Journal of Physics: Conference Series

PAPER • OPEN ACCESS

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To cite this article: Haoru Su *et al* 2020 *J. Phys.: Conf. Ser.* **1682** 012048

QTPC: A Q-Learning Transmission Power Control Mechanism for Edge-Cloud Wireless Body Area Networks

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Abstract. Wireless body area networks collect biological signals from human body and sensors connect wirelessly for various nonmedical and medical applications. Energy efficiency is one of the most essential problems in wireless body area networks since the limited battery capacity. In this paper, a Q-learning transmission power control (QTPC) mechanism for edge-cloud wireless body area networks is proposed. Simulation results show that the proposed scheme improves the network performance in the metrics of energy efficiency and system throughput.

1. Introduction

Wireless Body Area Network (WBAN) is a kind of communication network of wearable sensors and actuators, which may be on, inside, or around the human body [1]. Data related of human physiology condition are collected by sensors, such as breath, body temperature, heart-rate, blood pressure, electrocardiogram, electrocardiograph, and electroencephalogram. The activity sensors can be deployed to the knee or ankle to detect the posture of human body, such as sitting, walking, running and lying. The WBAN features enable the application of this emergent network technology in a wide variety areas, such as healthcare, sports, military, assisted living, disaster relief and Augmented Reality (AR) scenarios.

The WBAN collected information can be used for health monitoring and/or actuation, which is called E-Health system. The E-Health system consists of many WBANs, access gateway, and remote cloud servers. Each WBAN services one user. The nodes can gather specific data, such as vital signs, body posture and movements or environment parameters in real time, using wireless communication technologies, and deliver the information to a sink node, known as network coordinator or gateway, responsible to forward the information or to perform long-term and continuous monitoring.

In WBANs, one of the essential challenges is the energy efficiency. The sensor nodes of WBANs is attached to clothes or implanted in human body. The capacity of battery is limited and it's inconvenient to recharge or replace. In energy-restricted networks, transmission power control (TPC) mechanism is one of the most important methods to reduce the energy consumption and prolong the network life. The power control mechanism should balance between the reliable transmission of physiological data and the efficient utilization of energy, so that the transmission power can adapt to the changing link state quickly.

In order to overcome these issues, a number of transmission power control protocols have been developed to improve energy efficiency and reliability in WBAN by adapting the transmission power to the link state in real time [2-7]. In [3], the authors have proposed a relay-aided transmission power control method, attempting to provide reliable transmission and at the same time alleviate the relaying burden on relay nodes. It switches transmission strategy between direct transmission and relay aided transmission. A gait-cycle-driven transmission power control (G-TPC) [4] has been designed by exploiting the periodic channel fluctuation in the walking scenario. An accelerometer acquired the user's gait cycle information, which is used to arrange the transmission power. A transmission power control based on time correlation model (TCM-TPC) is proposed in [5]. This method uses a long-term average channel gain, the last known channel gain, and a time-dependent model to determine the channel conditions.

These studies have proposed a variety WBAN power control mechanisms, which are all based on the node-cloud architecture, without considering the edge-cloud network architecture. In the edge computing network architecture, power control is required for data transmission between sensor nodes and coordinator, coordinator and mobile edge computing (MEC) server. Moreover, the existing works did not discuss the relationship between data transmission link reliability and energy consumption in WBANs. In addition, the power control protocol based on threshold updating cannot meet the real-time requirements of the system due to the rapid change of link state and mobility.

In this paper, we propose a Q-learning transmission power control (QTPC) mechanism for wireless body area networks. The edge-cloud network architecture is adopted to the E-Health system. The energy utility optimizing is modelled. The Q-learning algorithm is used to solve the optimization promblem. Simulation results show that the proposed scheme improves the network performance in the metrics of energy efficiency and system throughput.

2. Q-learning transmission power control mechanism based on edge-cloud architecture

The traditional healthcare monitoring system applying Wireless body area networks (WBANs) is usually designed based on the cloud architecture. The collected data is transmitted from sensor node to the remote cloud server. However, some emergencies need to be responded quickly, such as heart attack. Thus we adopt the edge-cloud network architecture. The mobile edge servers locate near WBANs and users. They can response users' urgent request immediately and send out the nearest ambulance.

In addition, the mobile edge servers can process and fuse the collected data from sensor nodes. The data amount send from the mobile edge server to the cloud server can be significantly reduced. It can release the burden of remote cloud servers. Thus the system's Quality of Service (QoS) and Quality of Experience (QoE) can be improved significantly.

In the edge-cloud network architecture, the sensor nodes detect the physiological data and transmit to the WBAN coordinator. The coordinator transmit the data and task to the mobile edge server. Then mobile edge servers process the task and execute the emergent ones according to its priority. After data fusion, the edge servers send the processed data to the remote cloud server through Internet.

The sensor nodes of WBANs is attached to clothes or implanted in human body. The capacity of battery is limited and it's inconvenient to recharge or replace. Study shows that in WBAN, the data transmission is the main part of energy consumption of sensor nodes. The system energy consumption can be greatly reduced by using the transmission power control mechanism.

We assume the mobile edge server coverage area is consist of many WBANs. It is referred as: $B=\{B_0, B_1, \ldots B_M\}$, in which B_0 stands for the edge server; $B_1, B_2, \ldots B_M$ stand for the WBAN coordinators. U_b is the set of bth WBAN. Specifically, $U_b=\{u_{b,1}, u_{b,2}, \ldots u_{b,Nb}\}$, in which $u_{b,\mu}$ is μth sensor node in bth WBAN. $p_{b,\mu}$ is the transmission power of $u_{b,\mu}$. $p^c{}_{b,\mu}$ is the constant power consumption of $u_{b,\mu}$. $SINR_{b,\mu}$ is the signal interference noise ratio of B_b. $I_{b,\mu}$ is the interference signal. The throughput of the network is $R_{b,\mu}$, which can be calculated by $SINR_{b,\mu}$. $g^b{}_{b,\mu}$ is the channel gain of $u_{b,\mu}$ and B_b. Wn_0 is the power of Gaussian white noise with power spectral density of n_0. The transmission energy efficiency of sensor node is defined as the throughput of unit transmission energy. $\eta_{b,\mu}$ is the energy utility of $u_{b,\mu}$. $P_{b,\mu}$ is the total energy consumption of $u_{b,\mu}$. The energy utility of WBAN b is defined as the sum of the sensor node in this WBAN. The model of the optimizing energy utility is:

$$\begin{gathered}\max_{p_{b,\mu}} \sum_{\mu\in U_b} \frac{W\log_2\left(1+\dfrac{p_{b,\mu}g^b_{b,\mu}}{I_{b,\mu}+Wn_0}\right)}{p_{b,\mu}+P^c_{b,\mu}} \\ \text{s.t. } SINR_{b,\mu} \geq SINR^{\min}_{b,\mu}, \forall b\in B, \forall\mu\in U_b \\ p_{b,\mu} \leq p^{\max}_{b,\mu}, \forall b\in B, \forall\mu\in U_b \end{gathered} \tag{1}$$

in which, $SINR^{min}{}_{b,\mu}$ is the minimum signal interference noise ratio. $p^{max}{}_{b,\mu}$ is the maximum transmission power of $u_{b,\mu}$. These two consist the constraint conditions of the system.

We use Q-learning reinforcement learning algorithm to solve the aforementioned optimization problem. Q-learning is a form of reinforcement learning. In reinforcement learning, system states are mapped to actions that try to either maximize a scalar reward or minimize a cost. It will arrange the transmission power of coordinator and sensor nodes in WBANs. There are three elements in Q-learning, which are action space (A), rewards (R), and status (state space) (S). Figure 1 shows the process of agent interaction with environment.

The action space is all the possible actions that the control entity can perform in a certain state. The reward function is the reward value brought by the execution of action under the entity state *s*. The state space is defined as the set of states that the entity may be in. *Q(s, a)* indicates the function of “state-action” function. The vector of transmission power P_b indicates the sensors’ transmission power allocated by coordinator. The coordinator takes the action $a_b=P_b$. The state of the agent is defined as $s_b=[I_b\ l_b]$, all of which may constitute the coordinator's state space *S*. I_b is the interference vector. l_b is the coefficient vector, which is used to determine the relationship between the I_b and the actual $SINR_{b,\mu}$. The reward function of the coordinator is the transmission energy efficiency. In next step, the transmission power is adjusted according to the reward. The value of Q-function is calculated. The optimal transmission power can be acquired through learning.

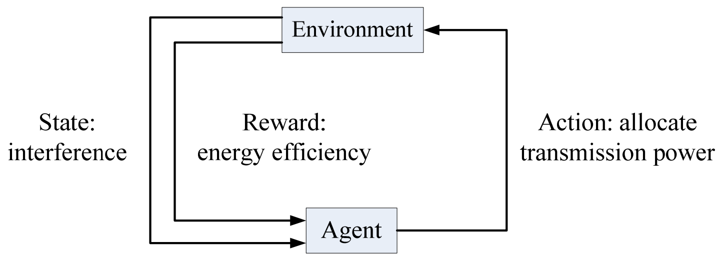

Figure 1. Agent interaction with environment.

3. Performance evaluation

We compare the proposed transmission power control machoism with TCM-TPC [5] in terms of the energy efficiency and throughput. The energy efficiency indicates the average amount of data transmission per Joule. The throughput measures the average amount of data transmitted from body sensor to the coordinator.

Figure 2 displays the simulation results of energy efficiency. The figure shows that the system energy efficiency is considerably reduced by using the proposed power control protocol. Adopting the adge-cloud network architecture and Q-learning reinforcement learning, the system energy can be saved. From figure 3, we can see the system throughput using proposed protocol is higher than TCM-TPC. As it can reduce the data frame collisions, which cause retransmission. Less collision and accompanying shorter latency bring increase of system throughput.

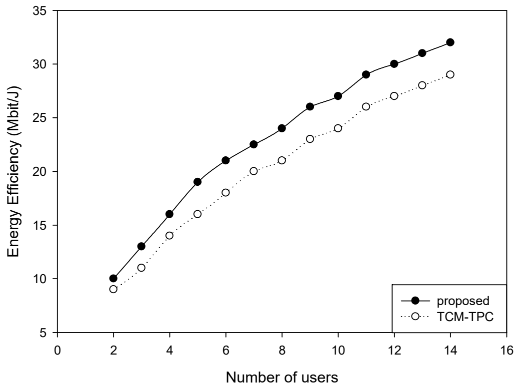

Figure 2. The energy of efficiency varying with number of users.

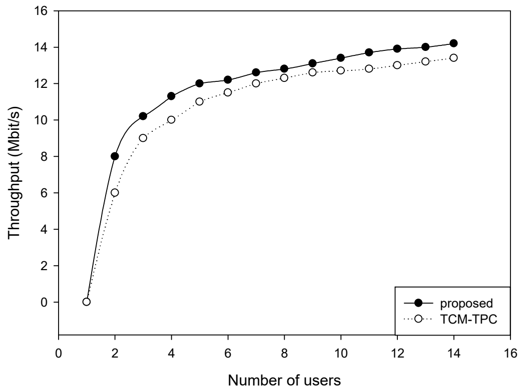

Figure 3. The system throughput varying with number of users.

4. Conclusion
E-Health systems based on wireless body area networks have developed rapidly recently years. Energy efficiency in WBAN is an essential issue because most body sensor nodes have limited battery capacity. Also, there are many other problems, including the rapidly changing link state, the mobility, and the short communication distance. We adopt the edge-cloud network architecture to E-Health systems, and propose a transmission power control algorithm based on reinforcement learning. Simulation results show that it improves the performance in terms of of energy efficiency and throughput.

Acknowledgments
This work was supported by the National Natural Science Foundation of China (Grant No. 61901099), the Fundamental Research Funds for the Central Universities (Grant No. N182303032), Beijing Municipal Natural Science Foundation (Grant No. 4182055), and Beijing University of Technology Project-Research on Key Technologies and Application for National Speed Skating Oval Intelligent Service (Grant No. 40106002201902).

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