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Cross-layer Fault Tolerant Data Aggregation for Improved Network Delay in Healthcare Management Applications

Xiaojing Yuan, Haoying Liu, *Member, IEEE*

***Abstract*—The escalation of American health care costs compels a new approach to manage chronic diseases. Wireless sensor networks (WSN) have been applied successfully in remote monitoring in military, aerospace, civil structure, and healthcare. However, existing wireless network framework cannot provide required quality of service (QoS) due to communication device failure, message loss caused by link error, collision, and hidden terminal for personalized disease management applications. In this paper, we present scalable network architecture and an operating mechanism that tolerates network structure changes caused by failure, with the application level data aggregation algorithm able to heal from the failure. We provide close form solutions that can achieve optimized network delay. Performance analysis was done to evaluate the significance of different nodes' failure in both homogeneous and heterogeneous sensor network and the effects of sensing and communication speed on failure impact in heterogeneous sensor networks.**

I. Introduction

Recent advances in miniature wireless sensors supported by ubiquitous computing have fostered a growth of interest in personalized pervasive disease management based on distributed sensor networks [1-4]. Remote health monitoring, typically referred to as *Telemedicine* is emerging as a key area of research that integrates wireless telecommunications, sensing, and health care. Pioneer research projects have set up small scale sensor network systems [5-8] to help physicians keep track of their patients whose chronic condition includes risk of sudden acute events where early intervention may significantly improve the survival rate and reduce the recovering time. The miniature and unobtrusive sensor nodes can be enclosed in patches or clothing (wearable sensors) [9], or embedded in furniture and building structures.

Due to the nature of the low-end embedded devices with limited energy budget, radio communication, and primitive user interface, WSNs are highly prone to hardware and software faults, security threats, and intrusion attacks [10]. Recent researches on fault tolerant sensor network focusing on the networking stack [11-14] and various backup mechanisms have been developed to recover from the failure caused by faulty nodes and / or links [15-18].

With better and improved processing and storage capability, WSNs have spread to data-centric and mission critical applications that use multimedia information such as sound, image, and video streams. The larger data packets and the real-time requirement put the challenge on minimizing the network delay. We developed efficient data aggregation method [19-20] to study the dynamic changes of the network delay at the application layer. We define the "*total response time*" as the time needed for central node to assign sensing tasks to each selected node (include network delay), each node accomplish its sensing task and on-board processing, and reporting back to the central node. In this paper, we extend the model to study the impact of the node/link failure on the total response time in single hop wireless network based on optimum data aggregation sequence.

In section II, we discuss the system model, notations, and strategy used in the paper. Section III details the close form solution of the data aggregation delay overhead caused by failure in single hop heterogeneous networks. In section IV, we present simulation results with detailed discussion on the impact of failure node/link to the total response time with respect to its location in the data aggregation route. Finally, in Section V we conclude and point to possible future direction.

II. Fault Tolerance Model and Notation Used

The data aggregation route is continuously changing in ad hoc network especially when sensor node or wireless links fails. In order to characterize such dynamic behavior, we define a temporal unit "*cycle*" as the minimum time during which the route remains fixed. Without loss of generality, we assume any sensing task can be accomplished either within one *cycle* when there is no failure, or in two cycles when failure occurs in the first *cycle.*

Within each cycle, the cluster head (Fig.1) discovers reachable border sensor nodes and set up an optimum data aggregation route. Then the algorithm finds the optimal task distribution resulting in minimum total response time. The partitioned sensing tasks are distributed to the sensor nodes within the cluster. After each node finished their sensing task, the results are reported back to the cluster head through optimum sequence identified. The reporting sequence is implied by nodes' superscripts: the node that reports last is denoted as SSN^1 (Smart Sensor Node) and the one that reports second last is SSN^2. SSN^0 is the cluster head.

While gathering data, the cluster head continuously checks the data integrity and detect any missing data and its source, i.e., fault detection and identification. After it retrieves the health status of nodes and decide that the missing data will

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X. Yuan is with the University of Houston, Houston, TX 77024 USA. (phone: 713-743-1129; email: xyuan@uh.edu).

H. Liu was with the University of Houston (e-mail: liuhaoying@gmail.com).

affect the data integrity, a second cycle will be automatically scheduled to complete the sensing task. If the faulty sensor node recovered from the failure and has all data still available (such as in the case of temporary link loss), it will retransmit the data while other nodes starting their new sensing task. When the sensor node cannot be recovered for the consequent cycle or the recovered node does not have all data available, the cluster head reschedules the remaining sensing task among all available sensor nodes like it is a new sensing task. The cluster head gathers health status of each node and determines whether to keep the previous route or to identify a new route or a network structure change (Fig. 1).

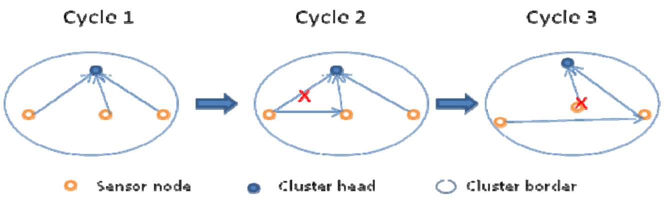

Figure 1 Different data aggregation routes between cycles due to failure

To quantitatively model the failure event, we define the failure time (t) as the time from the start of result reporting to the failure point (Fig. 2). If $t < 0$, i.e. failure occurs before data aggregation, the entire data is lost. If $t > 0$, i.e. failure occurs after data aggregation begins, the missing task will be proportional to t. The notations used in the model are:

α_i: The sensing task portion that is assigned to SSN^i. It is assumed that every node will be assigned non-zero task, i.e., $0<\alpha_i<1$, and the task for all nodes sums up to 1 ($\sum_{i=1}^{n} \alpha_i = 1$).

y_i: Sensing capability of SSN^i, a constant that is inversely proportional to its sensing speed.

z_i: Communication capability of $link_i$, a constant that is inversely proportional to the communication speed of the link.

T_{ms}: Sensing intensity constant, the time SSN^i takes to finish the whole sensing task when $y_i = 1$.

T_{cm}: Communication intensity constant, the time $link_i$ takes to transmit the entire sensing task over a link when $z_i = 1$.

T_i: The total time from the start of the scheduling process at $t = 0$ and the time when SSN^i completes its reporting.

T_r: The total response time, $T_r = \max(T_1, T_2, \ldots, T_n)$.

ΔT: The delay overhead caused by node's failure

There are many different data aggregation strategies for sensor nodes to report their data back to the cluster head. In this study we consider the case where the sensor nodes start sensing immediately upon receiving the sensing task portion α_k, as shown in a Gantt-chart timing diagram in Fig. 2. After sensing tasks are done, sensor nodes report their data sequentially to the cluster head which supports only one receiver channel. This is called Simultaneous Sensing Start Sequential Data Aggregation (S^4DA).

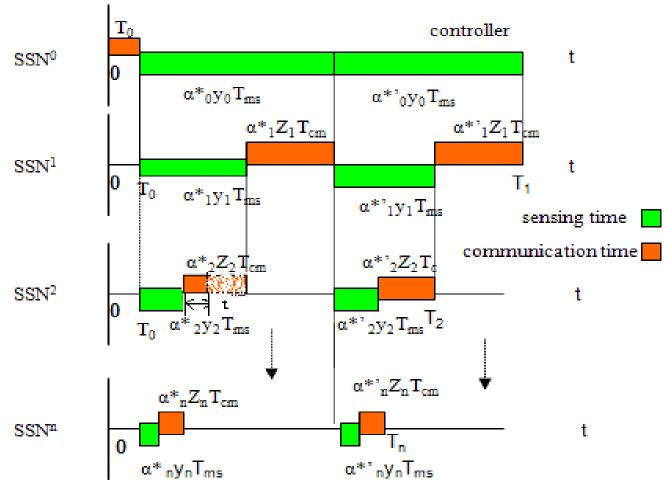

Figure 2 (a) Two cycles when failure recovers before the 2nd cycle

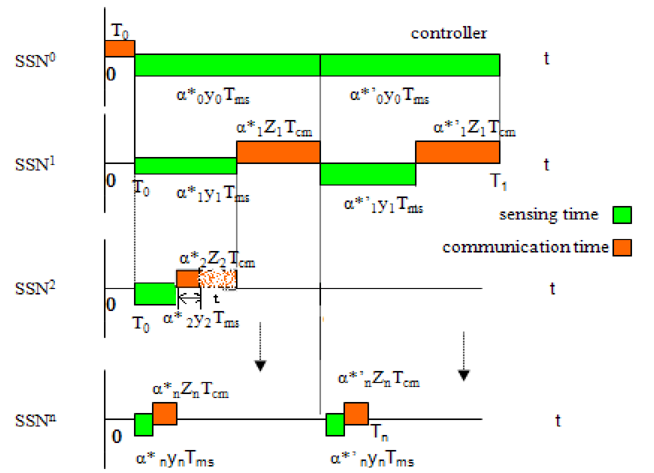

Figure 2(b) Two cycles when failure does not recover before the 2nd cycle

III. Closed Form Solution for Fault Tolerant Model

Based on the given notation, we will derive the closed form solution for S^4DA of single hop wireless sensor network. We assume the data aggregation route remains the same for two consecutive cycles. The closed form solution for optimum task partition results in minimum total response time in the first cycle is the same as the one without any failure for both *homogeneous* and *heterogeneous* sensor network [19-20]. (Note: All the sensor nodes in the *homogeneous* network have the same sensing and communication capability, i.e., $y_i=y$ and $z_i=z$. Otherwise, we consider it a *heterogeneous* network.)

When failure occurs at node SSN^k, the cluster head will automatically initiate a second cycle to gather the remaining data $\Delta\alpha = \alpha_k - t / z_k T_{cm}$. To study the response delay caused by the faulty node and/or faulty connection, we look into the relationship between the sensing (y_k) and communication (z_k) capability and the failure node position in the reporting sequence.

For single hop wireless *homogeneous* network [21] using S^4DA strategy, the impact of the failure on the total response time, i.e., the delay overhead ΔT_r, is proportional to the remaining sensing task $\Delta\alpha$. It is straightforward to conclude that the later a sensor node reports, i.e., the lower the k in SSN^k, the more delay overhead caused by the node failure. When the node failure recovers before the 2nd cycle, the delay overhead is $\Delta T = \Delta\alpha \cdot T_r$, in which T_r is the optimum response time when there is no failure. When the node failure cannot recover before the 2nd cycle, the delay overhead can be computed as in Eq. 1, in which $f^k = \dfrac{y_k + z_k T_{cm} / T_{ms}}{y_{k-1}}$.

$$\Delta T_r = \Delta\alpha (T_0 + \frac{f^{n-1}}{1 + \sum_{i=1}^{n-1} f^{n-i}} y T_{ms}) \qquad (1)$$

The matter is much more complicated for *heterogeneous* networks. When the failure node or link recovers before the second cycle starts, the cluster head reassign the remaining task $\Delta\alpha$ to all nodes as in the first cycle. Substituting the task assigned in the first cycle in a heterogeneous network, we get:

$$\Delta\alpha = \alpha_k - \frac{t}{z_k T_{cm}} = \frac{\prod_{j=k+1}^{n} f^j}{1 + \sum_{i=1}^{n} \prod_{j=i}^{n} f^j} - \frac{t}{z_k T_{cm}} \qquad (2)$$

The delay overhead is $\Delta T = \Delta\alpha \cdot T_r$, which implies that the most significant failure node resulting in the longest ΔT is the one that results in largest $\Delta\alpha$, i.e., the node reports last. When the failure node or link does not recover before the second cycle starts (Fig. 2(b)), the remaining task will be reassigned to the remaining sensor nodes by the cluster head. The set of linear equation is shown in Eq.(3) (without node SSN^k). Together with $\sum \alpha^{*'}_j = \Delta\alpha$, we derive the closed form solution for delay overhead ΔT_f as shown in Eq. 4.

It is clear that the impact of the failure is proportional to the remaining task $\Delta\alpha$. Keeping the $\Delta\alpha$ constant, the delay overhead ΔT_r relates to the tradeoff between sensing and communication capability of a node, i.e., $y_k/(y_k+z_k)$.

$$\begin{aligned}
\alpha^{*'}_0 y_0 T_{ms} &= \alpha^{*'}_1 y_1 T_{ms} + \alpha^{*'}_1 z_1 T_{cm} \\
\alpha^{*'}_1 y_1 T_{ms} &= \alpha^{*'}_2 y_2 T_{ms} + \alpha^{*'}_2 z_2 T_{cm} \\
&\ldots \\
\alpha^{*'}_{k-1} y_{k-1} T_{ms} &= \alpha^{*'}_{k+1} y_{k+1} T_{ms} + \alpha^{*'}_{k+1} z_{k+1} T_{cm} \\
&\ldots \\
\alpha^{*'}_{n-1} y_{n-1} T_{ms} &= \alpha^{*'}_n y_n T_{ms} + \alpha^{*'}_n z_n T_{cm}
\end{aligned} \qquad (3)$$

$$\Delta T_r = \Delta\alpha (T_0 + \frac{\prod_{j=1}^{n} f^j}{\dfrac{1 + \sum_{i=k+2}^{n} \prod_{j=i}^{n} f^j}{\dfrac{y_k}{y_k + z_k}} + \sum_{i=1}^{k} \prod_{j=i}^{n} f^j} y_0 T_{ms}) \qquad (4)$$

IV. Simulation Results

We present the simulation results for a 9-node one-hop sensor network assuming $T_{cm} = T_{ms} = 1$ to study the impact of different failure scenarios on the total response time.

The first set of experiments assume all failure occurs at $t = 0.01*T_{cm}$ and study the impact of the failure with respect to the data aggregation sequence when varying the sensing and communication speeds of each nodes. The first experiment looks at two extreme cases when the reporting sequence is based on the sensing speed: (a) the node with slowest sensing speed ($2*T_{ms}$) will report first while the node with fastest sensing speed ($0.6*T_{ms}$) will report last; and (b) the fastest sensing node report first and the slowest report last. Fig.3 shows the results ($\Delta Tr/Tr$ and $\Delta\alpha$) when SSN^k fails.

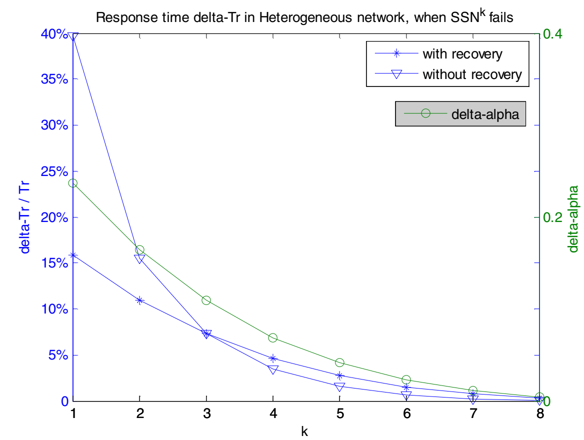

Figure 3. case (a) data aggregation sequence: from largest y to smallest y

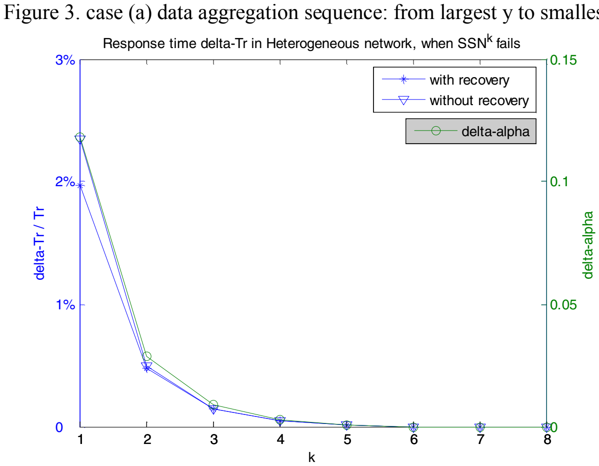

Figure 3. case (b) data aggregation sequence: from smallest y to largest y

From Fig. 3, we observe that the earlier a sensor node reports back, i.e., the higher the k, the smaller the delay overhead $\Delta T_r/T_r$ of the total response time. The figures also show that the portion of remaining task $\Delta\alpha$ dominates the failure impact and thus determines the trend. However, comparing (a) and (b), we can see $\Delta\alpha$ and the delay overhead of case (b) are much smaller than those of case (a), reduced from 15% to 25% for $\Delta\alpha$ and from 15%~40% to 2~2.5% for the delay overhead respectively. This indicates the data aggregation sequence (b) is the optimal reporting sequence.

Similarly, Fig. 4 shows the failure impact is smaller for the case when the nodes aggregate data from the slowest z to fastest z. This set of experiments not only demonstrates the impact of node failure, but also the optimal reporting sequence with respect to total response time.

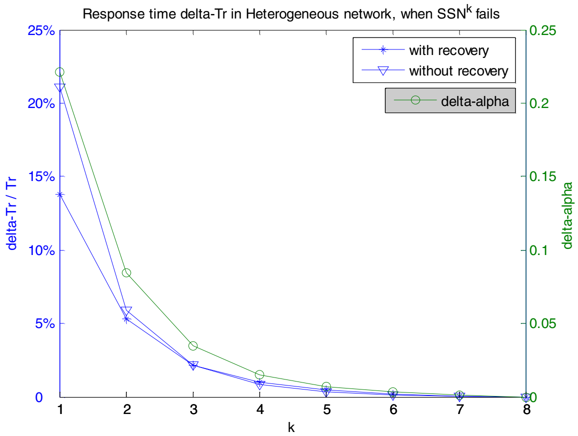

Figure 4. ΔTr/Tr when SSN[k] fails, reporting from largest z to smallest z

The second set of experiments study the impact of other variables (such as reporting sequence in both cycles, failure time, and sensing and communication speed) when keeping the dominant factor Δα constant (Δα=0.2). Fig. 5 shows the impact of the failure when the reporting sequence is (a) from fastest z to slowest z; and (b) from fastest y to slowest y. From Fig. 5, we observe that when there is no recovery, the earlier a node reports back, i.e., the higher the k, the smaller the delay overhead $\Delta T_r/T_r$ of the total response time for both case.

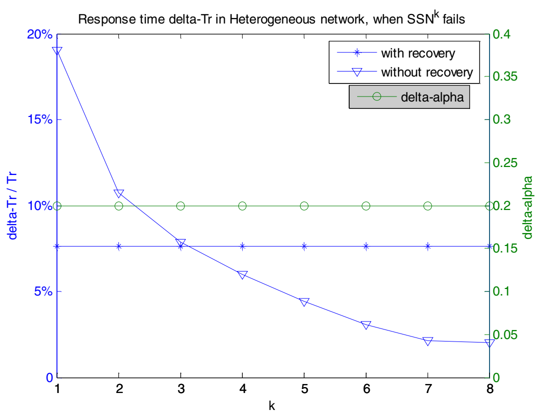

Figure 5. ΔTr/Tr when SSN[k] fails, reporting from smallest z to largest z

V. CONCLUSIONS

In this paper, we presented a general fault-tolerant data aggregation framework to study the dynamic behavior of an ad hoc WSN for personalized disease management system. To meet the stringent requirements on total response time and delivery rate posed by such systems, we developed a fault tolerant data aggregation algorithm based on linear programming and derived the closed form solution for optimal sensing task assignment that results in minimum impact of failure in a single-hop WSN. Counter-intuitively, simulation results show that whether the faulty node recovers or not has little impact. The simulation of a 9 node sensor cluster studies the influence of several key properties of the sensor network. The remaining task portion Δα, which directly relates to the time of failure and the order of the data aggregation of the sensor node, has dominant factor for the delay overhead.

Future directions include expanding the current model to handle the data aggregation route changes caused by faulty nodes in ad hoc wireless sensor network.

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