J Inf Process Syst, Vol.15, No.3, pp.593~603, June 2019
https://doi.org/10.3745/JIPS.03.0118

ISSN 1976-913X (Print)
ISSN 2092-805X (Electronic)

JOURNAL OF INFORMATION PROCESSING SYSTEMS JIPS

An Adaptive Transmission Power Control Algorithm for Wearable Healthcare Systems Based on Variations in the Body Conditions

Woosik Lee*, Namgi Kim**, and Byoung-Dai Lee**

Abstract

In wearable healthcare systems, sensor devices can be deployed in places around the human body such as the stomach, back, arms, and legs. The sensors use tiny batteries, which have limited resources, and old sensor batteries must be replaced with new batteries. It is difficult to deploy sensor devices directly into the human body. Therefore, instead of replacing sensor batteries, increasing the lifetime of sensor devices is more efficient. A transmission power control (TPC) algorithm is a representative technique to increase the lifetime of sensor devices. Sensor devices using a TPC algorithm control their transmission power level (TPL) to reduce battery energy consumption. The TPC algorithm operates on a closed-loop mechanism that consists of two parts, such as sensor and sink devices. Most previous research considered only the sink part of devices in the closed-loop. If we consider both the sensor and sink parts of a closed-loop mechanism, sensor devices reduce energy consumption more than previous systems that only consider the sensor part. In this paper, we propose a new approach to consider both the sensor and sink as part of a closed-loop mechanism for efficient energy management of sensor devices. Our proposed approach judges the current channel condition based on the values of various body sensors. If the current channel is not optimal, sensor devices maintain their current TPL without communication to save the sensor's batteries. Otherwise, they find an optimal TPL. To compare performance with other TPC algorithms, we implemented a TPC algorithm and embedded it into sensor devices. Our experimental results show that our new algorithm is better than other TPC algorithms, such as linear, binary, hybrid, and ATPC.

Keywords

Healthcare System, Transmission Power Control, Wireless Body Sensor Network

1. Introduction

Our society is rapidly entering the age of super aging, and people's interest in health is increasing. Sensors are placed inside or outside the body to exchange critical information, such as human bio-information. There is an increasing demand for a system for monitoring human health status in real time. However, because a wearable healthcare system (WHCS) is placed in a part of the human body, unlike a wireless sensor network (WSN), the WHCS sensors have much smaller batteries with limited resources.

Therefore, it is essential to manage sensor energy in the WHCS, where the ultimate goal is to quickly

Manuscript received Novembe 29, 2017; first revision January 11, 2018; second revision March 29, 2018; accepted April 13, 2018.
Corresponding Author: Byoung-Dai Lee (blee@kgu.ac.kr)
* Research Center, Social Security Information Service, Seoul, Korea (wslee@ssis.or.kr)
** Dept. of Computer Science, Kyonggi University, Suwon, Korea ({ngkim, blee}@kgu.ac.kr)

and continuously monitor real-time physical changes to the human body.

A transmission power control (TPC) algorithm is a representative technique that is used to increase the lifetime of sensor devices for a continuously monitored real-time system. In detail, the WHCS sensor utilizes the CC1000 or CC2420 radio module for communication. The CC1000 has 21 transmission power levels (TPLs), and the CC2420 has 31 TPLs. If sensors use high TPLs for communication, their communication range is wide and the communication success rate is high, but the energy consumption is also high. On the other hand, if sensors use lower TPLs for communication, the sensor can be operated in an energy-efficient manner although it has a narrow communication range and a low data success rate. That is, it is possible to extend the lifetime of the sensor by using a TPL that has a proper communication range and ensures a high data success rate as well as consumes a minimum amount of energy. The TPC algorithm is a technique that helps to efficiently select TPLs.

Previous representative TPC algorithms [1-3] have used only received signal strength indication (RSSI) values to control the current TPL. They did not consider variations in the human condition or other elements, such as sensor placement, human movement, and human-body radio attenuation [4,5].

The typical TPC algorithm operates in the following way. The transmitter collects human body data in real time and transmits the data to a gateway device with the currently set TPL. The gateway device measures the RSSI value, which is the received power strength measured when receiving data. Based on the TPC model, the gateway device determines whether the current RSSI value falls within the target RSSI margin range, and if it does, the gateway device does not send a control message to the transmitter to update the TPL. Conversely, if the current RSSI value is outside the target RSSI margin range, the gateway device uses the transmit power adjustment algorithm to find a new TPL value. The value of the newly discovered TPL is stored in the control message and the transmitter is informed. The transmitter receives the control message and performs a TPL update if the values contained in the TPL and the received control message are different. The transmitter then performs a communication with the updated TPL. However, the existing TPC algorithm does not consider efficient human energy conservation because it does not take into account human movement and the location of sensors placed around the human body, which is a characteristic of WHCS.

In order to reduce energy consumption with WHCS elements such as human movement, sensor placement, and so on, acceleration-assisted TPCs (ATPCs) [6] have been proposed recently. ATPC algorithms adaptively judge current channel conditions using accelerometers. If human movements are stable and the channel condition is static, ATPC algorithms quickly find the most appropriate TPLs, because estimated TPLs are more accurate than those found in dynamic environments, such as during walking and running. If human movements are unstable, ATPC algorithms increase the channel-checking interval in order to reduce excessive energy used by sensor devices due to incorrect TPLs. Through these procedures, ATPC algorithms improve on other TPC algorithms that only use RSSI values. However, ATPC algorithms do not cover various conditions when human movement is dynamic.

In this paper, we propose a novel TPC algorithm called the body-condition-based TPC (BCTPC) that considers human body-condition variations to reduce energy consumption when sensor real-time values are not changing over time. This approach can greatly increase the lifetimes of sensor devices. Moreover, the BCTPC algorithm considers other important factors, such as sensor placement and human movement. For example, if current human-condition variations are negligible, the BCTPC algorithm changes the current mode to a 'keeping' mode, in which the sensor devices maintain the current TPL without updates. However, if the BCTPC algorithm changes the current mode to a 'finding' mode, sensor devices will determine the proper TPL using TPC algorithms. Therefore, the BCTPC algorithm reduces the energy consumption of both the sensor devices and the sink device.

The contribution of this paper can be understood as follows. First, we propose a new state diagram by considering human body properties and defining two attributes, 'keeping' and 'finding'. Second, unlike the conventional closed-loop architecture, we consider both sensor and sink parts to reduce energy consumption of sensor devices. In addition, we implement the WHCS system and perform various analyses through experiments.

The composition of this paper is as follows. Section 2 shows the related works. Section 3 introduces the proposed algorithm. Section 4 defines the experimental environment and analyzes the experimental results. The final section summarizes this paper and discusses future research.

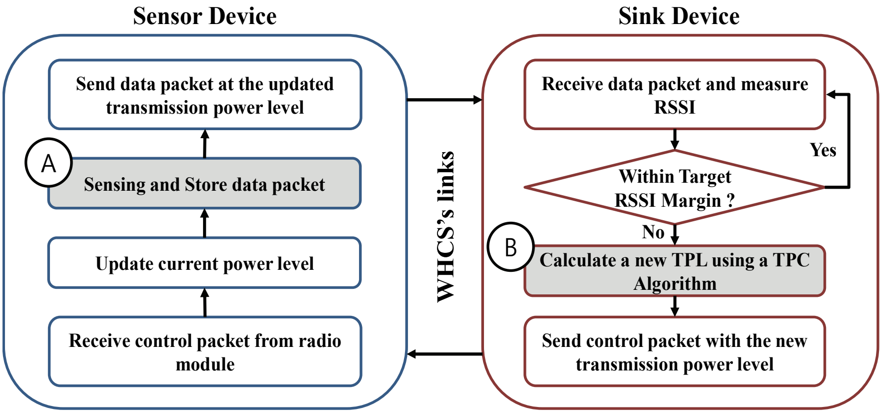


Fig. 1. Closed-loop architecture of TPC algorithms: 'A' is human condition-variation sensing aspect of sensor devices, and 'B' is TPC algorithm portion of the sink device.

2. Related Work

Fig. 1 illustrates the organization of the sensor devices and the sink device in the closed-loop architecture for TPC algorithms. It shows that the sensor devices include a process for sensing human-condition variations ('A'), while the sink device includes the TPC algorithms ('B'). Most previously used TPC algorithms [1-8] consider only part (B), without (A); their TPC algorithms are based solely on RSSI values. For example, the hybrid TPC algorithm [7] adaptively chooses either a linear TPC algorithm [1] or a binary TPC algorithm [2], depending on current channel conditions. Thus, the hybrid TPC algorithm has the advantages of both linear and binary TPC algorithms. However, a hybrid TPC algorithm does not solve many of the control packet problems found in unstable environments. In order to solve such problems, the ATPC algorithm was proposed. The ATPC algorithm [6] uses acceleration values to control current TPLs. Then, the ATPC algorithm adaptively increases or decreases the number of control packets depending on current human movements. If human movements are dynamic, as in the cases of walking and running, the ATPC algorithm reduces the number of control packets. In contrast, if human movements are stable, the ATPC algorithm increases the number of control packets, because TPC algorithms can estimate current channel conditions to easily find the optimal TPL. However, these two TPC algorithms only consider the TPC algorithm part of the sink device (B), without incorporating the human condition-variation aspect (A) shown in Fig. 1. Recently, most studies also include part of the sink device in a closed-loop mechanism [10-17]. In [10], the authors proposed a TPC algorithm that utilized channel correlation coefficients between a wireless body sensor network (WBSN) channel and body conditions. In [11], the authors analyzed the correlation of human motion with channel shaking to improve the TPC algorithm. In [12], the authors placed sender sensors on a wall to transmit control packets to a main sensor, and placed the receiver on the human wrist to control the TPLs. After communication between senders and receiver, the sensor device predicted the TPL. In [13], the authors proposed a new equation to determine the proper TPL. In [14], the authors extracted the feature value of the acceleration at every moment through the acceleration generated by human motion, and adjusted the TPL according to the current state. Furthermore, there are many recent studies [15-17] that proposed methods to reduce sensor energy consumption in consideration of human motion and the inherent characteristics of body sensors in the WHCS environment.

In this paper, we consider the human-condition variations of the closed-loop architecture in order to reduce the volume of massive data transmission packets. Then, we propose the BCTPC algorithm to adaptively operate the radio transmission chip according to the current variation in the human condition.

3. Body Condition-Based TPC Algorithm

The BCTPC algorithm has two modes: 'keeping' and 'finding', as shown in Fig. 2. If current body values (BVs) are similar to previous BVs, the BCTPC selects the keeping mode. In the keeping mode, sensor devices do not send sensing data packets to the sink device because the current packets should be the same as or similar to previous packets. In return, the sink device does not send control packets with TPL information; instead, it simply recognizes the current data packet, which is similar to the previous data packet. If BVs are different from previous BVs, the BCTPC selects the finding mode. In the finding mode, the sensor devices send data packets to the sink device at pre-configured times. Then, the sink device sends control packets with new TPLs to the sensor devices using a particular TPC algorithm. In this paper, we use the ATPC algorithm.

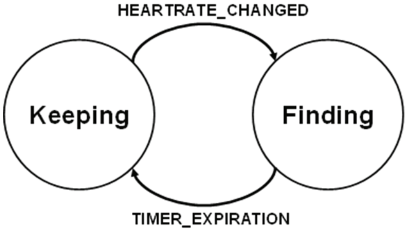


Fig. 2. BCTPC state diagram has two modes: 'keeping' and 'finding'.

Fig. 3 is a diagram of the BCTPC approach. In Fig. 3, the BVs are maintained from time T_1 to T_2. However, at time T_2, the BVs increase. Then, the BCTPC switches from keeping mode to finding mode, and the sensor devices send data packets to the sink device. The sink device receives these data packets, determines the proper TPL, and responds to the sensor devices with control packets containing the new TPL. Then, the BCTPC algorithm automatically returns the current mode to the keeping mode to save energy. Times T_4 and T_5 are the same. Using this approach, the BCTPC algorithm can reduce energy consumption during the keeping mode.

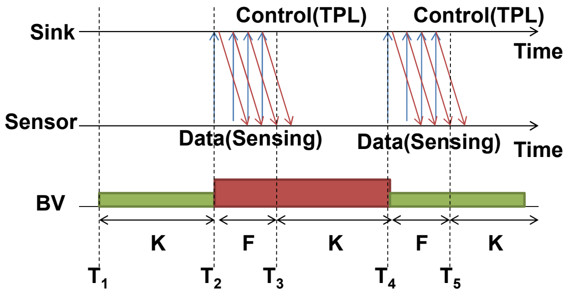


Fig. 3. BCTPC state diagram has two modes: 'keeping' (K) and 'finding' (F).

4. Performance Analysis

Table 1 includes diverse experimental parameters used to analyze various TPC algorithms in WHCSs. We used the Cricket Mote [18] with a CC1000 [19] radio chip operating at 433 MHz and 19.2 kbps. The CC1000 radio chip has 23 different TPLs ranging from -20 to -10 dBm. Using these devices, we collected sensor data every 1 second for 1,800 seconds. Then, we used the heart rates of various biosensors, such as ECGs, EMGs, EEGs, blood glucose, and heart rate, to measure variations in the human condition. Heart rates ranged from 0 to 200 bpm. In normal daily life, heart rates range from 60 to 100. In times of activity, they range from 100 to 200. We evaluated various TPC algorithms: linear, binary, dynamic, hybrid, ATPC, and the proposed BCTPC. Fig. 4 shows BCTPC pseudo-code.

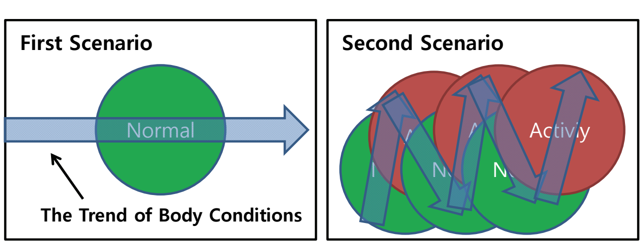
Table 1. Experimental parameters

Properties	Value
Mote model	Cricket Mote
Supply voltage (V)	2.5
Radio module	CC1000
Radio technology	Zigbee (IEEE 802.15.4)
Radio frequency (MHz)	433
Transmit bit rate (kbps)	19.2
Output power range (dBm)	-20 to -10
Current consumption, Tx (mA)	6.9 to 26.7
Current consumption, Rx (mA)	9.3
Packet size (bytes)	67
Accelerometer model	Kmote-Vib
Accelerometer module	SCA3000 – D01 (3 Axis)
Accelerometer current consumption (mA)	0.48
Human condition, heart rate (bpm)	Normal (60–100), Activity (100–200)
Experimental area	Indoor Corridor (3.6 x 9.0 m)
Sink device placement	Chest
Sensor device placement	Back
Body movement	Standing, Running
Target RSSI point (dBm)	-85
Target RSSI margin (dBm)	-88 to -82
TPC algorithms	Linear, Binary, Dynamic Hybrid, ATPC, BCTPC

```
Procedure BCTPC (RSSI)
Input: measured RSSI values
Output: Transmission Power Level
Initializing Global Values
curRSSI = current measured RSSI value
curTPL =  current TPL value
curSTATE =  current STATE value
preBV = previous BV value
curBV =  current BV value
curTime = 0
Switch(curSTATE):
  case KEEPING:
    curTime = 0
if preBV - α < curBV ≤ preBV + α:
curTPL is not changed
    else:
      curSTATE = FINDING
    break
  case FINDING:
    curTime ++;
if targetRSSI - β < curRSSI ≤ targetRSSI +β:
curTPL = generalTPCalgorithm(curRSSI)
    if timer_Expiration < curTime:
      curSTATE = KEEPING
    break
Return curTPL
```

Fig. 4. Pseudo-code of BCTPC.

For each scenario, we consider two different types as shown in Fig. 5. In the first scenario (Fig. 5(a)), the heart rate maintains its normal condition from 60 to 100 bpm, and human movement reflects a standing position. In the second scenario (Fig. 5(b)), the heart rate changes automatically from normal to active or from active to normal every 30 seconds. Similarly, human movement changes from standing to running or from running to standing every 30 seconds.



(a) (b)

Fig. 5. Scenarios for experimental testing: (a) first scenario and (b) second scenario.

Fig. 6 shows the experimental results of the BCTPC expiration timers (ETs) for the first scenario (i.e., normal heart rate and stable movement). We consider the range of ETs from 1 to 30 seconds. ETs are directly related to energy consumption because sensor devices send additional data packets in direct proportion to the duration of the expiration time, such that the energy consumption at ET=1 is lower than that at ET=30. Moreover, ET=1 and ET=2 have the same control energy consumption. ET=5 and ET=10 also have same control energy consumption. However, the energy consumption of ET=30 is greater than that of ET=20. Through these experimental results, we know that higher ETs increase energy consumption and lower ETs reduce control packets. This means that we must consider the most appropriate ETs for the energy-efficient operation of the sensor devices.

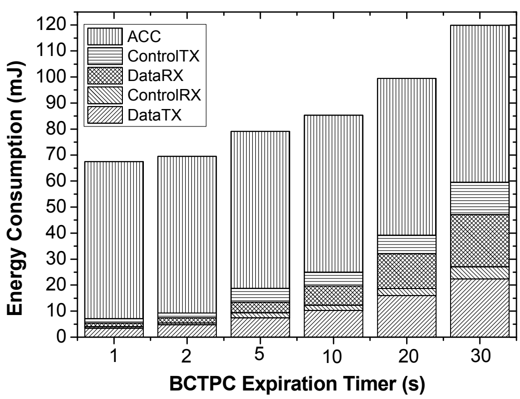


Fig. 6. Total energy consumption for the BCTPC expiration timers in the first scenario.

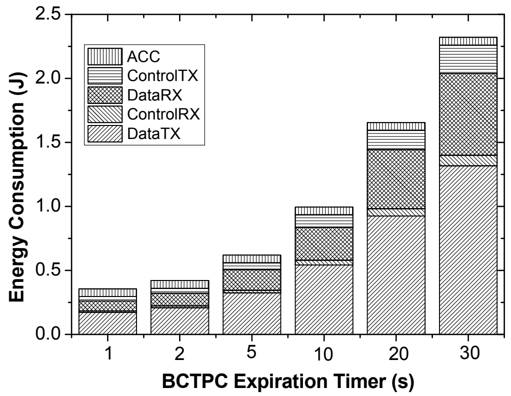


Fig. 7. Total energy consumption for the BCTPC expiration timers in the second scenario.

Fig. 7 shows the experimental results of the ETs for the second scenario, in which the heart rate and human movement are dynamically changed. The experimental results of the second scenario show changing trends similar to those of the first scenario, but higher. The reason for this is that the BVs are unstable and change every 30 seconds. Thus, the BCTPC algorithm updates the current TPL every 30 seconds. Moreover, in the second scenario, the energy consumption increases exponentially depending on the ETs, because longer ETs spend less time in keeping mode. If the changing time between body conditions decreases, the energy consumption gap between ETs increases.

The above two experimental results show that shorter ETs are best in terms of energy consumption. However, in WHCSs, we must consider the monitoring system that requires sensor devices to send packets continuously to the sink device. In this case, shorter ETs result in incorrect TPLs leading to higher energy consumption. In order to check TPL accuracy, we must show the RSSI values for each ET.

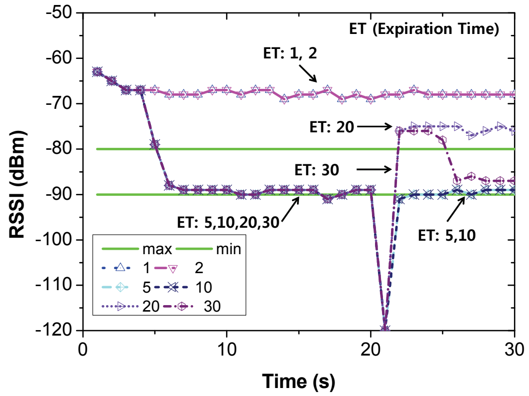


Fig. 8. RSSI trends of ET=1, 2, 5, 10, 20, and 30 for the first scenario.

Fig. 8 shows the RSSI trends of six ETs: 1, 2, 5, 10, 20, and 30. In Fig. 8, the two green lines represent the RSSI margin minimum and maximum, the x-axis represents the time line, and the y-axis represents the RSSI values. The RSSI values for ET=1 and ET=2 are deployed over the target RSSI margin. Thus, the current TPL is inaccurate. Conversely, the RSSI values for ET=5, 10, 20, and 30 are within the target RSSI margin. However, after 20 seconds, ET=20 and ET=30 change the current TPL to an incorrect TPL, due to the presence of dynamic channels. At the same time, ET=5 and ET=10 maintain the current TPL because the current mode of the sensor devices is a keeping mode. Through this result, we know that ET=5 and ET=10 are better than ET=1, ET=2, ET=20, and ET=30. The ET number reflects the duration of the finding mode. Thus, it is best for sensor devices to have low ETs to determine the proper TPLs. For example, in Fig. 7, the experimental results of ET=5 and ET=10 are the same; thus, ET=5 is better than ET=10. Therefore, in this paper, we use ET=5 as the configuration value of the BCTPC algorithm.

Fig. 9 shows the total energy consumption of each TPC algorithm for the first scenario, which involves a normal heart rate and stable movements. In Fig. 9, the non-BCTPC algorithms exhibit similar total energy consumption, while the BCTPC algorithm exhibits significantly reduced energy consumption. This is because the sensor devices in the BCTPC algorithm do not send data packets during times of stable body conditions while in the keeping mode.

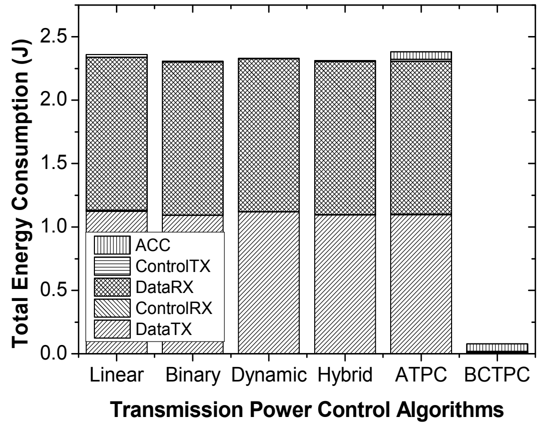


Fig. 9. Total energy consumption on the first scenario.

Fig. 10 shows the total energy consumption of each TPC algorithm for the second scenario, which involves dynamically changing heart rates and human movements. In this experimental result, the dynamic TPC algorithm exhibits the worst results, due to the high number of control packets and unstable channels. Moreover, the linear and binary TPC algorithms exhibit similar results. The hybrid TPC algorithm is better than the linear and binary TPC algorithms because it adaptively changes the current TPC algorithm depending on the current channel condition. Furthermore, the ATPC algorithm is better than the other four TPC algorithms (i.e., the linear, binary, dynamic, and hybrid TPC algorithms) because it reduces large control packets when human movements are dynamic. Finally, the BCTPC exhibits the best results for this scenario. Through the above two experimental results, we demonstrate that the BCTPC algorithm outperforms other TPC algorithms, including linear, binary, dynamic, hybrid, and ATPC algorithms.

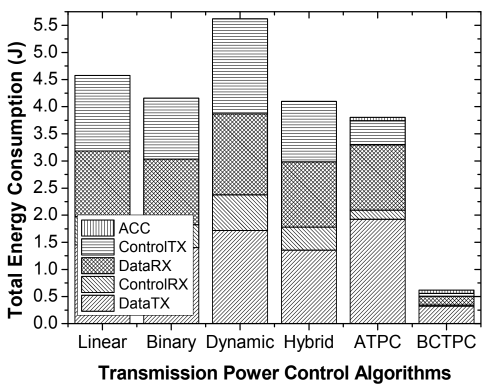


Fig. 10. Total energy consumption on the second scenario.

5. Conclusion

In WSN, sensor devices focus on only one goal, such as environment monitoring, earthquake detection, and so on. However, in WHCS, a sensor is placed around the human body. Thus, the set of sensing data are changing in real time. This environment is very different from the existing WSN environment, so there are more factors to consider. In addition, the batteries of the sensors deployed in the WHCS environment are smaller than those deployed in the WSN environment, and the available resources are also smaller. Therefore, energy saving of sensor devices deployed in a WHCS environment is more important. The TPC algorithm effectively reduces sensor energy consumption in the WHCS environment.

In this paper, we propose a novel TPC algorithm, which considers human conditions, called the BCTPC algorithm. The BCTPC algorithm has two modes: 'keeping' and 'finding.' According to the current body conditions, the BCTPC algorithm changes its mode from keeping to finding or from finding to keeping. The keeping mode increases the lifetime of sensor devices. ET values are directly related to the proper TPL and the energy consumption of sensor devices; thus, in this paper, we determine the optimal ET experimentally.

Moreover, we compare the BCTPC algorithm with other algorithms, such as linear, binary, dynamic, hybrid, and ATPC. Two different scenarios are considered for our experiments: only normal and a normal-active combination. In both of these scenarios, BCTPC showed better performance than other TPCs, indicating a reduced energy consumption by 80% or more. That is, the experimental results prove that the BCTPC algorithm outperforms other TPC algorithms in both scenarios.

The TPC algorithm is an algorithm that occurs when performing communications. Therefore, it is possible to control the amount of communication through the MAC at a low application layer of the sensor device, or to selectively perform communication according to services in the application layer.

In future work, we are planning to adjust the amount of communication through the MAC in a low layer and to propose a cross-layer-based version of the TPC algorithm. In addition, we plan to develop an algorithm that can efficiently analyze TPC by processing the large dataset collected from the WHCS and analyzing the processed data using artificial intelligence. Finally, we plan to create various service models and integrate them into a system platform that can be expressed mathematically.

We also have plans to expand into ICT convergence technology, not only by a sensor network but also by convergence with other humanities and social sciences. If the technology of sensor networks and other fields converge, it will be synergistic and a number of service models are expected. Furthermore, because a sensor network can be easily linked with artificial intelligence technology, we are also considering combining the two technologies in the future.

Acknowledgement

This work was supported by the GRRC program of Gyeonggi Province.

References

[1] D. E. Knuth, *The Art of Computer Programming (Volume 3. Sorting and Searching)*, 3rd ed. Upper Saddle River, NJ: Addison-Wesley, 1998.

[2] T. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein, *Introduction to Algorithms*, 3rd ed. Cambridge, MA: MIT Press, 2009.

[3] M. Quwaider, J. Rao, and S. Biswas, "Body-posture-based dynamic link power control in wearable sensor networks," *IEEE Communications Magazine*, vol. 48, no. 7, pp. 134-142, 2010.

[4] W. S. Lee, M. Choi, and N. Kim, "Experimental link channel characteristics in wireless body sensor systems," in *Proceedings of the International Conference on Information Network 2012*, Bali, Indonesia, 2012, pp. 374-378.

[5] W. Lee, M. Choi, and N. Kim, "Different characteristics of radio modules in wireless body sensor network systems," in *Network and Parallel Computing*. Heidelberg: Springer, 2012, pp. 308-314.

[6] W. Lee, B. D. Lee, and N. Kim, "An accelerometer-assisted power management for wearable sensor systems," *KSII Transactions on Internet & Information Systems*, vol. 9, no. 1, pp. 318-330, 2015.

[7] W. Lee, B. D. Lee, and N. Kim, "Hybrid transmission power control for wireless body sensor systems," *International Journal of Distributed Sensor Networks*, 2014. https://doi.org/10.1155/2014/259181.

[8] W. Lee and N. Kim, "Comparisons of transmission power control algorithms in wireless body sensor systems," *International Journal of Multimedia and Ubiquitous Engineering*, vol. 8, no. 4, pp. 303-311, 2013.

[9] W. Lee, M. Choi, and N. Kim, "Extended dynamic transmission power control algorithm in wireless body sensor network systems," *International Journal of Control and Automation*, vol. 6, no. 6, pp. 339-350, 2013.

[10] N. Kim, J. A. Hong, and B. D. Lee, "Equation-based transmission power control for wearable sensor systems," *IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences*, vol. 98, no. 7, pp. 1558-1561, 2015.

[11] W. Zang and Y. Li, "Motion aware transmission power control scheme in wireless body area network," in *Proceedings of 2015 IEEE Workshop on Signal Processing Systems (SiPS)*, Hangzhou, China, 2015, pp. 1-5.

[12] G. Newell and G. Vejarano, “Human-motion based transmission power control in wireless body area networks,” in *Proceedings of 2016 IEEE 3rd World Forum on Internet of Things (WF-IoT)*, Reston, VA, 2016, pp. 277-282.
[13] A. H. Sodhro, Y. Li, and M. A. Shah, “Energy-efficient adaptive transmission power control for wireless body area networks,” *IET Communications*, vol. 10, no. 1, pp. 81-90, 2016.
[14] W. Zang, S. Zhang, and Y. Li, “An accelerometer-assisted transmission power control solution for energy-efficient communications in WBAN,” *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 12, pp. 3427-3437, 2016.
[15] Y. Zhang and B. Zhang, “A relay-aided transmission power control method in wireless body area networks,” *IEEE Access*, vol. 5, pp. 8408-8418, 2017.
[16] W. Zang and Y. Li, “Gait-cycle-driven transmission power control scheme for a wireless body area network,” *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 3, pp. 697-706, 2017.
[17] Y. Li, L. Kong, F. Wu, Z. Zheng, and G. Chen, “MAPM: movement-based adaptive prediction mechanism for energy conservation in body sensor networks,” in *Proceedings of 2016 IEEE Global Communications Conference (GLOBECOM)*, Washington, DC, 2016, pp. 1-6.
[18] B. Moulton, L. Hanlen, J. Chen, G. Croucher, L. Mahendran, and A. Varis, “Body-area-network transmission power control using variable adaptive feedback periodicity,” in *Proceedings of 2010 Australian Communications Theory Workshop (AusCTW)*, Canberra, Australia, 2010, pp. 139-144.
[19] S. Kim, S. Kim, and D. S. Eom, “RSSI/LQI-based transmission power control for body area networks in healthcare environment,” *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 3, pp. 561-571, 2013.

Woosik Lee https://orcid.org/0000-0003-0065-1682

He received the B.S. degree in Computer Science from the Kyonggi University, Korea, in 2009, and the M.S. and the Ph.D. degrees in Computer Science from Kyonggi University in 2011 and 2016. From 2016 to 2017, he was a research member of Korea Institute of Civil Engineering and Building Technology. From 2017 to 2018, he was an assistant professor at the Department of Computer Science, Kyonggi University, Korea. Since 2018, he has been a research fellow at the Social Security Information Service. His research interests include wireless systems, sensor networks, and energy management protocols.

Namgi Kim https://orcid.org/0000-0002-0077-6576

He received the B.S. degree in Computer Science from Sogang University, Korea, in 1997, and the M.S. and the Ph.D. degrees in Computer Science from KAIST in 2000 and 2005, respectively. From 2005 to 2007, he was a research member of Samsung Electronics. Since 2007, he has been on the faculty of Kyonggi University. His research interests include sensor systems, wireless systems, cloud computing, SDN, and mobile platform.

Byoung-Dai Lee https://orcid.org/0000-0002-4028-6168

He is an assistant professor at the Department of Computer Science, Kyonggi University, Korea. He received his B.S. and M.S. degrees in Computer Science from Yonsei University, Korea in 1996 and 1998, respectively. He received his Ph.D. degree in Computer Science and Engineering from the University of Minnesota, Minneapolis, MN, USA in 2003. Before joining Kyonggi University, he worked at Samsung Electronics Co. Ltd., as a senior engineer from 2003 to 2010. His research interests include cloud computing, mobile multimedia platforms, and mobile multimedia broadcasting.