Link Layer Behavior of Body Area Networks at 2.4 GHz

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ABSTRACT

Body Area Networks (BANs) can perform the task of continuous, remote monitoring of a patient's physiological signals in diverse environments. Apart from providing healthcare professionals with extensive logs of a patient's physiological history, BANs can be used to identify and react to emergency situations. We identify three important factors that afflict wireless communication in BANs: impermeability of the human body to radio waves at frequencies commonly used in BANs, efficient operation in mobile and time-varying environments, and mission-critical requirements for quick response to emergencies. An understanding of the link layer behavior of wireless sensor nodes placed on the body is crucial to address these and other challenges such as reducing energy consumption and increasing network lifetime.

In this paper, we investigate link layer behavior by placing nodes on the body and directly measuring metrics of interest to engineers such as packet delivery ratio (PDR) and RSSI. Emulating a possible real-life BAN operating at the 2.4 GHz band with 12 sensor nodes, we collect over 80 hours of data from 14 volunteers in 3 different environments that BANs are expected to operate in. We analyze the data to reveal several link layer characteristics to provide insight and guidelines for the designing of BANs. We also evaluate the performance of common routing metrics on our data.

Our analysis helps us make the following conclusions. Link PDR is highly affected by the environment and not significantly by the volunteer for the experiment. Routing between nodes on the same side of the body is preferred to routing between nodes on the opposite sides. For links with the same source, failure of packet transmission to a certain node, in some cases, implies the increased probability of reception for other nodes. Most errors occur in bursts of length 1, but a small fraction occur in longer periods (40 packets or more).

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1. INTRODUCTION

The UN Population Fund reports that the number of persons aged 65 and above will be close to 1.9 billion by 2050 [23]. Continuous, remote monitoring of patients' health will have to be employed to provide effective healthcare to this large population. One approach to achieving this goal is via sensors deployed on or in human bodies that record and evaluate patients' physiological signals. These sensors can be networked together to form a *Body Area Network* (BAN).

In this paper, we focus on an important class of BANs in which energy and memory constrained wireless sensor devices are placed on the human body to continuously monitor physiological and other relevant signals (electro-cardiogram, temperature, etc.). This information is communicated to a gateway device, such as a PDA, which identifies hazardous situations and triggers the necessary response (e.g., calling for an ambulance).

One of the main challenges in engineering BANs is ensuring that communication between the sensor nodes and the gateway is prompt, reliable and energy-efficient. Since sensors should not be intrusive, wires are not an option to provide communication as they restrict the motion of the user. Wireless communication, while being less intrusive, poses several challenges to the network engineer of BANs. In addition to the usual obstacles faced in wireless communication, engineers need to contend with the high attenuation through the human body of radio waves at frequencies typically used for WSNs (433 MHz, 2.4 GHz, etc.) [6]. Further, the node positions in a single BAN are not static relative to each other. Movement of limbs and various postures of the human body could significantly alter performance characteristics. Finally, it is well known that wireless communication is highly affected by the conditions in the environment. Since humans are mobile, BANs will have to be capable of reliable communications in a wide variety of environments.

The typical approach in BANs to investigate link layer behavior is extrapolating from the data obtained through

physical layer measurements [9, 20]. Note that the link layer behavior models in these cases are contingent on the assumptions used for interference, multipath, etc. We contend that using commercially available devices in real world environments and directly observing the metrics of interest, as in [1, 4], can significantly improve our understanding of link layer behavior and aid network engineers. Firstly, the measurements are real world measurements and accurately detail the wireless channel at the link layer. Secondly, the intuition gained from analysis of this data can be used to guide link layer protocol design. Finally, link layer design choices such as network architecture, Medium Access Control (MAC), routing protocols, etc. can be evaluated on the empirical traces obtained from these experiments.

Our study is conducted using this approach. We emulate a possible real-life BAN with 12 nodes to collect link layer metrics, over 14 volunteers, in three different environments where BANs are likely to operate in - office, residence and open space environments. The data is collected in the 2.4 GHz band, a popular choice as several BAN specific sensor nodes operate in this band (for example, Imperial College BSN mote [25] and Harvard's Pluto mote [24]). Our data consists of traces of received packets and the RSSI at which they were received. Compared to previous studies which use a similar approach our data is a significant improvement [10, 16, 21] with more volunteers and more packets transmitted. To realistically capture the behavior of communication in BANs, volunteers were allowed to conduct their normal activities. The only constraint was that they not leave the confines of the environment.

The main metric we extract from this data is Packet Delivery Ratio (PDR), the ratio of successful transmissions to the total number of transmissions, which is the basic requirement to make decisions at the link layer level. Note that, this is a basic metric that also contains information regarding throughput, energy consumption and delay.

Our main contributions in this paper are as follows:

- Analysis of our data is used to highlight several properties of the links such as channel symmetry, variation of performance across different people, and environments and the temporal variation of these links.
- We use our data to provide guidelines into the network design for BANs. Among other topics, we comment on node placement on the body, acknowledgment schemes and static routing.
- We show the utility of our data by conducting a preliminary evaluation of link estimation metrics and their ability to identify good routes for nodes during BAN operation. We evaluate their performance against end-to-end PDR and average number of retransmissions (ANR). Note that the data has also been used to study network architecture for BANs in [17].
- Finally, our data set is a vast improvement on the data that exists for BANs operating in the 2.4 GHz band. We will release this data at [15] to the research community with the intent to aid design and development of link and routing layer protocols for BANs.

From our analysis we make the following observations:

- Node placement on the body has significant implications for PDR. In particular, routing between nodes on the opposite sides of the body is not wise.
- Difference in PDR between forward and reverse links in nodes (channel symmetry) in cluttered environments is much lower than in open space environments.
- Variations in link behavior are significant for a single volunteer in the same environment. In addition, difference in link behavior is largely affected by the environment rather than the person on whom the experiment is conducted.
- Interestingly, links that have the same source are largely not independent. When some nodes fail to receive a packet from a broadcasting source, certain other nodes have higher probability of receiving those packets.
- Packet reception in a link at time scales of a few seconds ($< 8s$) is strongly correlated. However, in the time scale of a few minutes ($> 8min$) links show noticeable variations in PDR particularly in open space environments.
- The ETX [7] and RNP metrics [5] have similar performance and come close to achieving minimum ANR.

2. RELATED WORK

Most of the work done in BANs is on the development of sensor devices [18, 24, 25]. In understanding radio wave communication the focus has been on the propagation of radio waves in and around the human body. Studies such as [8, 9, 12, 20] typically approximate the human body using small tissue samples or using materials resembling human tissue. [8] and [12] investigate properties of human tissue such as the dielectric constant and the energy absorption mechanism. [20] and [9] develop propagation models for RF communication in and around the human body.

In contrast, studies such as [11, 26, 27] use human volunteers to investigate radio wave propagation. In [11], the radiation patterns and how it varies for differing body size and body posture is investigated. In [26], the authors build models for path loss and delay spread from antennas placed on human volunteers in anechoic chambers and an office room. [27] uses antennas placed on either side of a human head and conclude that diffraction is the main propagation mechanism of radio waves in the 1.5 – 8 GHz band.

The goal of these studies is mainly to understand radiation patterns, develop path loss models and understand radio wave propagation. Apart from their uses for physical layer data characterization, this data can be used in the design of physical layer components for a BAN. An example is in [26] where the authors use their data to design a RAKE receiver customized for BANs. However, network engineers operating at the link layer will have to make several assumptions regarding interference and multipath effects in the environment to actually use these physical layer models. This is fraught with difficulties, since inaccurate assumptions and descriptions of the environment will lead to incorrect link layer models.

To the best of our knowledge, three other studies [10, 16, 21] adopt the approach of directly measuring link layer metrics by placing commercially available nodes on human volunteers in real world environments. A comparison between

these studies and our study is shown in Tab. 1. It is clear that we have significantly more data and from more volunteers than what is available. Note also that the three other studies do not investigate several important properties of the links such as temporal variations and RSSI behavior.

Table 1: Comparison of link layer behavior studies

	[10]	[16]	[21]	Our Study
Frequency range	433 <i>MHz</i>	IEEE 802.15.4 (2.4 <i>GHz</i>)	IEEE 802.15.4 (2.4 <i>GHz</i>) and Blue-tooth	IEEE 802.15.4 (2.4 <i>GHz</i>)
Volunteers	1	2	5	14
Environments	3	2	2	3
Total number of packets	274,000	N.A	N.A	1,476,000

Our analysis of the link layer behavior is inspired by the work done in WSN studies of this nature [1,5,14,19]. [1] identifies several properties of the links formed by IEEE 802.11 devices. [5] conducts a detailed study of the temporal variations inherent in wireless links.

Our focus on evaluating link estimation metrics is due to the work done in [3,16,17,26]. These studies highlight that multihop is an important architecture consideration for BANs. Therefore, the question of how one should configure routes becomes quite crucial. Further, our previous work in [17] is particularly relevant here. In that paper, we used the dataset we analyze here to study network architectures for BANs. We believe that this shows the applicability of our data in making decisions for the link layer.

3. METHODOLOGY

Our goal was to analyze several aspects of link layer behavior of BANs operating at 2.4 *GHz* in realistic environments by using commercially available devices. To do so, we designed the following experiments.

3.1 Description

Twelve nodes were placed on the bodies of the volunteers as shown in Fig. 1. The reason for the large number of nodes was that it was important to capture not only the current BAN systems, but also future ones. Further, we do not show a bias toward any application and simply concentrate on the communication between the various nodes in a BAN. Crossbow TelosB motes were used for these experiments.

A mote connected to a computer coordinated the experiment. Upon starting the experiment, the nodes on the body were synchronized and began their scheduled transmissions. First, node 1 would start by broadcasting 40 packets at intervals of 200 binary *ms* at each of the three lowest power levels (-25 *dBm*, -15 *dBm* and -10 *dBm*). The other 11 nodes listened and logged the received packets. In the same way, each of the nodes, 2 through 12, took their turns broadcasting packets at the 3 power levels while the other nodes logged information. After all the nodes had finished transmitting, node 1 would again begin to transmit. The experiments lasted typically for 2 hours and across all volunteers we collected a total of more than 80 hours of experiment data making it a significant improvement on the existing data sets.

Figure 1: Node ID and position on the body. Node 10 is not shown in picture as it is on the volunteer's back.

Figure 2: Images of the different environments used for experiments. (a) Lab (Office) environment, (b) Home (Residence) environment, (c) Roof (Open Space) environment

The experiments were carried out in three different environments shown in Fig. 2. The first was a cluttered lab environment with several reflective surfaces which led to significant amount of multipath. The second environment was a home environment with a large uncluttered room which was expected to give rise to less multipath. In this paper, we do not make the claim that all home and lab environments will behave in this way, instead that the rooms in *this* home environment and *this* lab environment behaved as described. The final environment was a roof environment with very few reflective surfaces. Volunteers were allowed to move around the environments during the experiments.

3.2 Experiment Design Choices

We now explain the reasons for our choices in designing the above experiment.

Choice of environment: BANs that conduct continuous, remote monitoring will most likely operate in diverse environments. Therefore, we selected three environments where BANs were most likely to operate - the office, residence and open space environments. We then picked representative samples (Fig. 2) of these environments to conduct our experiment in. Our university lab environment was used for the office setting as it is a space quite similar to a modern urban office. The hall of an apartment was used as an example of a residence environment. A roof top was chosen as an example of open space environments.

Traffic model: We synchronize all nodes and do not let the transmissions of one node interfere with another. This implies our data is immediately useful in TDMA based protocols and they provide an upper bound to what can be

Figure 3: Received PDR for all volunteers. All environments.

Figure 4: CDF of link probabilities. All environments.

Figure 5: Visualization with PDR averaged over all volunteers. All environments.

achieved through contention based MACs. TDMA is particularly feasible in BANs due to the low data rates [2].

Frequency range: We have chosen to use the 2.4 GHz ISM band for our experiments. Several groups [24, 25] are using this band for the development of their devices making it important to understand the band.

User movements: Studies such as [10, 21] characterize their link behavior based on the posture and specific movements of the users. However, we wanted our experiments to be as close to snapshots of real-world operation of BANs as possible. Therefore, volunteers were allowed to go about their normal activities. The only constraint imposed was that volunteers do not leave a certain environment.

3.3 Modes of Analysis

We first describe some metrics we use to inspect link layer behavior. Let PDR_{ij} be the PDR for transmission by node i and reception by node j . Then, *average received PDR* for node j is $E[PDR_{ij}]$ where the expectation is over all nodes i , $i \neq j$. *Average transmitted PDR* for node i is $E[PDR_{ij}]$ where the expectation is over all nodes j , $j \neq i$.

We also use and extend the tool introduced by us in [16, 17] to discern patterns from large sets of data. Given any two variable function f_{ij} where i and j are finite and discrete then the visualization tool is a matrix of dimension $i \times j$. Then, the ij^{th} entry reflects the value for f_{ij} . For example, we repeatedly use this to depict PDR between nodes. In this case, the color of the ij^{th} entry shows the PDR from transmission by node i to node j , PDR_{ij} . An example is shown in Fig. 5.

4. PRELIMINARY RESULTS

Several parameters of an environment influence radio communication. As has been noted in [16, 17] the number of reflective surfaces - the greater the number of reflective surfaces, the better the reception. This would predict that the lab environment would see the highest PDR, and the roof environment the lowest.

The other factor that significantly influences reception is interference due to other devices operating in the same frequency range. The 2.4 GHz band is an Industrial, Scientific and Medical (ISM) band with WiFi, Bluetooth, microwave ovens, etc. emitting radiation in the same range. Note that interference and multipath have opposing effects. Since the roof environment has the lowest interference and multipath, and the lab the highest, these results inform us regarding the relative importance of these effects.

Fig. 3, which informed our network architecture study in

[17], shows the received PDR for all volunteers in these three environments at the two lowest power levels. The cluttered lab with its many reflective surfaces clearly creates more multipath, thus aiding reception. This is despite the fact that the lab has the highest amount of interference with heavy WiFi traffic. The worst case scenario is the roof, where no WiFi reception is possible, with the received PDR as low as 53%. Clearly, in a BAN application with mission-critical requirements this will not suffice.

Finally, by observing Fig. 3 we see that average received PDR improves with an increase in transmission power. Even at the lowest power level in the lab environment, received PDR (average of 95.8%, variance of 1.43) are quite high.

Interestingly, increasing the power level in areas with lower multipath gives rise to larger gains. In the lab environment, by increasing the power level from -25 dBm to -15 dBm one can only attain a 4% increase in average PDR. However, increasing the power by the same amount in the home environment, on average, we see a 16% increase in reception and a 17% increase in the roof environment.

We also show the cumulative distribution function (CDF) for the PDRs of all the links in Fig. 4. In the lab environment, more than 70% of the links have PDR of 90% or greater, whereas in the roof this is the case for only 50% of the links. This further exhibits the impact of the environment on the performance of BANs.

5. CHANNEL SYMMETRY

Channel symmetry is an important metric for applications, especially when considering the feasibility of acknowledgment schemes. Sending acknowledgments back to nodes from the gateway might be especially important in BANs where reliable communication of data can be critical.

To investigate channel symmetry we observe PDR_{ij} and PDR_{ji} . The difference between the two highlights the extent of channel symmetry. From Fig. 5, the pattern of channel symmetry seems to hold approximately in our data i.e., the forward links and reverse links are close to being equal. In particular, averaged over all the experiments and all the links, the difference between PDR_{ij} and PDR_{ji} is 4.93%.

We further wish to inspect whether the environment has any role to play in how much the links deviate from channel symmetry. Fig. 6 shows the scatter plots of forward and reverse links in each of these environments.

We observe that channel symmetry is observed to hold highly in the lab situation (Average of 3.90%) and the least in the roof environment (average of 7.3%). The home environment has average difference between forward and reverse

Figure 6: Forward versus reverse link PDRs in different environments

links of 6.9%. The results are due to the fact that the roof has the least number of reflecting surfaces and the lab has the most. From our results, we can say that acknowledgement schemes for BANs operating in closed room environments are more viable in closed room environments compared to BANs that need to operate in open spaces.

6. IMPACT OF NODE PLACEMENT

Given the heavy attenuation of the human body to communication at 2.4 GHz, node placement is expected to play a significant role in link performance. Node placement, while obviously constrained by sensor modality, is a significant concern for network engineers of BANs. For example, an SpO2 monitor can only be placed in certain locations (finger, ear, etc.) due to the design of the sensor device. However, choices can be made within these available positions to aid in better communication between sensor devices.

We observe from Fig. 5 that the correlation between distance and PDR is not very strong. If such a correlation were prominent, nodes 1 and 2, for example, which are at the left and right ankles, would have high PDR, whereas nodes 1 and 11, left ankle and left side of the head, would have lower PDR. However, this is not the case.

What we do observe is a checkerboard pattern. To investigate this, nodes are partitioned into two sets - set $L = \{1, 3, 5, 7, 11\}$ and $R = \{2, 4, 6, 8, 12\}$ whose elements are the nodes on the left side and right side of the body respectively. Nodes 9 and 10 are ignored as they are on the front and back of the body respectively.

By taking all the possible node pairs and finding the PDR between the two nodes, we find that for set L (left side of the body) the average PDR is 94.9% and for set R (right side of the body) is 94.4%. When we investigate the PDRs of links formed by one element of set L and one element of set R and vice-versa, i.e., pairing nodes on the left side of the body exclusively with nodes on the right side and vice versa, we observe a significant drop in the average PDR. Averaged over all experiments the average PDRs of these links is 84.3%.

These results indicate that the body blocks the line of sight and that the nodes are able to communicate through multipath from reflective surfaces in the surrounding. As further confirmation of this hypothesis, the difference in PDRs between nodes on the opposite side of the body and the same side becomes larger as the environment has fewer reflective surfaces. For example, while in the cluttered lab

this drop in PDR is on average 4%, in the home the drop is 10%, and for the roof the drop is 14%.

The impact of the multipath effect is most observable in the links between nodes 9 and nodes 10. We notice from Fig. 5 that nodes 9 and 10 have extremely bad links. In fact, over all the experiments, nodes 9 and 10 have links with PDR lower than 60% over 46% of the time. This implies that one needs to take care and make sure that when placing nodes on the back, other nodes can communicate with it if there is such a need.

Our results suggest that, in the cluttered environments, the multipath effect is able to compensate for the lack of line-of-sight. This is interesting to BAN designers as it has implications on where nodes can be placed on the human body. It suggests that routing packets between nodes on the opposite sides of the body is not preferable.

7. VARIATIONS IN EXPERIMENTS

So far we have discussed the average performance of links over all the experiments. An interesting question is regarding the variations one sees in performance between different experiments. Note that our experiments can be seen as snapshots of the operation of a possible real-life BAN. Therefore, the variations between experiments implies the variance one can see in operation of BANs.

One example of the utility of this investigation can be to show the impact on performance of the volunteer who conducts the experiment. We can first inspect the differences between performance in experiments conducted by a single volunteer. This can then be compared to differences observed between performance of BANs operating on 2 different volunteers in the same environment. This has been looked at in the physical layer by trying to understand radiation patterns around different body types [11].

Here we approach the question at the link layer and see the variations between experiments conducted on different volunteers and in different environments. Identifying and quantifying the differences can highlight the challenges we face when designing a BAN.

7.1 Average Difference in PDR (ADP)

We first define the matrix P^k of size $n \times n$ where the ij^{th} element of P^k is PDR_{ij} for the k^{th} experiment conducted and n is the total number of nodes.

Given two experiments, a and b , then the absolute difference between all links in both experiments is $abs(P^a - P^b)$.

Figure 7: ADP between experiments. Grouped by volunteers. Tx power: -25 dBm. Lab environment.

Figure 8: ADP between experiments. Grouped by environments. Tx power: -25 dBm. All environments.

Figure 9: ADR between experiments. Grouped by environments. Tx power: -25 dBm. All environments.

Figure 10: Mean rank for all links. Tx power: -25 dBm. Roof environment.

Figure 11: Mean rank for all links. Tx power: -25 dBm. Lab environment.

Then, the Average Difference in PDR (ADP) of the two experiments is computed by $\frac{r(\text{abs}(P^a - P^b)r^T)}{n(n-1)}$, where r is a row vector of size $1 \times n$ with all elements equal to 1. This is essentially the average of the absolute difference between all the links in the two experiments.

We first look at the ADP between all experiments in the lab in Fig. 7. The line and number markings demarcate the experiments conducted by particular volunteers. For example, the 4 bottom-most rows and the 4 left-most columns indicate the experiments conducted by volunteer 1. Therefore, ADP of volunteer 1's first experiment and his second experiment are shown by the cell in the second column on the bottom-most row. Note that the visualization is symmetric, since the *absolute* value of the difference is being averaged. Finally, the darker the color of the entry in the matrix the lesser the ADP.

We use Fig. 7 to depict the differences between different people of whom the experiment is conducted. Firstly, we see from the figure that ADP between two experiments can be quite large, with ADP being as high as 18%. This definitely poses a challenge for network engineers. For example, if a multihop scheme were to be used, even if a BAN were to operate in only one area and on a single volunteer, static routing might be insufficient. Observe also that volunteer 1 and 2 have roughly the same performance for most of their experiments. However, the same cannot be said for volunteer 3. This signifies a further complication for engineers as now even a single person exhibits high variation.

From our results, on average, the ADP between exper-

iments conducted in the lab by the same person (average of 8.5%) and ADP between experiments of different people (average of 9.4%) is approximately the same. In the home environment, the ADP between experiments by the same person is 13.3% on average, and the ADP between experiments between different people is 13.9%. This highlights that the problems designers face is not necessarily between designing for different people but can occur in designing for a single user itself.

We now focus on the behavior of ADP with experiments conducted in different environments. Fig. 8 shows the ADP between all experiments with the markings shown for different environments. From Fig. 8, we can make certain immediate observations. Notice that the ADP between experiments in the lab is lower than the ADP between experiments in the home which is in turn lower than that in the roof. While we would expect that the ADP between lab and roof experiment are high (average ADP of 22.3%), we see that the variation of the links in the roof environment itself is quite high (average ADP of 18%). This indicates that while, on average, the performance on the roof and home are worse than that in the lab, the performance of the individual links in between experiments conducted on the roof themselves vary significantly. This would mean that even for a single person in the roof environment, one can expect large variations from experiment to experiment.

From this analysis of ADP, we realize that the variations observed between experiments are typically not due to the person conducting the experiment. However, ADP increases

significantly in the home and roof environments, suggesting highly variable links in these environments.

7.2 Average Difference in Ranks

We have just considered the differing PDR of links between experiments. We now proceed to consider if the ranking of the links (according to descending PDR) remains unchanged in the different experiments. Particularly, while ADP captures the difference in link PDR, we wish to identify here if the relative performance of links stays the same. If the relative performance of links is not highly variable, one might try to engineer a BAN with static routing.

We compute the average difference in ranks (ADR) as follows. For each experiment, based on the PDRs of the links we rank each link, with rank 1 being the link with highest PDR and rank 132 being the link with lowest PDR. The matrix R^k represents the ranks of the links for the k^{th} experiment, where the ij^{th} element represents the rank of the link between node i and node j .

The ADR for two experiments a and b is given by $ADR = \frac{r(abs(R^a - R^b)r^T)}{n(n-1)}$, where r is a row vector of size $1 \times n$ with all elements equal to 1 and n is the number of nodes in the experiment. The results are shown in Fig. 9. Interestingly, while the ADP for experiments on the roof is the highest, the ADR is the lowest on the roof. This implies that the best links in an open space environment are very likely to stay the best links in that environment.

In the lab environment, the rankings vary quite significantly. This is probably due to most links having PDR above 90%. Therefore, even a small change in PDR could result in a large change in the rank of the link.

Figs. 10 and 11 identify the links that are consistently good and bad in the roof and lab environment. Let R_{ij}^m denote the rank of the link between i and j in experiment m , then the ij^{th} block of the visualization in Figs. 10 and 11 denotes $E_m[R_{ij}^m]$.

The existence of several dark and white spots in Fig. 10 shows that certain links are always highly ranked and certain links are always ranked low. This means that the relative performance of links is likely to stay constant in the roof environment. Further, the checkerboard pattern is more apparent here and links between nodes 9 and 10 are consistently bad. Also, links between nodes on the head (nodes 11 and 12) and those on the upper body (nodes 5 – 12) have very high PDR. This makes them a good candidate for the gateway or relay node from a networking point of view. Of course, placing a wireless transceiver on the head without being obstructive to human users is challenging.

Finally, Fig. 11 shows that most links have approximately equal mean rank. This reflects the fact that the ranking of links changes significantly between different experiments. As mentioned earlier, this is probably due to the small variations in PDR resulting in large changes in ranks.

Our analysis of ADR highlights that in the lab environment the rankings of the links vary significantly while in the roof environment the rankings are more stable. This suggests that relative performance of links does not change significantly in open space, low multipath environments.

8. NODE RECEPTION BEHAVIOR FOR SAME SOURCE LINKS

A crucial design choice for network engineers is whether

Figure 12: Percentage of other nodes that hear a packet when another node succeeds or fails to hear a packet from the same source. Tx power: -25 dBm. All environments.

to route packets through a single path or to pursue multiple paths in sending packets to a destination. In order to make this decision, it is crucial to know the reception behavior in links with the same source, i.e., whether the reception performance of links is independent of each other.

For example, let node i broadcast a packet. Then, conditioned on node j hearing the packet, what is probability that another node, node k heard the same packet? Similarly, conditioned on node j failing to hear the packet, what is the probability that node k also fails to hear it? Answering these questions can help the engineer decide if they should route through multiple paths or a single path.

In BANs, independence of links with the same source is a subtle issue. From one perspective, links with the same source are not expected to be independent for the following reasons. Firstly, since all nodes are situated quite close to each other (i.e., they are on the same human body), losses due to interference should be common. Secondly, as we have identified, the placement of the node on the human body has significant impact on the probability of receiving a packet. Since the human body exhibits certain limited possibility of movements, correlation between the links is to be expected. For example, moving the left wrist to the right side of the body could impede communication between this node and other nodes on the left side of the body. At the same time this could improve communication of this node with other nodes on the right side of the body.

We first inspect the case when a packet is transmitted to a link, and characterize the number of other nodes that can hear the same packet. In particular, we wish to know if a link with a certain average PDR succeeds or fails to hear a packet how many other nodes can hear the same packet. The results are shown in Fig. 12.

We notice that when a high PDR link fails that the probability that other links also fail is low. In particular, almost 85% of the other nodes are able to hear the packet. Further, on average, when a link succeeds, the probability that other links also succeed is higher than when the link fails. Finally, when high PDR links succeed in receiving a packet, the probability that other links receive the packet is also high.

We continue investigating this behavior in Fig. 13 which shows the average number of nodes that can hear a packet with the same source when a failure happens on a link. In the roof situation, more nodes are likely to hear a packet when a link fails than in the home and lab environments.

We first define two metrics, success PDR and failure PDR. Success PDR (sPDR) is a 3-variable function. For a link with node i as the source and node j as the destination, the

Figure 13: Number of nodes that hear packets when a certain link fails. Tx power: -25 dBm. Roof environment.

Figure 14: Average difference in sPDR and fPDR when $sPDR_{ijk} > fPDR_{ijk}$. Tx power: -25 dBm. Roof environment.

Figure 15: Average difference in sPDR and fPDR when $sPDR_{ijk} < fPDR_{ijk}$. Tx power: -25 dBm. Roof environment.

$sPDR_{ijk}$ is calculated as the PDR of the link between i and k when node j successfully received a packet from node i . Similarly, the failure PDR (fPDR) between the source i and another node k is calculated as the PDR of the link between i and k when node j failed to receive a packet from node i . We also define average sPDR between node i and j as $E_k[sPDR_{ijk}]$ $k \neq i, k \neq j$ and average fPDR between node i and j as $E_k[fPDR_{ijk}]$ $k \neq i, k \neq j$. These metrics are useful in evaluating how much links with the same source can vary under conditions of success and failure.

Fig. 14 shows the average improvement in PDR of other links only for cases where sPDR is greater than fPDR, i.e., the ij^{th} entry represents $E_k[sPDR_{ijk} - fPDR_{ijk}]$ $\forall k, k \neq i, k \neq j$ and $sPDR_{ijk} > fPDR_{ijk}$. On average, the difference in PDR is significant in the roof environment. Not shown here is that in the lab environment the difference in PDR has a maximum of 0.4. Further, in the lab environment when nodes 3 and 4 successfully receive packets, regardless of the source of the packets, the average sPDR increases.

Fig. 15 show the improvement in PDR of other links for cases when sPDR is lower than fPDR, i.e., the ij^{th} entry represents $E_k[fPDR_{ijk} - sPDR_{ijk}]$ $\forall k, k \neq i, k \neq j$ and $sPDR_{ijk} < fPDR_{ijk}$. In the roof situation one can observe almost 20% increase in PDR in other links with the same source when a node fails to hear a packet from the same source. In the lab the increases are quite small with at most a 9% increase in PDR.

Our data above shows us clearly that links are not independent of each other. In certain cases, when a node succeeds or fails to receive a packet, other nodes can have high PDR. Particularly, in the roof scenario, increases of 20% in PDR for other nodes are seen when certain nodes fail to hear packets from the same source. This presents evidence that network engineers might try to engineer BANs that use multiple paths when they operate in open space environments.

9. TEMPORAL PROPERTIES OF LINKS

Our analysis in previous sections has focused mainly on the average performance of a link over a whole experiment. However, equally important for the successful operation of BANs is for the network layer to be able to adapt to temporal changes in link performance. This is particularly important in BANs due to its mission-critical constraints. In this section, we examine the temporal changes in link performance at different scales of time.

9.1 Packet by Packet Variation

As a first step, we inspect the performance of the links on a short time scale. As per our description in Sec. 3, every time a node transmits, it transmits 40 packets. In this section, we look at how correlated packet reception is for a link at short time frames. In other words, given that a packet was received, what is the probability that another packet is received at a short time interval τ ($< 8s$) in the future? The results presented here have significant weight on the design of retransmission schemes.

9.1.1 Distribution of Errors

As a first step, we investigate the distribution of errors as follows. Given that an error occurred what is the probability of a certain number of errors occurring together? Clearly, the number of errors is lower bounded by 1. The upper bound is 40 because after every 40 packets, the broadcasting node changes. Since there is a gap of roughly 8 minutes between a node broadcasting packets, we do not consider errors occurring across two broadcasting periods.

We can see from Fig. 16 that in the lab environment over 80% of the error bursts are of 3 packets or less. In the lab environment, error bursts of length 40 have probability of 0.02. However, in the roof scenario, packet losses of 40 packets occur with probability of 0.12. This tells us that long losses of information do happen with a non-negligible probability in the links between the nodes. This is clearly not tolerable in a mission-critical BAN setting. Further, given any lost packet it is significantly probable (56% in the roof, 41% in the home, 28% in the lab) that it was lost in a 40 packet burst of errors.

A loss of 40 packets implies no communication for roughly 8 seconds. While this is a bad scenario, the length of the losses could be more than those we could capture in our experiment. This is due to the 40 packet length for each broadcast. In fact, the probability of a 40 packet error burst in Fig. 16 should be interpreted as the probability for error bursts of length 40 and above.

9.1.2 Autocorrelation of Links

For a link between node i and j , we generate a sequence of 1's and -1's for every packet transmitted from node i to j . Here a '1' refers to successful transmission and a '-1' to failed transmission. We then compute the autocorrelation for these sequences of 1's and -1's for each link. Fig. 17 shows the autocorrelation for all the links with each link

Figure 16: Distribution of errors. Tx power: -25 dBm.

Figure 17: Autocorrelation of links for different average PDR. Tx power: -25 dBm.

Figure 18: PDR versus RNP of all links. Tx power: -25 dBm. All environments.

Figure 19: Standard deviation of PDR observed over all the node pairs. Tx power: -25 dBm.

Figure 20: Mean versus standard deviation of PDR. Tx power: -25 dBm. Roof environment.

Figure 21: Impact of Delay on the Variation of link PDR. Tx power: -25 dBm.

put into bins at average PDR. Each curve represents the autocorrelation of a link that has an average PDR for that experiment between the values shown in the legend.

We observe that, as expected, the autocorrelation of links with high and low average PDR have quite high autocorrelation compared to mid-range PDR links. A link that continually alternates between success and failure would have low autocorrelation. In fact, with our mapping it would have an autocorrelation of 0. We see from our data that this is not the case even for links that have PDRs around 50% showing correlation of packet transmission at short time intervals.

9.1.3 Required Number of Packets

Finally, we also inspect a link quality estimation metric, [5], that takes into consideration the distribution of losses. Required number of packets (RNP) is the number of retransmissions of a packet before it reaches the destination assuming that lost packets are retransmitted in the next slot with other scheduled transmission. If all the losses occur together then the RNP for this link is high, whereas with alternating success and failure, the RNP is low. We consider the 40 packet transmission period and compute RNP over this interval. If the final transmission is a failure, we assume that the packets are received in the next time slot. Therefore, the maximum value for RNP in our case is $1 + 2 + 3 + \dots + 40 + 41 = 861$ and the minimum value is 40 packets.

Fig. 18 shows a scatter plot for the PDR of links versus the RNP. The RNP in the case of the mid-range PDR links deviates significantly from the minimum achievable suggesting errors occur in bursts larger than of size 1.

9.2 Temporal Variations in Link PDR

Beyond understanding the packet by packet variation we need to look at how the PDR of these links vary and what is the magnitude of the variance. To do so, we define *short-term PDR* as the PDR between nodes i and j over a 40 packet transmission period.

9.2.1 Standard Deviation of Short-term PDR

We first look at specific node pairs and compute the standard deviation of their short-term PDRs.

Fig. 19 shows the standard deviation of the links calculated over all environments in all experiments. Notice that there are several links that have high standard deviation (40%). This clearly shows that network engineers will need to take into account the variations in link quality over time. The question we now address is of the correlation between the link PDRs and the temporal variances of the links.

Fig. 20 shows the scatter plot of the mean of the links against the standard deviation observed in the open space environment. We see that links that fall in the middle range of PDR (50% to 80%) exhibit high standard deviation.

9.2.2 Temporal Differences in Short-Term PDR

Finally, we look at how short-term PDR varies from one transmission of 40 packets to the next. In our experiment, nodes broadcast packets every 8 minutes. Therefore, we wish to characterize the changes in short-term PDR for links at 8 minute intervals. We calculate the absolute difference between short-term PDRs, with delays of 8 minutes, 16 minutes, and so on. The average value of the differences between all links is shown for the 3 environments in Fig. 21.

In the lab environment, the differences in short-term PDR

Figure 22: Complementary CDF of PDRs for a given RSSI.

Figure 23: Mean PDR versus standard deviation of RSSI. Roof environment.

Figure 24: PDR for metrics used for routing. Tx power: -25 dBm. All experiments.

are 10% regardless of the delay. In the open space environment, the difference in short-term PDR recorded at 8 minute intervals is as high as 18%. Further, the difference continues to increase as the time difference increases.

Our results in this section show us that short-term PDR shows significant variation even when the time delay is a few minutes. Therefore, an important routing issue that needs to be dealt with is identifying good links during the operation of a BAN. To do so, one must be able to measure a metric over a short time period and it must successfully predict the long term PDR of the link. We have seen that measuring PDR over short time periods can show significant variance and does not predict the long term average PDR seen very accurately.

10. RSSI AND LINK QUALITY

One particular variable that has been used to predict the quality of the links is RSSI [22]. We look at the average RSSI observed over the experiments and see how they vary with the PDR of links as follows. Given a value for average RSSI over an experiment, what is the probability of observing links of a certain PDR? We look at links which have average RSSI of over -90 dBm in Fig. 22. Even at the lowest power level given an average RSSI of -90 dBm, 84% of the links are above 84% PDR (Correlation coefficient between RSSI and PDR is 0.56).

Since there is a certain amount of predictive information available in RSSI, we now inspect the standard deviation of the RSSI against the mean PDR of a link. This is shown in Fig. 23. The figure shows that for the links that are not above 80% PDR, the RSSI varies quite significantly. This is similar to the result obtained in Fig. 20 implying that RSSI does not have significantly increased predictive power over short-term PDR.

11. EVALUATION OF LINK ESTIMATION METRICS USED IN ROUTING

In this paper, we have used the data collected to highlight several properties of link layer behavior that will be useful to designers of BANs. Another purpose of our data is as an empirical trace on which to test protocols. We now highlight this use of our data with a preliminary evaluation of a few link quality estimation metrics used for routing in WSNs.

An important question in BANs is whether and how by using multihop networks we can achieve better performance than star networks. The topic of routing in BANs has gained

significant importance in recent years, with several papers calling attention to the need for multihop networks, [3, 13, 16]. However, there has not been significant work done on evaluating link estimation metrics for routing in BANs. We now proceed to define the link estimation metrics we want to evaluate using our data.

11.1 Link Estimation Metrics

We first define certain variables so we can describe the link quality estimation metrics. In addition, we highlight the optimal achievable by any of the link estimation metrics. For any network with N nodes, let the links between the nodes be denoted by $1, 2, \dots, N(N-1)$. The PDR of these links is denoted as p_l and for a link l with source i and destination j , $PDR_{ij} = p_l$ $i \neq j$. The average number of retransmissions (ANR) is $\frac{1}{p_l}$. A route r is defined as a set with multiple links, l . Therefore, the PDR of a source node i and a destination node j with a specific route is $PDR_{ij}^r = \prod_{l \in r} p_l$. The ANR of a source node i and a destination node j with a specific route is $ANR_{ij}^r = \sum_{l \in r} \frac{1}{p_l}$.

The optimal PDR and ANR is obtained as follows:

PDR: Find routes such that $PDR_{ij} = \max_r PDR_{ij}^r = \max_r \prod_{l \in r} p_l \forall i, j$.

ANR: Find routes such that $ANR_{ij} = \min_r ANR_{ij}^r = \min_r \sum_{l \in r} \frac{1}{p_l} \forall i, j$.

The previous two metrics show the optimal achievable PDR and ANR using static routes and therefore highlight the potential performance by using a multihop architecture. These metrics were used by us in [17] to compare the star and multihop architectures for BANs. In this paper, we compare the optimum achievable to real world routing algorithms. These typically work by nodes monitoring a link estimation metric over a short time period and keeping up-to-date information about this metric for their neighbors. This information allows one to choose how routes should be configured. Protocols such as those in [7, 14] use either a start-up phase or control messages, where nodes broadcast to each other to keep the link estimation tables accurate. We try and emulate this approach using our data.

Note that as explained in Sec. 3, each node takes turns broadcasting 40 packets at 3 power levels to all the other nodes who listen and log the packets received. We refer to the time from when node 1 begins to transmit till the time that node 12 finishes transmitting as 1 cycle. We emulate the protocols in [7, 14] by using the PDRs and ANRs calculated from 1 cycle of data and getting the optimal routes from

Figure 25: ANR for metrics used for routing. Tx power: -25 dBm. All experiments.

Figure 26: Trade off between ANR and PDR. Tx power: -25 dBm. All environments.

Figure 27: Comparison between 2.4 GHz (-25 dBm) and 433 MHz (-20 dBm).

them. The performance of these routes is then calculated for the whole experiment. The PDRs calculated here are what was referred to in Sec. 9.2 as short-term PDR.

Short-term PDR: We denote short-term PDR (Sec. 9.2) of a link between node i and j as $PDR_{s,ij} = p_{s,l}$. Similar to the optimal PDR metric, for the short-term PDR routing metric we find routes such that $PDR_{s,ij} = \max_r PDR_{s,ij}^r = \max_r \prod_{l \in r} p_{s,l} \forall i, j$.

Short-term ANR: We denote short-term ANR (similar to short-term PDR, i.e., ANR over a single cycle) of a link between node i and j as $ANR_{s,ij} = \frac{1}{p_{s,l}}$. For the short-term ANR routing metric we find routes such that $ANR_{s,ij} = \max_r ANR_{s,ij}^r = \min_r \sum_{l \in r} \frac{1}{p_{s,l}} \forall i, j$.

Short-term ETX: As described in [7], ETX is defined for i and j as $ETX_{ij} = \frac{1}{PDR_{ij} PDR_{ji}}$. Short-term ETX is computed for a route as the sum of the ETX of the links.

Short-term RNP: Required number of packets, [5], is defined for two nodes i and j as in Sec. 9.1.3. The sum of the RNP of the links in a route is the RNP between the source and destination for that route.

11.2 Results

We evaluate all the link quality estimation metrics against two important performance metrics. One is the end-to-end PDR of a route which is a good indication of how reliably one can communicate. It is also closely tied with the throughput achievable. We also evaluate it against the end-to-end ANR. ANR signifies the number of times a packet has to be transmitted before it is received. This is important for energy consumption and delay performance which are important metrics in BANs.

Fig. 24 shows the performance of all the routing metrics for received PDR of all the nodes with the routes from all the link estimation metrics used. For the metrics that use observation over a single cycle to determine the routes, we computed the routes using all cycles in each experiment. The performance was evaluated for the routes generated by each cycle in an experiment and then averaged.

We notice from the figure that the single-hop links results in significantly low PDR, with received PDR almost as low as 50% in the case of node 4. Optimal PDR, on the other hand, can achieve received PDR above 90% for all the nodes. Optimal ANR and the other metrics do not achieve this performance but still have a significant improvement on the single-hop link PDR. On average, short-term RNP and ETX perform better than the other metrics that route using observations of a single cycle.

Fig. 25 shows the evaluation of the metrics against the cri-

teria of end-to-end ANR. The x-axis shows the node and the y-axis the ANR for links averaged over the receiving nodes, i.e., $E_j[ANR_{ij}]$. Single-hop routes have significant problems in ANR with node 2's received ANR almost 15. Also, optimal PDR has much higher ANR than those achieved by the other metrics. This is due to several routes being 4 or 5 hops. We also observe that short-term ETX has performance closest to the optimal of ANR.

Finally, Fig. 26 shows the achievable tradeoffs between ANR and PDR for the various links from the experiments. The black line is for single hop, the red for two-hop routes and the blue for three-hop routes. We consider only up to three hop routes as routes with more hops significantly increase complexity. Fig. 26 shows the performance of all routes that can be found by a static routing protocol highlighting the tradeoff possible.

12. CONCLUSION

Our work in this paper has focused on the important task of understanding the link layer behavior in BANs. By adopting the approach of using commercially available devices and directly observing the metrics of interest, we captured the performance characteristics of BANs in real world situations. Our analysis sheds light on several important properties such as temporal variation, channel symmetry and covariance in same source links. We provided guidelines about network design in BANs and carried out a preliminary evaluation of link estimation metrics used in routing.

12.1 Comparison of Radio Devices for BAN

We compare the data from our data using the CC2420 radio (2.4 GHz) and the data in [10] using the CC1000 radio (433 MHz) in Fig. 27. Even though the transmit power for the CC1000 is higher, the performance in all environments is much poorer. In fact, even at the highest power level for the CC1000 (10 dBm), the PDR is not as high as in the home and lab environments using -10 dBm transmission power using the CC2420.

The comparison is not perfect as the experiments were conducted in different environments. Further, we do not wish to use these results to compare the 2.4 GHz band to 433 MHz. Instead, these results indicate that the CC2420 radio seems to perform better than the CC1000.

12.2 Future Work

Following from our investigation of link estimation metrics, important future work includes the actual implemen-

tation of these routing protocols and conducting detailed performance measurements.

Finally, we hope the approach we have adopted and the results obtained are valuable to others in building future BAN systems. In this spirit, researchers can access our code and data by following instructions provided in [15].

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