An Accelerometer-Assisted Power Management for Wearable Sensor Systems

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Abstract

In wearable sensor systems (WSSs), sensor nodes are deployed around human body parts such as the arms, the legs, the stomach, and the back. These sensors have limited lifetimes because they are battery-operated. Thus, transmission power control (TPC) is needed to save the energy of sensor nodes. The TPC should control the transmission power level (TPL) of sensor nodes based on current channel conditions. However, previous TPC algorithms did not precisely estimate the channel conditions. Therefore, we propose a new TPC algorithm that uses an accelerometer to directly measure the current channel condition. Based on the directly measured channel condition, the proposed algorithm adaptively adjusts the transmission interval of control packets for updating TPL. The proposed algorithm is efficient because the power consumption of the accelerometer is much lower than that of control packet transmissions. To evaluate the effectiveness of our approach, we implemented the proposed algorithm in real sensor devices and compared its performance against diverse TPC algorithms. Through the experimental results, we proved that the proposed TPC algorithm outperformed other TPC algorithms in all channel environments.

Keywords: sensors, transmission power control, power management, wearable devices

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1. Introduction

In order to quickly and persistently monitor people's physical conditions, sensors are deployed in, on, or around the human body. They form wearable sensor systems (WSSs) where all deployed sensor nodes gather sensing information and transmit data to a sink node, which forwards data sets to external servers. The effectiveness of WSSs is deeply related to the lifetime of sensor nodes. Sensor nodes of WSSs use energy-constrained batteries, and it may be difficult to replace old sensor batteries with new ones. Transmission power control (TPC) can solve this problem. The TPC algorithm reduces a sensor node's energy consumption by changing the transmission power level (TPL) depending on the channel conditions. If the channel condition is bad, the TPC algorithm should set the TPL as high. If the channel condition is good, it sets the TPL as low. Through these operations, it can efficiently save the sensor's energy without packet loss.

In order to effectively apply a TPC algorithm to WSSs, we must overcome many challenges such as high radio attenuation on the human body, the placement of sensor nodes, and human movement [1][2]. In WSSs, sensor nodes use radio bands that have capricious channel characteristics. These radio bands contend with high attenuation due to obstacles from parts of human bodies. Moreover, people in the real world do not remain in the same environment or perform the same movements over time. They go anywhere, from the ground to a room, to a corridor, etc. They also perform various body movements such as standing, walking, and running. Lastly, the sensor nodes can be placed anywhere on the body such as the arms, the the legs, the stomach, and the back. Consequently, the WSS exists in very diverse environments and the TPC algorithm should efficiently work well in all these diverse environments.

Most previous TPC algorithms operate based on the received signal strength indication (RSSI) values. By using RSSI, they predict the current channel condition and adjust TPL for reducing energy consumption. However, this approach needs an excessive number of control packets to find the optimal TPL in a dynamic environment. In the dynamic environment, the channel condition is drastically changed due to rapid human movement such as running. As a result, the predicted TPL is generally far from the optimal TPL, and control packets that are useless for changing a sensor node's TPL are frequently sent. Useless control packets cause significant energy waste in sensor nodes. Therefore, we need a sophisticated method of precisely estimating the channel condition of the human body and effectively adjusting the number of control packets based on the estimated channel condition.

In a static environment with no body movement, the channel is very stable and the estimated TPL is highly accurate. In this environment, the control packet should be sent frequently in order to change TPL quickly. By contrast, in a dynamic environment of high body movement, the channel is very unstable and the estimation of TPL is terribly inaccurate. In this environment, the TPC algorithm should restrain the sending of control packets and should change TPL slowly in order to prevent useless energy waste due to the control packets. In order to achieve this goal, we propose a new TPC algorithm called acceleration-assisted TPC (ATPC). The ATPC algorithm uses an accelerometer to quickly judge the current channel condition. If a body does not move, the channel condition is generally stable, and acceleration values are very low. In this case, we can easily approach the optimal TPL, so we have to frequently send the control packets to quickly change the current TPL to the optimal TPL. On the other hand, if a body moves frequently, the channel condition is very unstable, and the acceleration values are highly varied. In this case, it is hard to find the optimal TPL, so we should infrequently send control packets to slowly change the current TPL as much as possible.

The energy consumption for measuring acceleration value is quite low, and only the sink node needs to measure the acceleration value. Therefore, the proposed ATPC algorithm largely reduces the energy consumption of WSSs by adaptively saving the energy consumption of control packets.

2. Related Work

WSSs have diverse channel environments. These environments can be categorized into two environments: static and dynamic. A static environment has a stable channel condition because there is almost no human movement. Therefore, in the static environment, the TPC algorithm can quickly reach the optimal TPL by frequently transmitting the control packet for updating the current TPL. By contrast, in a dynamic environment, the channel condition is unstable and varies suddenly, due to frequent human movements. Accordingly, the channel prediction is inaccurate in the dynamic environment, so finding the optimal TPL based on the current channel condition is very difficult. Therefore, in a dynamic environment, the TPC algorithm should average the RSSI values for accurate channel prediction and should slowly transmit the control packets for updating the current TPL. For the practical WSS, we must consider both environments at the same time.

In WSSs, there are three representative TPC algorithms: linear [3], binary [4], and dynamic [5]. The linear TPC algorithm [3] approaches the optimal TPL by linearly changing the current TPL based on the previous RSSI value. The optimal TPL is a particular TPL value for which the current RSSI value falls within the target RSSI margin. The linear TPC algorithm is very simple. However, it is inefficient in a static environment because it requires many control packets for reaching the optimal TPL. The binary [4] and dynamic TPC [5] algorithms are more aggressive algorithm than the linear TPC algorithm. The binary TPC algorithm [4] approaches the optimal TPL by exponentially changing the current TPL. That is, if the previous RSSI value is higher than the target RSSI margin, it changes the next TPL as the midpoint level between the current and the minimum TPLs. Similarly, if the current RSSI value is lower than the target RSSI margin, the next TPL is chosen to be the midpoint level between the current and the maximum TPLs. The dynamic TPC algorithm [5] uses the equation of a straight line for finding the optimal TPL based on the two previous RSSI values. The binary and dynamic TPC algorithms can quickly reach the optimal TPL with a few control packets in the static environment. Therefore, in the static environment, the binary and dynamic TPC algorithms outperform. However, in the dynamic environment, these algorithms have a poor performance because they transmit a large number of control packets uselessly, based on the inaccurate channel estimation. The linear TPC algorithm has a better performance than the binary and dynamic algorithms in the dynamic environment due to its changing of the current TPL step-by-step. However, the linear TPC algorithm also sends control packets too frequently, based on the inaccurate channel prediction. Therefore, we propose a new TPC algorithm that efficiently estimates the current channel environment and adaptively controls the period of control packet transmission. In the static environment, the control packet should be transmitted frequently to reach the optimal TPL quickly. In the dynamic environment, the control packet should be transmitted slowly, and the RSSI values with a fixed TPL should be gathered for a while in order to estimate the channel condition precisely.

In WSSs, the factor that most affects the channel environment is body movement. If a human body does not move, as when it is standing, the body channel condition is close to a static environment. If a human body moves frequently or drastically, as in walking or running, the channel condition is close to a dynamic environment. Therefore, in this paper, we precisely estimate channel condition through human movement. In order to measure this movement, we use an accelerometer. In terms of accelerometers, there are many studies. Previous studies only considered one side of both wireless systems and other sensor modules. Wen-Chang et al. [10] proposed an accelerometer-based fall detection method using a self-constructing classifier. Their algorithm used training information for positive and negative examples. Through the information, they find the classifier and weight classifier. Lina Tong et al. [11] proposed a hidden Markov model (HMM)-based method using tri-axial accelerations of the human body. They used the acceleration time series extracted from human motion to recognize current human fall and make predictions. C. Wong et al. [12] proposed a pose estimation scheme based on a sparse network of accelerometer-based wearable sensors. They used a marker-based motion capture system and the partial least squares regression to capture 3D motion and establish the implicit model. However, all of them only considered human movement detection using an accelerometer. They did not use the accelerometer to measure the current channel condition [10][11][12][13].

Recently, L. Liang et al. [6] proposed an energy efficient routing scheme in multi-hop wireless body area networks to increase energy efficiency. They control current TPL based on the link and path energy-aware expected transmissions. S. Kim et al. [7] proposed an RSSI/LQI-based transmission power control scheme in the healthcare environment. They proposed a practical protocol using RSSI and link quality indication (LQI). B. Moulton et al. [8] proposed adaptive feedback periodicity in which the sink node transmits feedback packets to a sensor node regarding whether to raise or lower the TPL. S. Xiao et al. [9] proposed a TPC algorithm to consequently investigate the current channel condition and calculate moving average values to choose an optimal TPL. H. Cotuk et al. [16] investigated the effects of the granularity of power levels on energy dissipation characteristics and various transmission power assignment strategies by using experimental data. Moreover, they proved that a more fine-grained TPC algorithm can increase the lifetime of sensor nodes up to 20% in comparison to optimally assigned network-level single transmission power. L. Xu et al. [17] also proposed the effect of transmission power control algorithms in wireless sensor networks. They proved that the energy efficiency of TPC can benefit depending on the channel environment, MAC control, diverse sensor hardware, and communication types. A. Aprem et al. [18] proposed TPC policies to reduce total energy consumptions. They structured the optimal power policy in two levels. There are other studies about TPC energy saving techniques [14][15]. However, all of the above studies need control packets because all of them adopt a closed-loop mechanism. So, we must consider the energy efficiency of the control packet transmission for the closed-loop mechanism.

3. Accelerometer-Assisted TPC Algorithm

A large majority of sensors in WSSs periodically collect various data about human vital signs such as pulse, body temperature, breathing rate, and blood pressure. These sensor nodes have a limited lifetime and are very difficult to replace with new ones when the sensor nodes are deployed into the human body. Therefore, the WSSs need an energy management model and TPC mechanism for sensor devices.

We show the general TPC mechanism [19] in **Fig. 1**. The general closed-loop TPC mechanism automatically controls the TPL of sensor nodes based on feedback information. In the mechanism, there are sensor nodes and a sink node. The sensor nodes send data packets to the sink node. The sink node sends control packets to the sensor nodes with feedback information. In the mechanism, the sink node measures the value of RSSI when it receives the data packets. If the measured RSSI value exists within the target RSSI margin, the sink node does not calculate the next TPL and does not send a control packet in order to restrain unnecessary energy consumption. By contrast, if the RSSI value does not exist within the target RSSI margin, the sink node calculates the next TPL using a TPC algorithm. Then, it sends the control packet as feedback information to the sensor node. In the feedback information, there is newly updated TPL information from the sink node. The sensor node updates the current TPL when it receives control packet with feedback information from the sink node. Next, the sensor node sends data packets with the updated TPL to the sink node. This mechanism repeatedly performs the above sequential procedures during the lifetime of the sensor nodes.

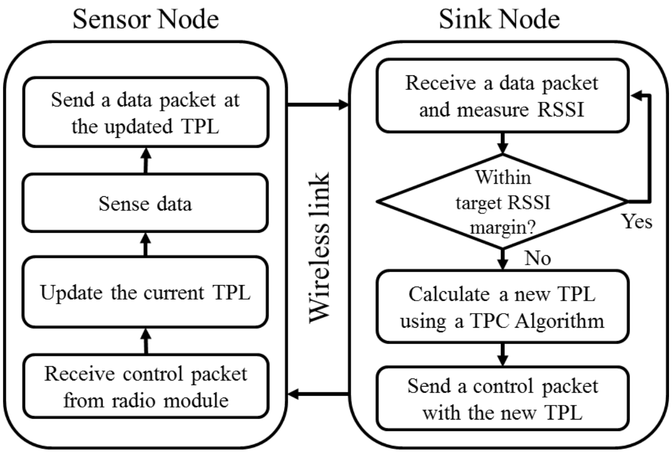


Fig. 1. General TPC mechanism

From now on, we propose a new TPC algorithm called ATPC. The efficient TPC algorithm should adaptively operate depending on the current channel condition. If the channel condition is stable, the TPC algorithm should quickly approach the optimal TPL by frequently sending a control packet for updating the TPL. In contrast, if the channel condition is unstable, the TPC algorithm cannot precisely estimate the optimal TPL. Thus, it should change the TPL slowly in order not to waste energy by transmitting control packets approaching the wrong TPL. As mentioned earlier, if a body moves frequently, the channel condition is unstable and if the movement is low, the channel is generally stable. Therefore, the proposed TPC algorithm directly estimates body movement with an accelerometer in the sink node. In the proposed algorithm, if an acceleration value is low, we think that the current channel condition is stable and control packets can be sent frequently. In contrast, if the acceleration value is high, we think that the current channel condition is unstable and control packets should be sent infrequently. Through these approaches, we adaptively save the energy of sensor devices in all channel environments.

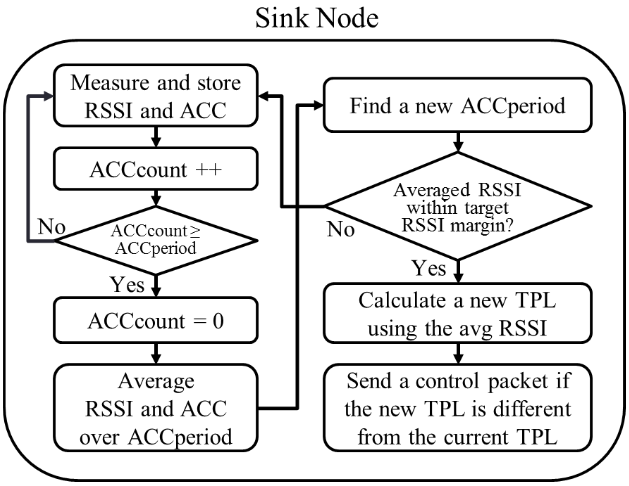


Fig. 2. Proposed TPC mechanism

Fig. 2 shows the extended closed-loop mechanism for the proposed TPC algorithm in the sink node. The mechanism of the proposed TPC algorithm is similar to the general TPC mechanism shown in **Fig. 1**. In the proposed algorithm, the RSSI and acceleration (ACC) values are measured when each packet is received. These values are accumulated until *ACCcount* reaches the *ACCperiod*. The *ACCperiod* is a period in which the RSSI and ACC values are gathered without sending a control packet for updating the TPL. If *ACCcount* reaches *ACCperiod*, the proposed algorithm calculates *avgACC* and *avgRSSI*, which are average values of the RSSI and ACC over the *ACCperiod*. Then, it finds a new *ACCperiod* based on the *avgACC*. If the *avgACC* is higher, the new *ACCperiod* is longer, whereas if the *avgACC* is lower, the new *ACCperiod* is shorter. After that, the proposed algorithm operates with the *avgRSSI* value as does the general TPC mechanism in **Fig. 1**.

```
procedure GetNewACCperiod(avgACC)
  if (avgACC ≤ 15) then
    ACCperiod ← 1
  else if (avgACC ≤ 45) then
    ACCperiod ← 2
  else if (avgACC ≤ 100) then
    ACCperiod ← 4
  else if (avgACC ≤ 250) then
    ACCperiod ← 8
  else
    ACCperiod ← 16
  end if
end procedure
```

```
procedure ATPC()
  curRSSI ← currently measured RSSI value
  curACC ← currently measured ACC value
  sumRSSI ← sumRSSI + curRSSI
  sumACC ← sumACC + curACC
  ACCcount ← ACCcount + 1
  if (ACCcount ≥ ACCperiod) then
    ACCcount ← 0
    avgRSSI ← sumRSSI / ACCperiod
    avgACC ← sumACC / ACCperiod
    call GetNewACCperiod(avgACC)
    call GeneralTPCAlgorithm(avgRSSI)
  end if
end procedure
```

Fig. 3. Pseudo code of proposed algorithm

Fig. 3 illustrates the pseudo code of the ATPC algorithm. The ATPC algorithm first measures the RSSI and ACC values. Then, it stores these values to *sumRSSI* and *sumACC* variables. And, the *ACCcount* is increased by one. If the *ACCcount* reaches the *ACCperiod*, the ATPC algorithm averages the *sumRSSI* and *sumACC* values over the *ACCperiod*. Then, it finds a new *ACCperiod* using the *avgACC* value. After that, the ATPC algorithm calls a general TPC algorithm with the *avgRSSI* value. The general TPC algorithm may be one of the previous TPC algorithms, such as linear, binary, dynamic, and hybrid. In order to decide an appropriate *ACCperiod* depending on the *avgACC* values, we analyzed the data set gathered from our WSS. Through the analysis, we set the *ACCperiod* to 1, 2, 4, 8, and 16 when *avgACC* value is 1-15, 16-45, 45-100, 100-250, and >250, respectively, in our algorithm. For example, if the *avgACC* value is under 15, we set the *ACCperiod* to 1. If the *avgACC* value is over 250, we set the *ACCperiod* to 16. Naturally, the system administrator can set the *ACCperiod* values and ranges differently based on their WSS.

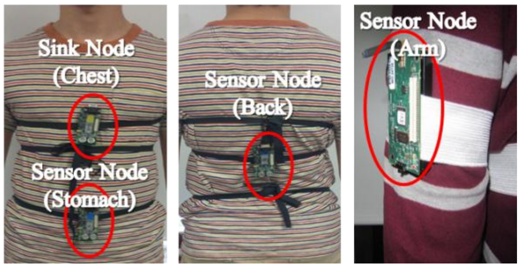
4. Experiments

Table 1 shows experimental parameters for analyzing various TPC algorithms in WSSs. We used the Cricket Mote [8] with a CC1000 [7] radio chip operating at 433 MHz, 19.2 kbps, and IEEE 802.15.4 Zigbee. The CC1000 radio chip provides 23 different TPLs corresponding to a range between -20 and -10 dBm. We also used the Kmote-Vib accelerometer with an SCA3000-D01 module which has a 3-axis accelerometer whose sensitivity is ±2g. With these devices, we collected sensor data every 1 second, and the target RSSI range was set from -88 to -82 dBm. We evaluated diverse TPC algorithms: linear (L), binary (B), dynamic (D), hybrid (H), and our ATPC (A) algorithms. In our ATPC algorithm, we used the hybrid algorithm as a general TPC algorithm.

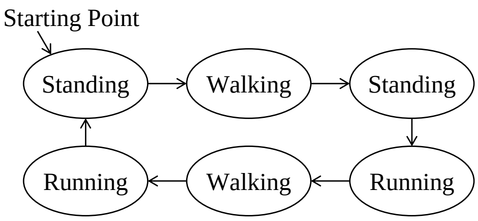
Table 1. Experimental parameters

Properties	Values
Mote Model	Cricket Mote
Supply Voltage	2.5 V
Radio Module	CC1000
Radio Technology	Zigbee (IEEE 802.15.4)
Radio Frequency	433 MHz
Transmit Bit Rate	19.2 kbps
Output Power Range	-20 to -10 dBm
Tx Current Consumption	6.9 to 26.7 mA
Rx Current Consumption	9.3 mA
Packet Size	67 Bytes
Accelerometer Model	Kmote-Vib
Accelerometer Module	SCA3000 – D01 (3 Axis)
Accelerometer Range	±2g
Accelerometer Sensitivity	1333 counts/g
Accelerometer Current Consumption	0.48 mA
Experimental Area	Indoor Corridor (3.6 x 9.0 m)
Sink Node Placement	Chest
Sensor Node Placement	Stomach, Back, Arm
Body Movement	Standing, Walking, Running
Target RSSI Point	-85 dBm
Target RSSI Margin	-88 to -82 dBm
TPC Algorithms	Linear, Binary, Dynamic, Hybrid, ATPC

Fig. 4 shows the experimental environment. The sink node is deployed on the chest, and the sensor nodes are deployed on the stomach, back, and arm, as shown in **Fig. 4(a)**. In the experiments, we used a body movement pattern consisting of three different body movements: standing, walking, and running, as shown in **Fig. 4(b)**. In the pattern, each state of body movement was maintained for 30 seconds and transited to the next body movement state.



(a) Sensor placements: a sink node and sensor nodes (stomach, back, and arm)



(b) Body movement pattern

Fig. 4. Experimental environment

Fig. 5 demonstrates the control packet delivery ratio (CPDR) per data packet. In the graph, the stomach sensor has the smallest CDPRs because the sensor node on the stomach and the sink node on the chest are line-of-sight. The back sensor has the largest CDPRs because of the non-line-of-sight propagation. The CDPRs on the arm sensor are between these two. This is because the channel condition of the arm sensor varies between line-of-sight and non-line-of-sight propagations, depending on arm movement. In the graph, the dynamic TPC algorithm shows the worst results for all of the sensor placements. This is because the dynamic TPC algorithm sends control packets every time to make a new equation of a straight line in the dynamic environment such as running body movement. The ATPC algorithm has the best results on all sensor placements. This is because the ATPC algorithm restrains the transmission of control packets as much as possible in the dynamic environment.

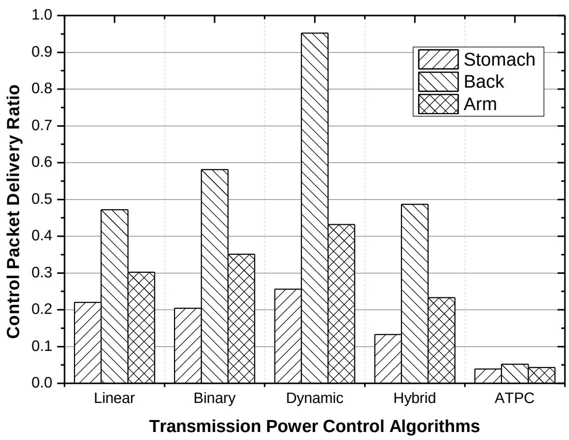


Fig. 5. Control packet delivery ratio

Fig. 6 demonstrates the ratio of successfully received packets from sensor nodes to the sink node. As shown in the figure, all TPC algorithms perform well above a packet delivery ratio (PDR) of 0.95. This is because all TPC algorithms immediately increase the current TPL when a packet is dropped.

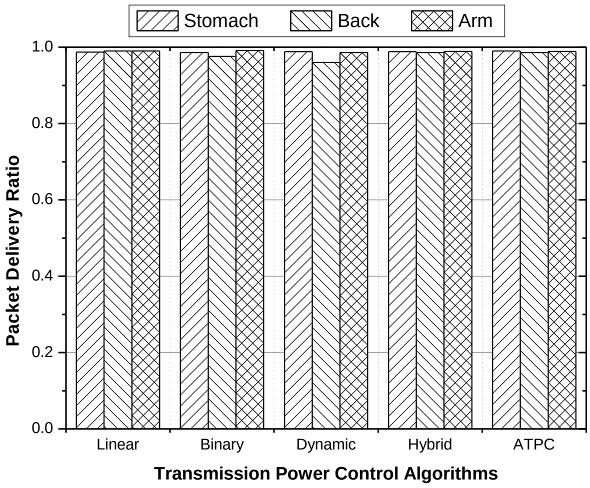


Fig. 6. Packet delivery ratios of TPC algorithms

Next, we measured the energy consumption according to each TPC algorithm. The total energy consumed by a TPC algorithm includes energies for sending and receiving the data and control packets. We used the model in [5] to calculate the packet energy cost, *E*, as follows:

$$E = V \cdot I \cdot L/C$$

where V, I, L, and C represent the supply voltage, current drawn, packet size, and transmission bit rate, respectively. In the experiments, the supply voltage, packet size, and transmission bit rate are 2.5 V, 67 Bytes, and 19.2 kbps, respectively. The current drawn at a packet reception is 9.6 mA and the current drawn at a packet transmission depends on the TPL. The transmission current drawn depending on TPLs is shown in Table 2. The sensors use the maximum TPL then they send control packets. In the ATPC algorithm, the energy consumed by measuring the acceleration value must also be added. The current drawn at a sensing of the accelerometer is 0.48 mA. This is a very low value in comparison to the current drawn at packet transmission and reception.

Table 2. Transmission currents and output powers according to TPLs

TPL	0	1	2	3	4	5	6	7	8	9	10	11
Current (mA)	6.9	7.1	7.4	7.6	7.9	8.2	8.4	8.7	8.9	9.4	9.6	9.7
Power (dBm)	-20	-18	-15	-12	-10	-8	-7	-6	-5	-4	-3	-2
TPLs	12	13	14	15	16	17	12	19	20	21	22	
Current (mA)	10.2	10.4	11.8	12.8	13.8	14.8	15.8	16.8	20.0	22.1	26.7	
Power (dBm)	-1	0	1	2	4	5	6	7	8	9	10	

Fig. 7 shows the total energy consumption of diverse TPC algorithms for the reception of 1,000 data packets on standing body movement. In this graph, each TPC algorithm incudes five energy consumption factors: acceleration (ACC), control packet transmission (ControlTX), data packet reception (DataRX), control packet reception (ControlRX), and data packet transmission (DataTX). In the results, the ATPC algorithm has a similar performance

to the other TPC algorithms. This is because the accelerometer consumes energy but the amount of consumed energy is negligible.

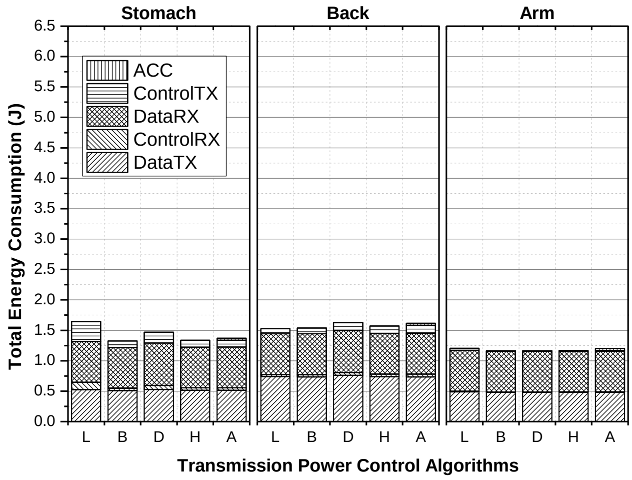


Fig. 7. Energy consumption on standing

Fig. 8 demonstrates the total energy consumption of each TPC algorithm on running body movement. In the graph, the dynamic algorithm has the worst performance at all sensor placements. This is because the dynamic algorithm sends control packets too frequently based on inaccurate prediction. In the results, the ATPC algorithm has the most outstanding performance for all sensor deployments. Particularly, at the back placement, the ATPC algorithm consumed only 30% energy in comparison to the dynamic algorithm. In addition, the ATPC algorithm has 59% energy consumption compared with the hybrid TPC algorithm at the same placement.

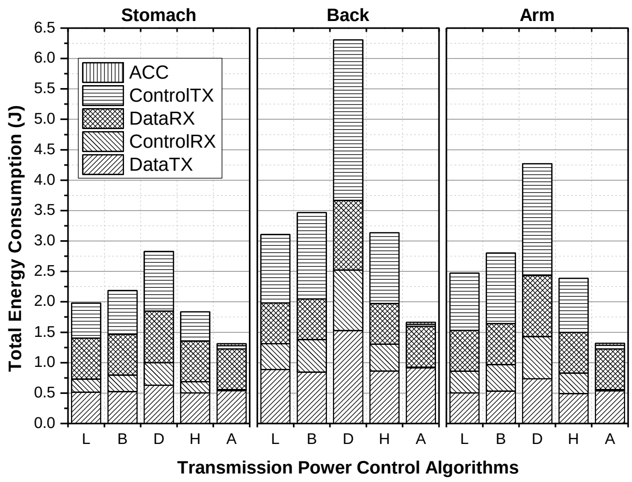


Fig. 8. Energy consumption on running

Fig. 9 shows the total energy consumption on the body movement pattern as shown in **Fig. 4(c)**. The body movement pattern includes all representative body movements such as standing, walking, and running. In the graph, the ATPC algorithm still has the best performance at all sensor placements, even though the differences between the ATPC and the other TPC algorithms are lower than those for the running movement. This is because the ATPC and other TPC algorithms have little performance difference in the standing movement but they have a large difference in the running movement. Therefore, we can say that the ATPC algorithm has the best performance at all sensor placements in all channel environments.

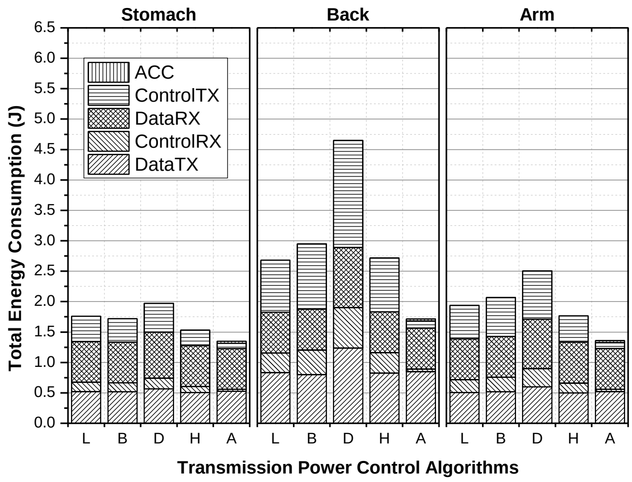


Fig. 9. Energy consumption on the body movement pattern

5. Conclusion

In this paper, we proposed a new TCP algorithm called ATPC. The ATPC algorithm uses the accelerometer to quickly judge the current channel condition. When the human body does not move, the channel condition stays static and the acceleration values are low. In this case, we can easily approach the optimal TPL, so we have to change the current TPL frequently. In contrast, when the body moves a great deal, the channel condition varies dynamically and the acceleration values vary drastically. In this case, it is hard to approach the optimal TPL, so we have to change the TPL slowly. In order to implement this idea, the proposed TPC algorithm adaptively sets the period of control packet transmission depending on the acceleration values. If the acceleration value is low, it sets the period to short. If not, it sets the period to long. The power consumption of the accelerometer is low. Moreover, only the sink node needs to measure the acceleration value. Therefore, the proposed TPC algorithm has more gain than the overhead of measuring acceleration values in the sink node. Lastly, through the real sensor experiments, we prove that our proposed TPC algorithm has the best performance at diverse sensor placements for diverse body movements. For future work, we will conduct more experiments with diverse sensor devices and will analyze the experimental results to find the optimal period of control packet transmission in all channel conditions.

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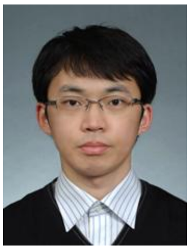

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