θ, to 0.7, 0.8 or 0.9, and observe similar results (as explained). All the results presented below use θ = 0.8.
- **Choice of K:** To deal with packet losses, a node sends a burst of K heartbeat messages in each time unit. For the binary feedback scheme, we can derive the minimum K that is needed for failure node detection from the necessary condition. Specifically, under our assumption of independent packet losses, p_c, $K = p^K{}_c$, and we have

$$\geq \frac{\log(\ /-)-\ 1-}{\quad} \tag{1}$$

For instance, when θ = 0.8 and $p_d = 0.01$, the minimum K is 1, 2 and 3 for $p_c = 0.001$, $pc = 0.05$ and $pc = 0.1$, respectively. For all the settings we explored, a small value of K (no more than 3) is sufficient to achieve good performance. The above is for independent losses. When that is not the case (i.e., $p_c, K > p^K{}_c$), the minimum K can be larger than that under independent losses. For the non-binary feedback scheme, we can derive the minimum K that is needed for failure node detection from the necessary condition. Specifically, under our assumption that $p^{(1)}{}_{c,K} =$

$p_{c,K} = p^K{}_c, \forall i$, we have

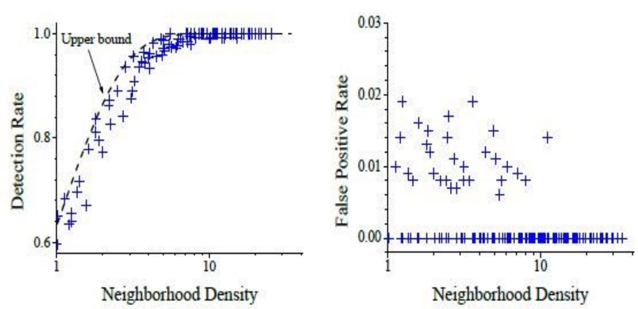
$$\geq \frac{\log\ \ /-\ -\log(1-\ )}{\quad} \tag{2}$$

Comparing (1) and (2), it is easy to see that the minimum K required for the non-binary scheme can be significantly smaller than that for the binary scheme. For instance, our simulation results show that when $p_d = 0.01$; $p_c = 0.01$; $N =$

80, and $r = 80$m, the binary scheme requires $K \geq 2$, while

the non-binary scheme only requires $K \geq 1$. last, for a given

scenario, both the binary and non-binary schemes can achieve high failure detection rate and low false positive rate using the minimum required K derived from (1) and (2) respectively.

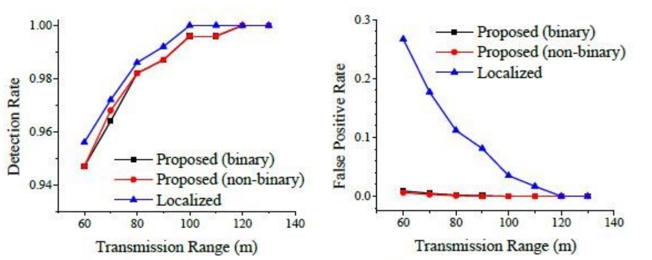


(a) Detection rate. (b) False positive rate.

Fig.2. Detection Rate and False Positive Rate of Our Scheme ($K = 2$, $p_c = 0.01$, $p_d = 0.01$, $\sigma_W = 1$m, low speed).

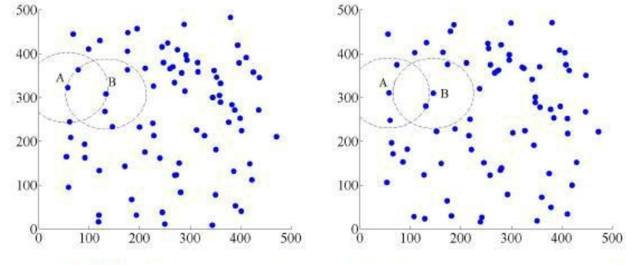
C. Detection Rate and False Positive Rate

In our setting, the neighborhood density $\rho = \pi r^2 N/S$, where S = 500m×500m. Figs 2(a) and (b) plot the detection rate and false positive rate of our scheme versus neighborhood density when $K = 2$, $p_c = 0.01$, $p_d = 0.01$, and nodes move at low speed. The various neighborhood densities are obtained using the combinations of r (ranging from 30m to 140m) and N (ranging from 20 to 140). For clarity, we only plot the results for the combinations leading to neighborhood density of at least 1. In Fig. 2(a), we also plot the upper bound of the failure detection rate, since for the random waypoint model the node distribution can be well approximated by a 2D Poisson distribution [8]. Observe that the detection rates of our scheme are very close to the upper bound, indicating that our scheme achieves very good detection rates. As expected, the detection rate increases while the false positive rate decreases with neighborhood density. Specifically, when the neighbor density is above 3, our scheme achieves a detection rate of above 0.9 and a false positive rate of below 0.02. The performance is worse when nodes move faster (figures omitted). This is expected. Consider an arbitrary node, A, that is in the neighborhood of node B at time t. When nodes move fast, A is more likely to be out of the range of B at time t+1, which is more likely to lead to missed detections (when B fails) or false positives (when B does not fail). We next compare the detection rate and false positive rate of our scheme and the other two schemes. Under ideal network conditions (i.e., packet delays and losses are negligible), the centralized scheme can always detect failed nodes and does not cause false alarms. On the other hand, as we shall see, its communication overhead is much higher than that of our scheme. The detection rate of the localized scheme is no less than that of our scheme since when our scheme detects a node failure, the localized scheme can detect that node failure as well. However, the localized scheme suffers from many more false positives. Fig. 3 plots the detection rate and false positive rate of our scheme and the localized scheme when the transmission range is varied from 60 to 130m, and the number of nodes in the area is 80. We observe that the detection rate of our scheme is slightly lower than that of the localized scheme, while the false positive rate of our scheme is much lower than that of the localized scheme. For instance, when r = 60m, the false positive rate under our scheme is 0.01 versus 0.27 under



(a) Detection rate. (b) False positive rate.

Fig.3. Comparing Detection Rate and False Positive Rate of Our Scheme and the Localized Scheme (K= 2, N= 80, p_c = 0.01, p_d= 0.01, σ_W= 1m, high speed).



(a) Node locations at time t. (b) Node locations at time $t + 1$.

Fig.4. An Example That Illustrates False Positives in the Localized Scheme

the localized scheme. We also plot the results for the non binary feedback scheme, which has slightly better performance than the binary feedback scheme. The much lower false positive rate under our scheme is because of its ability to differentiate a node failure from the node moving out of the transmission range, while the localized scheme cannot differentiate these two cases. Fig. 4 shows an example observed in the simulations. Nodes A and B are within each other's transmission range at time t, and are out of each other's transmission range at time t+1. In the localized scheme, since A cannot hear from B at time t+1, it suspects that B has failed, and broadcasts an inquiry to its one-hop neighbors. Since none of A's neighbors is in B's transmission range at time t + 1, A does not hear anything from its neighbors about B, and concludes that B has failed. Similarly, B concludes that A has failed. Therefore, the localized scheme leads to two false positives in this example. Our scheme does not lead to any false positive since A finds the probability that B has failed is below the threshold, and hence does not suspect that B has failed; similarly, B does not suspect that A has failed.

D. Communication Overhead

Let H denote the average number of hops from a node to the manager node. The centralized scheme leads to an average of $N \times K \times H$ messages in each time unit, where N is the number of nodes and K is the number of heartbeat messages per time unit. In our scheme and localized scheme, the number of heartbeat messages is $N \times K$ in each time unit, significantly lower than that of the centralized scheme especially when H is large. In addition to heartbeat messages, our scheme and the localized scheme also lead to two other types of messages: one is the localized inquiries and responses during node collaboration (on average $K \times (1+\rho)$ messages since each inquiry and the corresponding responses are sent K times to deal with packet losses), the other refers to the alerts sent to the manager node (on average $K \times H$ messages). Fig. 5 plots communication overhead for the three schemes versus transmission range when $K = 2$, $p_c = 0.01$, $p_d = 0.01$, $\sigma_W = 1$m, $N = 120$, and nodes move at high speed. For all three schemes, when sending a message to the manager node, we use shortest-path routing and ignore the message overhead caused by routing (this is in favor of the centralized scheme which may incur increased overhead due to routing because of more frequent messages to the manager node).

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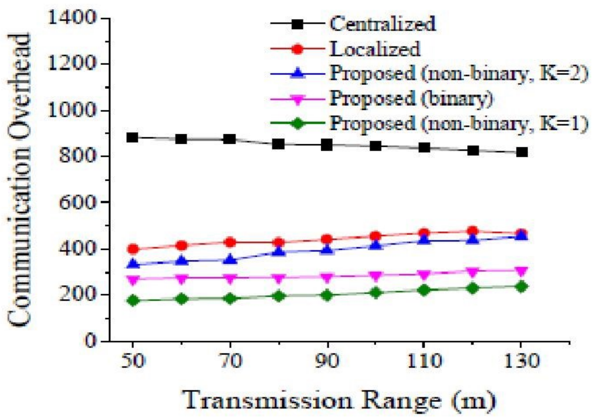
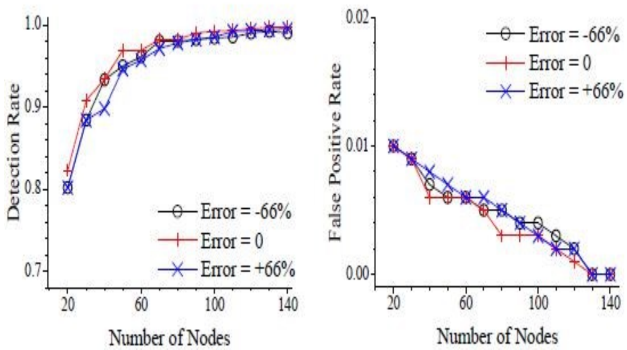


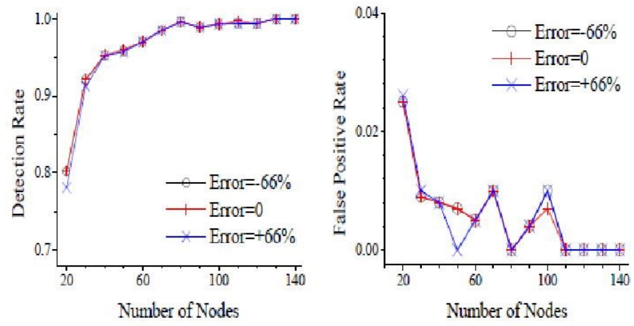
Fig.5. Communication Overhead of the Three Schemes (K = 2, P_c = 0.01, P_d = 0.01, Σ_w = 1m, N = 120, High Speed).



(a) Detection rate. (b) False positive rate.

Fig.6. Impact of Estimation Errors in p_d (K = 2, p_c = 0.01, p_d = 0.03, r = 80m, σ_w = 1m, High Speed).

We observe that the centralized scheme leads to much higher communication overhead than our scheme. Furthermore, the localized scheme also leads to higher communication overhead than our scheme, which is due to two reasons. First, the localized scheme has more inquiries and responses during node collaboration. Suppose node A hears from node B at time t but not at time t+1. In the localized scheme, A will suspect that B has failed, leading to an inquiry from A and the corresponding responses from A's neighbors. In our scheme, A only sends an inquiry when the failure probability of B is larger than the threshold. Secondly, the localized scheme leads to more alerts to the manager node due to more false alarms. Of all the settings we explore, when the neighborhood density is larger than 3, the communication overhead of the centralized scheme is 3.4 to 5.0 times as large as that of our scheme; the communication overhead of the localized scheme is 1.9 to 2.3 times as large as that of our scheme. In the above, "our scheme" refers to the binary feedback scheme. Fig. 5 also plots the results for the non-binary feedback scheme when K = 2 and K = 1, respectively.



(a) Detection rate. (b) False positive rate.

Fig.7. Impact of Estimation Errors in p_c (K = 2, p_c = 0.03, p_d = 0.01, r = 80m, σ_w = 1m, High Speed).

As explained in Section III-B2, the non-binary scheme requires $K \geq 1$ while the binary scheme requires $K \geq 2$ for this setting. When K = 2, the communication overhead of the non binary scheme using is larger than that of the binary scheme, while is lower than that of the localized scheme. When K = 1, the non-binary scheme leads to lower overall communication overhead compared to the binary scheme that uses K = 2 because the number of heartbeat messages is reduced by half. Last, note that with the number of nodes fixed the centralized scheme's communication overhead decreases with the transmission range (due to shorter routes to the manager node), while for our scheme and localized scheme, the communication overhead increases with the transmission range due to more nodes in the neighborhood and hence more responses during node collaboration. This indicates the tradeoffs between schemes that use centralized monitoring and those using localized monitoring. If the transmission range is large enough that the routes to the manager node are comparatively short (meaning that the effective neighborhood density is high), it might be beneficial to use schemes based on centralized monitoring, and vice versa.

E. Impact of Probability Estimation Errors

We now investigate the impact of estimation errors in p_d and p_c on the performance of our scheme. The relative estimation error is up to 66.6%. We next present results under two settings where the relative estimation error is 66.6%. In Fig. 6, the actual p_d is 0.03, while the estimated p_d is 0.01 or 0.05. We observe that the performance of our scheme when using the estimated p_d is similar to that when using the actual p_d. Fig.7 plots the performance of our scheme when the actual pc is 0.03, while the estimated pc is 0.01 or 0.05. We again observe similar performance when using the estimated pc and the actual p_c. This demonstrates that, as explained, our scheme is not sensitive to estimation errors in p_c and p_d. We have also investigated the cases when both the estimates of p_d and p_c have errors. The results again confirm that our scheme is not sensitive to estimation errors in p_d and p_c (figures omitted).

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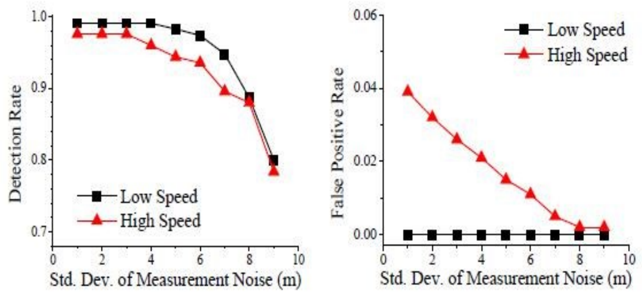
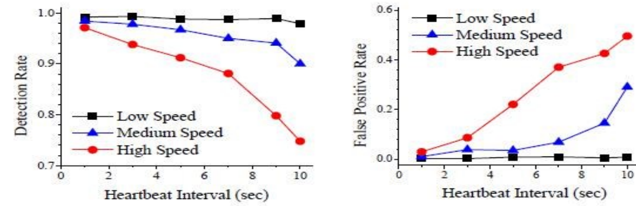


(a) Detection rate. (b) False positive rate.

Fig.8. Impact of Location Measurement Deviation (K= 2, p_c = 0.01, p_d= 0.01, r= 80m, N= 100).

1. Impact of Location Measurement Errors: Fig. 8(a) plots the detection rate of our scheme while increasing σ_W, the standard deviation of the measurement noise, from 1m to 10m. The results under both low and high movement speeds are shown in the figure. We observe that when increasing σ_W, the detection rate first decreases slowly, and then decreases sharply when σ_W is above a certain value. This indicates that our scheme can tolerate inaccuracy in location measurements. Fig. 8(b) plots the false positive rate of our scheme versus σ_W. When increasing σ_W, the false positive rate under low speed remains low while the false positive rate under high speed decreases. This is consistent with the lower detection rates when increasing σ_W: when location prediction is inaccurate, the confidence in node failure probability is low, leading to missed detections as well as fewer false positives.

2. Impact of Heartbeat Interval: So far all the results are obtained when the heartbeat interval is one second. When increasing the heartbeat interval, the communication overhead decreases. On the other hand, the location estimation becomes less accurate. In addition, a node, A, in the neighborhood of another node, B, is more likely to be outside of the neighborhood of B in the next heartbeat interval. Both factors may have adverse impact on the detection rate and false positive rate. Fig.9 plots the detection rate and the false positive rate of our scheme when increasing the heartbeat interval from 1 to 10 seconds. As expected, the detection rate and the false positive rate degrade more slowly when node speeds are low, while degrade more quickly when node speeds are high. Fig. 10 plots the communication overhead when increasing the heartbeat interval. As expected, the communication overhead decreases when increasing the heartbeat interval. On the other hand, when the heartbeat interval is large, inaccurate location estimation leads to more inquiries and responses as well as more messages to the manager node (due to increased false positive rate), causing the gain in communication overhead to level off. The above indicates that it is not beneficial to set the heartbeat interval too large, especially when nodes move fast. In fact, in addition to degraded detection rate and false positive rate, larger heartbeat intervals also lead to longer delays in detecting node failures, which is undesirable for many applications.



(a) Detection rate. (b) False positive rate.

Fig.9. Impact of Heartbeat Interval on Detection Rate and False Positive Rate of Our Scheme (K= 2, p_c = 0.01, p_d= 0.01, r= 80m, N= 100, σ_W= 1m).

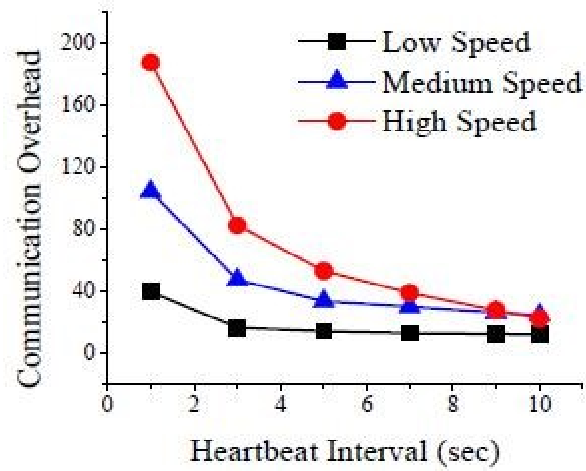


Fig.10. Impact of Heartbeat Interval on Communication Overhead of Our Scheme (K= 2, p_c = 0.01, p_d= 0.01, r= 80m, N= 100, σ_W= 1m).

F. Evaluation Results in Disconnected Networks

The evaluation setting for disconnected networks is motivated by the hiking application. We consider low movement speed of [0.4-0.6]m/s and transmission range of 50m. The number of nodes is varied from 30 to 100. There are 10 sinks distributed uniformly randomly in the 500m×500m area. The sinks are connected to a manager node located in the central region of the area. Due to low node density, the network only has intermittent connectivity. We use the following routing strategy. Suppose that node A generates an alarm that B has failed at time t. Then A transmits this message to all of its current neighbors. Each of these nodes (A and its neighbors) carries the information; when one of them meets a sink, it uploads the information to the sink, which in turn relays the information to the manager node. In addition to performance metrics described earlier, we consider another metric, discovery delay, which is the delay from when a node is found to be failed to when the message reaches the manager node (we assume negligible delay from a sink to the manager node). We only report the results under random waypoint model; the results under the smooth random model are similar.

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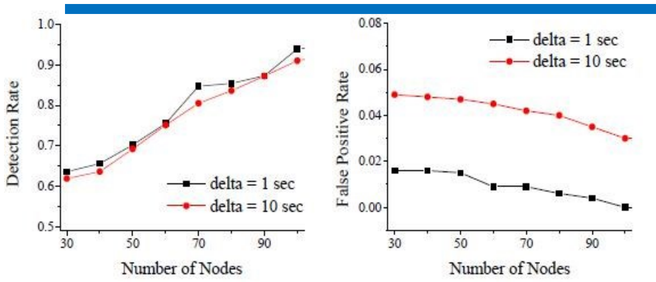
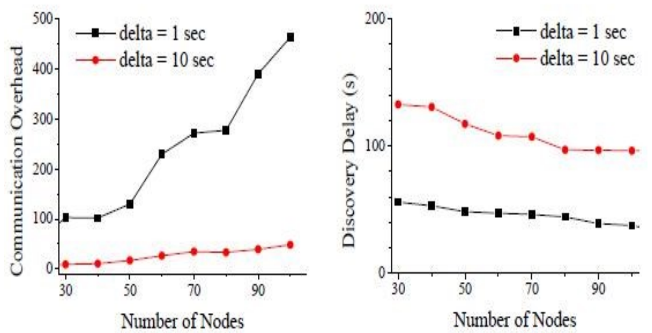


(a) Detection rate. (b) False positive rate.

Fig.11. Detection Rate and False Positive Rate in Disconnected Networks (K = 2, p_c = 0.01, p_d = 0.01, r = 50m, σ_W = 1m).



(a) Communication overhead. (b) Discovery delay.

Fig.12. Communication Overhead and Discovery Delay In Disconnected Networks (K = 2, p_c = 0.01, p_d = 0.01, r = 50m, σ_W = 1m).

Fig. 11 plots detection rate and false positive rate under two heartbeat intervals, δ = 1 and 10 seconds. The false positive rate under δ = 1 second is lower than that when δ = 10 seconds. The detection rate under the two heartbeat intervals is similar, perhaps because of slow node movement. As expected, the detection rate increases with node density while the false positive rate decreases with node density. Even with only 30 nodes, the detection rate is above 0.6 and the false positive rate is below 0.05. Fig. 12 plots communication overhead and discovery delay. When δ = 10 seconds, the communication overhead is significantly lower than that when δ = 1 seconds, while the discovery delay is still in a few minutes. The discovery delay decreases when increasing the number of nodes since more nodes can carry the failure information, providing more opportunities to report the information to the sinks.

IV. CONCLUSION

We have evaluated our two schemes using extensive simulation in both connected and disconnected networks (i.e., networks that lack contemporaneous end-to-end paths). Simulation results demonstrate that both schemes achieve high failure detection rates, low false positive rates, and incur low communication overhead. Compared with approaches that use centralized monitoring, while our approach may have slightly lower detection rates and slightly higher false positive rates, it has significantly lower communication overhead (up to 80% lower). In addition, our approach has the advantage that it is applicable to both connected and disconnected networks. Compared to other approaches that use localized monitoring, our approach has similar failure detection rates, lower communication overhead (up to 57% lower) and much lower false positive rate (e.g., 0.01 versus 0.27 in some setting).

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