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Application of Evaluation Parameters for Successful Transmission in wireless sensor networks

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Abstract: In this paper, we have presented a novel transmission protocol which is suited for battery-powered sensors that are worn by a patient when under medical treatment, and allow constant monitoring of health indices. These body-wearable sensors log data from the patient and transmit the data to a base-station or gateway, via a wireless link at specific intervals. The signal link quality varies because the distance between the patient and the gateway is not fixed. This may lead to packet drops that increase the energy consumption due to repeated retransmission. The proposed novel transmission power control protocol combines a state based adaptive power control (SAPC) algorithm and an intelligent adaptive drop-off algorithm, to track the changes in the link quality, in order to maintain an acceptable Packet success rate (PSR)(~99%). This removes the limitation of the SAPC by making the drop-off rate adaptive. Simulations were conducted to emulate a subject's movement in different physical scenarios—an indoor office environment and an outdoor running track. The simulation results were validated through experiments in which the transmitter, together with the sensor mounted on the subject, and the subject themselves were made to move freely within the communicable range. Results showed that the proposed protocol performs at par with the best performing SAPC corresponding to a fixed drop-off rate value.

Keywords: adaptive transmission; energy efficiency; mobile sensors

1. Background Work

The emergence of Internet of Thing (IoT) has enabled technological capabilities to exchange data and to create a healthcare system that is efficient interms of time, energy and cost [1]. In healthcare, body wearable sensors are used to continuously monitor the vital physiological parameters of patients in hospitals and the elderly at home, allowing them to enjoy independent living [2]. Hospitals use IoT to monitor the location of medical devices, personnel and patients. The healthcare professionals are then able to use data to create a system of proactive management with this network of devices. At the same time, such procedures are effective and are cost-effective ways of monitoring age-related illnesses [3]. For example, one Texas hospital reportedly cut the re-admission rate for patients with heart failures by 50% using predictive analysis of their individual healthcare records [4].

There have been significant developments in building body wearable sensors that have low computational complexity, require little memory storage, and can be suitably implemented using simple hardware. For example, Shih-Hong Li et al. have designed a wearable sensor to detect real time wheezing [5]. In the field of medicine, the wheezing sound is usually considered as an indicator of the degree of airway obstruction. In [6], authors have developed a wearable instrumented vest for posture monitoring, especially for aged people. The vest provides a portable and low-cost solution that can be used indoors and outdoors to provide long-term care at home. The recognition abilities of accelerometer-based detection and activity monitoring can help in assessing rheumatic and musculoskeletal diseases [7]. There are several other examples of similar research and development studies that are shifting the paradigm of patient care and welfare.

Figure 1 shows a simple representation of a wireless sensor network application used in healthcare. The body-wearable and implanted sensors collect vital health parameters such as the pulse rate, EEG, blood insulin level etc., and transmit to the gateway. The gateway that is shown in Figure 1 can be with the person or with the access point.

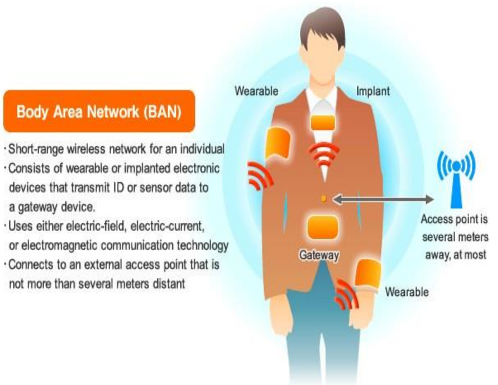


Figure 1. A body area network with sensors connects with the access point via a gateway [8,9].

Data communication, not just data collection, is an important component to build such success stories. When independent living is considered, the healthcare solution should be such that the monitored person is able to move seamlessly within the house with minimum loss of data. In order to support such a scenario, the transmitting module of the body wearable sensors should adapt with the changing radio link quality. Therefore, the radio transmitter must keep track of the changing environment so that the transmission power can be adjusted for reliable transmission [10].

2. Description of the Adaptive Algorithm

The adaptive algorithm consists of two components. The first component controls the value of the drop-off rate (R) depending on the current packet error rate. It maintains a window (typically set to 50 transmissions) during which it uses a fixed R value. At the end of the window interval, the PSR is calculated. If the PSR is less than the target PSR, then the R value is decremented by 0.05. The lower

limit to which R can go down is set to be 0. The reason to reduce the drop-off rate is to delay the system switching to a lower state so that the PSR is maintained at a target level.

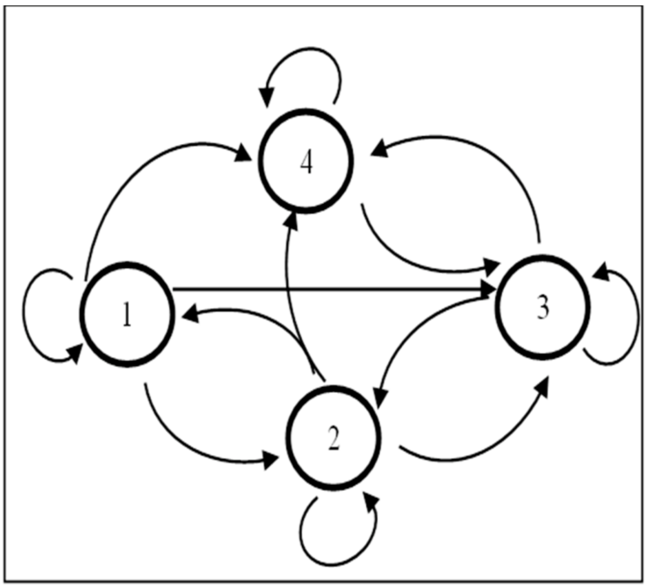
Table 1 shows the power levels based in these states. In the experiments that follow the simulation, the nRF24L01p radio modules have been used. This radio module has four programmable output power levels. They are 0 dBm, −6 dBm, −12 dBm and −18 dBm. The state transition model can be extended to any number of states, depending on the available power levels of the particular radio module. As the number of states grows, the algorithm can become computationally expensive. It is therefore advisable to choose power levels with a difference of approximately 5 dB in between them.

Table 1. States, power levels and retry limits.

State	1	2	3	4
Available power levels	Minimum (M) Low (L) High (H) Maximum (X)	Low (L) High (H) Maximum (X)	High (H) Maximum (X)	Maximum (X)
Number of retries	3	2	1	3

Figure 2. State transition diagram of the adaptive algorithm.

Figure 2 shows the state transition diagram of the



adaptive power control algorithm. State transition occurs depending on the power level at which the transmission is successful or has failed.

Tables 2 and 3 explain the state transition matrices.

Table 2. State transition matrix when state levels go up [12,13].

State	1	2	3	4
Available power levels	Minimum (M) Low (L) High (H) Maximum (X)	Low (L) High (H) Maximum (X)	High (H) Maximum (X)	Maximum (X)
Number of retries	3	2	1	3

Results and Discussion—Simulation Set 2

In this simulation, the subject ran at an average speed of 24 km/h around a track (shown in Figure8),

Choice of Hardware

For experimental purposes, nRF24L01p transceiver modules from Nordic semiconductors have been used. The transceiver module at the gateway or hub has an additional power amplifier (PA) and a low-noise amplifier (LNA). The output power level of the receiver is 20 dBm. The reason for using a high power transmitter at the hub is to ensure near error-free communication between the hub and the sensor. The major specifications of the receiver and the transmitter are presented in Tables 4 and 5 respectively.

Table 4. Features of nRF24L01p receiver [15].

Device: Receiver (Hub)	nRF24L01p with PA and LNA
Tx mode current	115 mA
Rx mode current	45 mA
Power Amplifier gain	20 dB
Low Noise Amplifier gain	10 dB

Table 5. Features of nRF24L01p transmitter [16].

Device: Transmitter	nRF24L01p
Tx at 0 dBm (MIN)	11.3 mA
Tx at −6 dBm (LOW)	9 mA
Tx −12 dBm (HIGH)	7.5 mA
Tx −18 dBm (MAX)	7 mA

A set of heart rate data from PhysioNet is preloaded into the transmitter module and set to transmit after every 2 s [17,18]. Physionet has a huge repository of human physiological data and can be downloaded from their web-based application. These values are chosen to make the target mobile scenario as realistic as possible.

Evaluation Parameters

The evaluation parameters are

- Mean cost of successful transmission (Cmean)
- Protocol efficiency [19]

One of the parameters for optimization is the energy consumed per useful bit transmitted over a wireless link [20,21]. This paper has used the following Equation (1) to evaluate C_{mean}.

$$C_{mean} = \frac{C_{Total}}{P_S - P_L} \quad (1)$$

$$Prot_{eff} = \frac{P_S - P_L}{P_S + Ret_T} \quad (2)$$

The protocol efficiency ($Prot_{eff}$) includes the average number of retries [20]. Mathematically, where Ret_T = Sum of all retries.

Here $P_S - P_L$ = total successes (P_{succ}). In % form, it is represented by Equation (3) when both the numerator and denominator in Equation (2) are divided by the total number of packets to send (P_s).

$$Prot_{eff}\,(\%) = \frac{PSR}{1 + Ret_{mean}} \quad (3)$$

where Ret_{mean} = mean retries per packet and is defined as

$$Ret_{mean} = \frac{Ret_T}{P_S} \quad (4)$$

$$PSR = \frac{P_{succ}}{P_S}100 \quad (5)$$

3. Simulation Design and Result

Two sets of simulations were conducted to capture two different geometrical spaces. In the first set, an indoor office environment was considered. A subject was fitted with wearable sensors, and the locations of the subject were divided into a docked position, and a number of undocked positions with respect to the base station. The docked position is defined as the location where the subject mostly stays. Occasionally, the subject changes location when he/she moves out of the docked position, for example, to visit the washroom, collect printouts, get a drink etc. This results in variable radio link conditions because of the change in the distance between the base station and the sensors, and also because the signal has to travel through intervening walls. In the second set, an outdoor environment was considered where the subject is assumed to be an athlete, and different health indices were monitored while she/he runs. An outdoor Olympic size running track was considered with the base station at the center of the field, and the subject running at an average speed along the track.

and transmits data every second. Therefore, in terms of distance, the body wearable sensors transmitted after an approximate distance of 7 m. Since the size of the track is not circular, the distance varied with time.

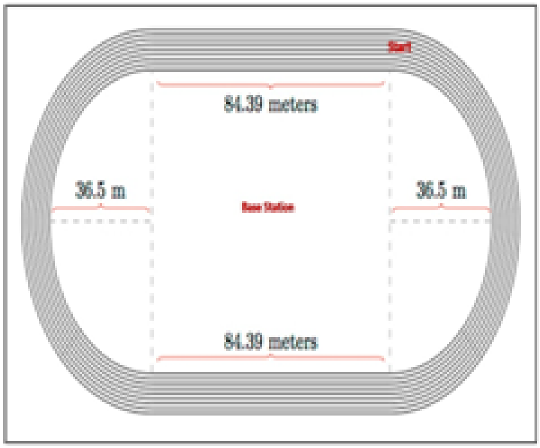


Figure 8. Shape and dimension of a standard Olympic track.

In this simulation, free space path loss model was considered, and a Rician fading channel model was used, as there was at least one direct line-of-sight path between the transmitting sensors and the receiver (gateway) [24]. The available power levels of the transmitter were changed to 0 dBm, 5 dBm, 10 dBm and 15 dBm, as the distance between the transmitter and the gateway is higher than the indoor scenario. Transmission power below 0 dBm does not result in any meaningful communication. However, for the sake of simplicity, the current consumptions corresponding to the power levels remained the same. This may not be practical, but the RF modules nRF24L01p does not support power levels above 0 dBm. This however did not affect the overall objective of the simulation, as the protocols were compared to in terms of their energy consumptions, and individual energy usage was not a concern.

The result of the simulation is presented in Figure 9. The efficiency values were comparable, with the cost of successful transmission of the proposed protocol (S-ATPC) being less than the average cost for SAPC when R = 1. This result again indicated that if SAPC can be modified with a single R value that adapts with the changing radio link condition, we can achieve desirable energy savings per successful transmission.

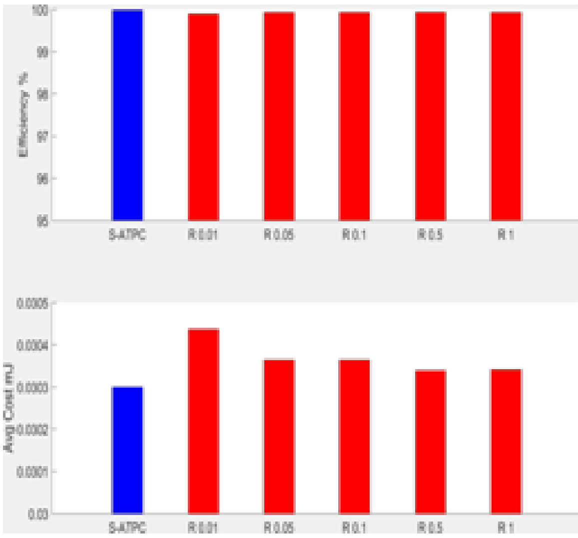


Figure 9. The protocol efficiencies and the average cost of success transmissions are compared when the PSR for all the cases are equal to 100%.

3. Experimental Method and Results

In this section, the experimental methodology and the results are presented.

Experimental Methodology

The experimental setup was a university building with the base station powered by mains, while the transmitting sensor was piggybacked on the subject. The subject was allowed to roam freely inside the building and his routine activities were followed. The traversal path of the sensor is shown in Figure 10.

Data was collected for a period of approximately two hours on different days of the week. The sensor transmitted packet data every 2 s. The average of five such runs was used and is presented in this paper.

Figure 10. Traversal path of the sensor is shown in dotted red line. The distance between the sensor and the gateway is not constant.

Experimental Results

The results are tabulated in Table 10, and the bar diagram is shown in Figure 11. The plots show that for a target PSR of 99%, the proposed S-ATPC can deliver an energy efficient solution that is comparable with that of SAPC at *R* that corresponds to minimum energy consumption.

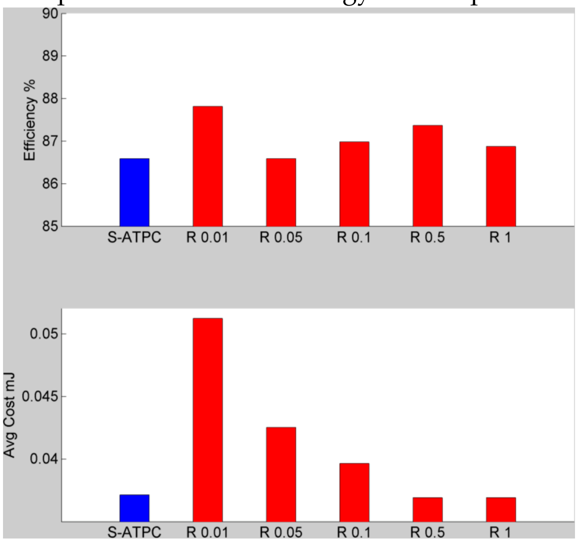


Figure 11. Experimental results: The protocol efficiencies and the average cost of success transmissions are compared when the PSR for all the cases are equal to 99%.

3. Conclusions

The results of the simulations and the experiments suggest that we have a new adaptive transmission power control protocol in place, which can be implemented in mobile wireless sensor scenarios. The efficacy of the protocol has been demonstrated by two sets of simulation results in two different environments. The proposed protocol will work well in scenarios when the activity of the subject under question is moderately high. In general, the protocol is well suited for mobile sensors. This will introduce a new paradigm in the adaptive transmission domain, as this approach is unique and tested in a variable real world environment where not only the distance between the sensor and the base station affects the link quality, but also fading, due to multipath propagation of complex indoor environment and movements of other people within the vicinity of the sensors. The outdoor environment is comparably less complex, with a direct line of sight. The proposed protocol will also be tested in other outdoor environments as part of future research plans.

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