A Utility-Based and QoS-Aware Power Control Scheme for Wireless Body Area Networks

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Abstract

Power control is widely used to reduce co-channel interference in wireless networks and guarantee the signal-to-interference plus noise ratio (SINR) of ongoing connections. This technique is also effective for wireless body area networks (WBANs). Although achieving satisfactory SINR is important for WBAN users, they may not be willing to achieve it at arbitrarily high power levels since power is a scarce resource in WBANs. Besides, for WBANs with different purposes, the QoS requirements and concern about the power consumption may be different. This motivates us to formulate the power control problem using the concepts from microeconomics and game theory. In this paper, the QoS objective is viewed as a utility function, which represents the degree of user satisfaction, while the power consumption is viewed as a cost function. The power control problem consequently becomes a non-cooperative multiplayer game, in which each player tries to maximize its net utility, i.e., the utility minus the cost. Within this framework, we investigate the Nash equilibrium existence and uniqueness in the game and derive the best response solution to reach the Nash equilibrium. To obtain the optimal transmission power in a distributed way, we further propose a utility-based and QoS-aware power control algorithm (UQoS-PCA). Tunable cost coefficient in UQoS-PCA enables this scheme to be flexible to satisfy diverse service requirements. Simulation results show the convergence and effectiveness of the proposed scheme as well as improvements over existing algorithm.

Keywords: utility, QoS, power control, game theory, wireless body area network

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1. Introduction

A typical wireless body area network (WBAN) consists of a number of low-power and miniature sensors with wireless communication capabilities, in the vicinity of, or inside, a human body [1][2]. These wireless sensor nodes can monitor the human body functions, both physiological and physical, and characteristics from the surrounding environment. They typically communicate with a body coordinator in a star topology. The envisioned applications of WBANs span from the medical field, e.g., health monitoring, to the entertainment and ambient intelligence areas, e.g., motion control gaming and smart home. The diversity of the envisioned applications raises different quality of service (QoS) requirements in terms of expected performance metrics, as throughput, packet loss rate and delay, therefore flexible QoS-aware solutions are needed.

Like in other wireless networks, WBAN faces the problem of interference. In a dense WBAN environment, each user may carry his/her own WBAN for a specific use. They are likely to be close to each other and will interfere with each other due to using same frequency bands. The inter-WBANs interference will severely degrade the system performance, like throughput degradation and more packet losses, which could also consume the power of body sensor nodes more quickly. Co-channel interference can be mitigated through many ways, e.g., power control [3][4][5], channel allocation [6], cooperative transmission [7] or combination of multiple techniques [8]. In this paper, we mainly focus on using power control to mitigate the interference. Power control has been used to guarantee the signal-to-interference plus noise ratio (SINR) of ongoing connections. Furthermore, distributed power control schemes are of special interest and importance. In practice, although achieving satisfactory SINR is important for WBAN users, they may not be willing to achieve it at arbitrarily high power levels. It is worth noting that the power is a scarce resource in WBANs due to the fact that most sensors are battery-powered. Even if nowadays there are battery-free sensors which can harvest energy from surroundings, the harvested energy is quite limited and cannot support continuous operations [9]. Cutting power consumption not only decreases the interference to other users, but also prolongs the lifetime of WBANs. In addition, for WBANs with different purposes, the QoS requirements and concern about the power consumption may be different. For example, in medical applications, the collected health data are critical and must be delivered to the data center reliably even at the sacrifice of more power consumptions, while for entertainment applications, the loss of data is tolerable but the power consumption is of more concern. Actually, user satisfaction depends on both QoS and power consumption. This observation motivates us to formulate the problem using the concepts from microeconomics and game theory. In multi-user communication systems, game theory has proved a powerful tool for resource allocation [3][4][5][10][11]. Generally, the QoS objective is viewed as a utility function, which represents the degree of user satisfaction; while the power consumption is viewed as a cost function. The distributed power control problem consequently becomes a non-cooperative multiplayer game, in which each user (player) tries to maximize its net utility, i.e., the utility minus the cost. Within this framework, we formulate our problem and propose a utility-based and QoS-aware power control scheme for WBANs.

The main contribution of this paper is summarized as follows:

- We formulate a non-cooperative power control game in order to maximize the net utility. The existence and uniqueness of Nash equilibrium (NE) in such a game are proved and the best response solution to reach the NE is derived.

- In order to obtain the optimal transmission power in a distributed way, we further propose a utility-based and QoS-aware power control algorithm (UQoS-PCA). Tunable cost coefficient is adopted in UQoS-PCA which enables this scheme to be flexible to satisfy diverse service requirements.
- Extensive Simulations are conducted and show effectiveness of the proposed scheme as well as improvements over existing algorithm.

The remainder of the paper is organized as follows. Section 2 gives literature review. Section 3 presents the system model. Section 4 defines the power control game and proves its convergence. A novel utility-based and QoS-aware power control algorithm is proposed in Section 4. Simulations are conducted in Section 5 to evaluate the algorithm performance. Finally, Section 6 concludes the paper.

2. Literature Review

Power control is a widely adopted method to mitigate interference and it has been studied in traditional wireless networks such as wireless local area networks (WLANs) [12], cellular networks [3][13] and wireless sensor networks (WSNs) [14][15], etc. However, WBANs are different from traditional wireless networks in the nature. Firstly, in terms of data stream type, cellular networks mainly deal with multimedia data which requires high throughput and WSNs are mostly applied in event-based monitoring which generates sporadic data, while WBANs carried by different people may generate different types of data which have different QoS requirements. Secondly, power efficiency is not the first concern for WLANs and cellular networks, whereas for WBANs and WSNs, it is indispensable because most sensors are battery-powered. To provide uninterrupted body monitoring service, WBANs need to pay more attention to power efficiency to obtain extended network lifetime. Thirdly, WSNs are usually static once deployed while WBANs are highly mobile and the links are dynamic and vulnerable, thus less information exchange is expected for WBAN protocols. Consequently, traditional power control algorithms designed for WLANs, cellular networks and WSNs cannot be directly applied to WBANs. Specific lightweight power control scheme has to be proposed for WBANs considering both QoS and energy efficiency.

There has been some pioneering work on design of power control schemes for WBANs. In [4], game theory is introduced to maximize the network throughput while minimizing the power consumption. A transmission link at certain time slot within a WBAN is considered as a player and the power levels of the link is the action of the player. Each action has a payoff function which describes the tradeoff between the throughput and the power consumption. Each WBAN in the game maximizes its own payoff function to obtain the best response, e.g., the best transmission power. The work in [5] further improves the game theoretic power control approach by augmenting people's social interaction information. Specifically, each WBAN detects the distances between others before updating its transmission power. With the social interaction information, channel state can be estimated and the transmission power can remain unchanged until the social network topology changes. In [16], a power control scheme based on the Bayesian game is proposed to mitigate the inter-WBAN interference. Different from previous work, the Bayesian game model reflects the diversity of intra-WBAN links and the independency of inter-WBAN links. A distributed algorithm that needs no message passing is proposed to approximate the Bayesian equilibrium. In [17] and [18], the power control problem is modeled as a multi-agent system with self-play, self-interested and single-action learners. A lightweight power controller is proposed using reinforcement learning to control the transmission power while learning from experience to improve system performance. The advantage of this approach is that it does not need any negotiation or cooperation between WBANs. Different from the above work using the SINR to characterize the throughput, [19] presents a power control protocol based on link estimation. It adjusts the transmission power depending on the measured RSSI information. [20] proposes a class of schemes feasible for practical implementation that adapt transmit power in real-time based on link quality feedbacks from the receiver. The major purpose of these protocols is to satisfy the requirement of link reliability and power efficiency. One can refer to literature [21] for more power control schemes for WBANs. All the previous work has made beneficial efforts in solving the power control problem for WBANs. However, the deficiency is that they cannot provide differentiated QoS for different data priorities. In this paper, game theoretic model is also used as in [4][5], but different from previous work, the objective is viewed as a utility function with tunable parameters to characterize different data priorities and different tolerance of power consumption. With this framework, a distributed utility-based and QoS-ware power control algorithm is developed to maximize the net utility and thus the power resource is allocated in the best way to satisfy the QoS requirement of diverse data priorities.

3. System Models

In this section, we present the system models that our power control scheme is to be developed upon. First, we introduce the network model. Then we illustrate the utility function which considers different QoS requirements of WBAN traffic. Finally we present the cost function which is used to measure the power consumption.

3.1 Network model

Consider a scenario where there are m WBANs close to each other. Nearby WBANs will interfere with each other since their transmission ranges may overlap. Within each WBAN, a TDMA based MAC scheme is used to avoid the intra-network collision. Thus at any moment t, there are at most m body sensor nodes transmitting simultaneously. Since our paper mainly focuses on how to mitigate inter-network interference, to simplify the network model, we assume that there is only one sensor node and one coordinator inside each of the m WBANs. In the following, we refer to node i or coordinator i as the sensor node or body coordinator in WBAN i (i=1, 2,…, m). Then the SINR at coordinator i can be expressed as:

$$SINR_i = \frac{G_{ii} p_i}{\sum_{j=1, j\neq i}^{m} G_{ji} p_j + \eta_i}, \tag{1}$$

where p_i and p_j are the transmission powers of node i and node j, respectively, G_{ii} is the channel gain from node i to its own coordinator, G_{ji} is the channel gain from node j to node i's coordinator, η_i is the background noise received at coordinator i.

3.2 Utility Function

In WBANs, various types of traffic can be transmitted. IEEE 802.15.6 standard [22] specifies a total of 8 traffic types with different priorities, as shown in **Table 1**. The traffic defined by IEEE 802.15.6 standard can be roughly classified into three categories, namely best effort traffic (user priority 0~2), QoS traffic (user priority 3~4) and medical traffic (user priority 5~7). It is widely known that different traffic has different preference to bandwidth, packet error rate or delay. Therefore, their utility functions may take various forms, which make the objective function in mixed traffic scenario complex. Thus a unified utility function is needed for all kinds of traffic. Without loss of the generality, we assume the form of the unified utility function is a universal sigmoid function, which has different characteristics with different parameters, expressible as:

$$U_i\left(SINR_i\right)=\frac{1}{1+e^{-\alpha_i\left(SINR_i-\beta_i\right)}}, i=1,2,\ldots,m, \quad (2)$$

where α_i and β_i are two tunable parameters determined by specific traffic type. In **Fig. 1**, we illustrate the utility functions for different values of α_i and β_i. The parameter β_i is the inflexion of the utility function, which represents the amount of resource requirement of users. When the resource allocated to user i is smaller than β_i, the utility function is concave, which represents that the user requires the resource of β_i strongly. While the resource allocated to users is larger than β_i, the utility function is convex, which represents that the user requires the resource of β_i not so strongly. The parameter α_i is used to adjust the slope of the utility curve around β_i. It reflects the demand degree of the user for the resource requirement β_i. The larger α_i is, the higher the slope of the utility curve around β_i is, so that the user demands the resource β_i more strongly, or on the contrary, the demand is weaker. The three utility functions illustrated in **Fig. 1** can represent the three categories of traffic mentioned above. Specifically, for WBAN i with the best effort traffic, the requirement for bandwidth is not so high while the packet loss is tolerable, so both α_i and β_i can take relatively small values. For WBAN i with the QoS traffic, the requirement for bandwidth is high while the packet loss is tolerable, so α_i can take a relatively small value while β_i should take a relatively large value. For WBAN i with the medical traffic, the requirement for bandwidth is not so high while the packet loss is intolerable, so α_i should take a relatively large value while β_i can take a relatively small value.

Table 1. Priorities of different traffic types defined by IEEE 802.15.6 standard

Priority	User priority	Traffic designation
Lowest	0	Background
↓	1	Best effort
	2	Excellent effort
	3	Video
	4	Voice
	5	Medical data or network control
	6	High-priority medical data or network control
Highest	7	Emergency or medical implant event report

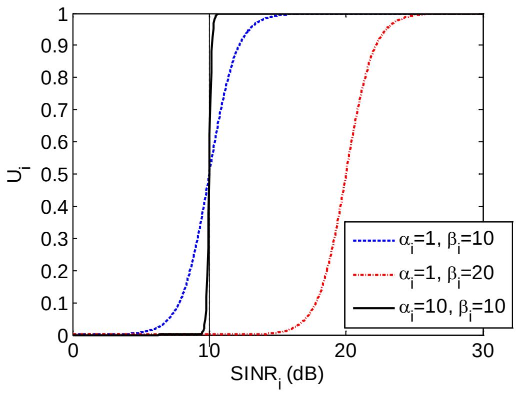


Fig. 1. Sigmoid utility function versus SINR with different values of α_i and β_i for WBAN i.

3.3 Cost Function

As aforementioned, power is itself a valuable commodity. WBAN users may not be willing to achieve satisfying performances at arbitrarily high power levels. Therefore, a cost function should be introduced to reflect the expenses of power consumption. We introduce a cost function C_i to measure the power consumption of node i with transmission power p_i. Actually, the cost function $C_i(p_i)$ can be any function of p_i, provided two requirements are satisfied: $C_i(0)=0$ and $C_i(p_i)$ increases in power p_i. Here we use a linear function, which has been widely adopted in the literature [3][5], to describe the relationship between C_i and p_i, i.e.:

$$C_i(p_i) = k_i p_i , \tag{3}$$

where k_i is the cost coefficient of node i. k_i can be either a constant or a function of other factors. Different forms of the cost coefficient are discussed in Section 4.2.

4. Problem Formulation

In this section, we formulate the utility-based and QoS-aware power control problem as a non-cooperative m-person game and prove its convergence.

4.1 Problem Formulation

In the multi-WBANs coexistence game, each WBAN makes an independent decision on the transmission power of the next packet. Therefore, we define a power control game $G=\{M, P, NU\}$ in Definition 1.

Definition 1 ***(Power Control Game)*** *A power control game $G=\{M, P, NU\}$ is defined as follows:*

- *$M=\{1, 2, \ldots, m\}$ is a finite set of players, indexed by i;*
- *P represents the global strategy space, which is the Cartesian product of all players' strategy space, i.e., $P=P_1 \times P_2 \times \ldots \times P_m$. The strategy set of any player i, P_i, is a finite set of discrete transmission powers in the range of $\left[p_i^{\min}, p_i^{\max} \right]$, where $p_i^{\min}$ and $p_i^{\max}$ are the minimum and maximum transmission powers of node i, respectively. The action of player i at any time slot t is denoted as $p_i(t) \in P_i$;*
- *Given the utility function U_i representing the traffic QoS requirement and the cost function C_i representing the cost incurred, the net utility NU_i is defined as:*

$$NU_i(p_i) = U_i(SINR_i(p_i)) - C_i(p_i) , \tag{4}$$

where the expressions of U_i $(SINR_i$ $(p_i$ $))$ and $C_i(p_i$ $)$ are defined by (2) and (3), respectively.

At the end of each time slot, players update their transmission power levels to maximize the outcome from applying the net utility based on the latest transmission power and the current SINR:

$$p_i(t+1) = \arg\max \ NU_i(P_i) , \tag{5}$$

where $P_i = \left\{ p_i \mid p_i \in \left[p_i^{\min}, p_i^{\max} \right] \right\}, \forall i \in M$.

4.2 Existence and Uniqueness of Nash Equilibrium

A necessary condition for the power control game in Definition 1 to converge is that a unique NE exists. In the following, we first prove the existence and uniqueness of the NE and then provide a best response approach to calculate the transmission power and reach the NE.

Theorem 1 *There exists a NE for the power control game G={M, P, NU} in Definition 1 if* $\forall i \in M$, $p_i > \frac{R_i \beta_i}{G_{ii}}$, *where* $R_i = \sum_{j \neq i} G_{ji} P_j + \eta_i$.

Proof: On one hand, since the strategy set of any player *i* is defined on $\left[p_i^{\min}, p_i^{\max}\right]$, the global strategy space *P* is a nonempty, convex and compact subspace of Euclidean space R^n. On the other hand, the net utility function NU_i is continuous in the domain $\left[p_i^{\min}, p_i^{\max}\right]$, we take the derivative of NU_i in (4) and get:

$$\begin{aligned}\frac{\partial NU_i(p_i)}{\partial p_i} &= \frac{\partial\left(U_i(SINR_i) - C_i(p_i)\right)}{\partial P_i} \\ &= U_i'(SINR_i) \cdot \frac{\partial SINR_i(p_i)}{\partial P_i} - C_i'(p_i) \\ &= U_i'(SINR_i) \cdot \frac{G_{ii}}{R_i} - C_i'(p_i)\end{aligned} \quad , \tag{6}$$

where U_i' and C_i' are the derivatives of U_i and C_i, respectively. According to the sigmoid utility function and cost function defined in (2) and (3), we obtain:

$$U_i'(SINR_i) = \alpha_i \cdot \left(\frac{1}{4} - \left(\frac{1}{1+e^{-\alpha_i(SINR_i - \beta_i)}} - \frac{1}{2}\right)^2\right) , \tag{7}$$

$$C_i'(P_i) = k_i . \tag{8}$$

Combining (2), (7) and (8), (6) is rewritten as:

$$\frac{\partial NU_i(p_i)}{\partial p_i} = \frac{\alpha_i \cdot G_{ii}}{R_i} \cdot \left(\frac{1}{4} - \left(U_i(SINR_i) - \frac{1}{2}\right)^2\right) - k_i . \tag{9}$$

Taking second derivatives gives:

$$\begin{aligned}\frac{\partial^2 NU_i(p_i)}{\partial^2 p_i} &= \frac{\alpha_i \cdot G_{ii}^2}{R_i^2} \cdot U_i'(SINR_i)\left(1 - 2U_i(SINR_i)\right) \\ &= \frac{\alpha_i^2 \cdot G_{ii}^2}{R_i^2} \cdot U_i(SINR_i)\left(1 - U_i(SINR_i)\right)\left(1 - 2U_i(SINR_i)\right)\end{aligned} . \tag{10}$$

Based on (1) and (2), we get that:

$$U_i(SINR_i) = \frac{1}{1+e^{-\alpha_i\left(\frac{G_{ii} p_i}{R_i} - \beta_i\right)}} . \tag{11}$$

Since $p_i \in \left[p_i^{\min}, p_i^{\max}\right]$ and $p_i > \frac{R_i \beta_i}{G_{ii}}$, it is straightforward that $\frac{1}{2} < U_i(SINR_i) < 1$. Then we have $\frac{\partial^2 NU_i(p_i)}{\partial^2 p_i} < 0$, which means that NU_i is strictly concave in p_i. As a result according to Theorem 4.4 in [23], we can conclude that at least one NE exists in the game if and only if $\forall i \in M$, $p_i > \frac{R_i \beta_i}{G_{ii}}$.

Theorem 2 *The NE for the power control game G={M, P, NU} in Definition 1 is unique.*

Proof: First, if $p_i^* \in \left[p_i^{\min}, p_i^{\max} \right]$ is a local optimum for problem (5), according to Theorem 1, $p_i^* > \frac{R_i \beta_i}{G_{ii}}$ and it is required that:

$$\left.\frac{\partial NU_i(p_i)}{\partial p_i}\right|_{p_i = p_i^*} = \frac{\alpha_i \cdot G_{ii}}{R_i} \cdot \left(\frac{1}{4} - \left(U_i\left(SINR_i(p_i^*) \right) - \frac{1}{2} \right)^2 \right) - k_i = 0 . \tag{12}$$

It can be easily shown that for all $p_i \in \left[p_i^{\min}, p_i^* \right]$, $\frac{\partial NU_i(p_i)}{\partial p_i} > 0$ and in that case NU_i (p_i) is strictly increasing; similarly, for all $p_i \in \left[p_i^*, p_i^{\max} \right]$, $\frac{\partial NU_i(p_i)}{\partial p_i} < 0$ and NU_i (p_i) is strictly decreasing. If the maximum of (5) occurs at the boundary, i.e., $p_i^* = p_i^{\min}$ or $p_i^* = p_i^{\max}$, NU_i (p_i) is still strictly increasing or decreasing in p_i, Hence the net utility function NU_i is concave on p_i. According to Theorem 4.1 in [23], the NE for the game is unique.

Finding the best response to reach the NE requires finding the solution to Eq. (12). By solving Eq. (12), we obtain:

$$p_i^* = \frac{R_i \beta_i}{G_{ii}} - \frac{R_i}{G_{ii} \alpha_i} \ln \left(\frac{\alpha_i G_{ii}}{2 k_i R_i} - 1 - \sqrt{\left(\frac{\alpha_i G_{ii}}{2 k_i R_i} - 1 \right)^2 - 1} \right) . \tag{13}$$

Note that this result is based on the condition $p_i > \frac{R_i}{G_{ii}} \beta_i$. However, the actual value of p_i can be any nonnegative number which does not always satisfy the above condition. In fact, in some cases p_i=0 achieves the optimum, though it corresponds to zero NU_i. Thus the optimal power p_i^{opt} is either p_i^* or 0. To illustrate the point, we plot both the utility and the cost versus SINR in **Fig. 2**. Because $C_i = k_i p_i = k_i (R_i/G_{ii}) SINR_i$, the slope of the cost line in **Fig. 2** is $k_i(R_i/G_{ii})$. With the changing of the slope, the postion of C_i relative to U_i is different. The optimal p_i is achieved when $U_i'(SINR_i) = k_i(R_i/G_{ii})$. Thus the lower bound and upper bound of the slope of the C_i line should have been the minimum and maximum derivatives of the utility function. However, considering the fact that $R_i \geqslant \eta_i$, the lower bound of the slope of the C_i line should be $k_i(\eta_i/G_{ii})$ instead of 0, as illustrated by line 1 in **Fig. 2**. This nonzero lower bound can prevent infinite SINR in power control. As the slope is getting larger, the C_i line has two nonzero intersections with the U_i line, as shown by line 2. As the slope further increases, the two intersections come closer, and eventually meet on line 3. If the slope continues to increase until it equals to the maximum derivative of the utility function, the C_i line reaches line 4. As shown in **Fig. 2**, if the C_i line (e.g., line 2) lies between line 1 and line 3, there will be some positive net utility corresponding to p_i^*, i.e. $p_i^{opt} = p_i^*$. If the C_i line reaches line 3, the maximum net utility is 0, which is achieved at power levels p_i^* and 0. If the C_i line (e.g., line 4) is beyond line 3, the best choice is to let $p_i^{opt} = 0$, because all other power levels will result in negative net utility.

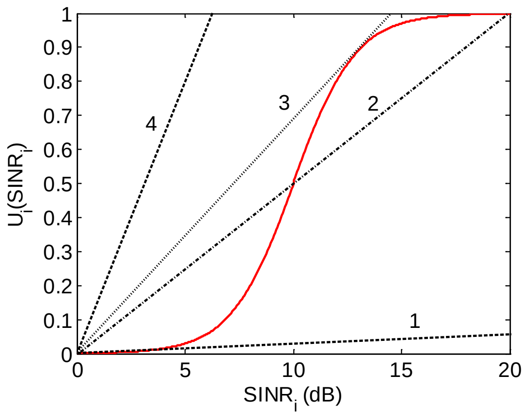


Fig. 2. Sigmoid utility function and different cost functions versus SINR for node *i*.

In summary, for the optimal power of node *i*, we obtain the following result:

Proposition 1 *The NE for the power control game G={M, P, NU} in Definition 1 is the strategy profile* $\left\{p_i^{opt}\right\}_{i\in M}$, *where* p_i^{opt} *is the best response of player i and is given by:*

$$p_i^{opt} = \begin{cases} \max\left(p_i^{\min}, \min\left(p_i^*, p_i^{\max}\right)\right), & p_i^* > \dfrac{R_i\beta_i}{G_{ii}} \\ 0, & p_i^* \le \dfrac{R_i\beta_i}{G_{ii}} \end{cases}. \tag{14}$$

5. Power Control Algorithm

In this section, we propose a distributed utility-based and QoS-aware power control algorithm optimizing the net utility, which is called UQoS-PCA for short.

5.1 Basic Algorithm

We have proved the existence and uniqueness of a NE in the power control game in Definition 1. If each player in the game uses the optimal transmission power, the system can reach a point that balances the overall system utility and power consumption. However, the optimal transmission power of each player cannot be obtained in one step because the change of the transmission power of one player leads to the variation in other players' SINR. In our proposed UQoS-PCA, each player has an initial transmission power and the players update their transmission powers at each turn by (14). When the transmission powers of all the players do not change or the maximum number of iterations is reached, the algorithm terminates and outputs the transmission powers for all the players. The details of the algorithm are shown in Algorithm 1.

Algorithm 1: UQoS-PCA

Input: Each player $i \in M$ is initialized with a random transmission power $p_i \in \left[p_i^{\min}, p_i^{\max} \right]$ and respective cost coefficient k_i>0;

Output: Optimal transmission powers for all players in the game, i.e., $P_i^{opt} = \left\{ p_i^{opt} \mid p_i^{opt} \in \left[p_i^{\min}, p_i^{\max} \right] \right\}, \forall i \in M$

1: At each turn, player i updates its transmission power according to (14), $\forall i \in M$;

2: if all p_i do not change in the last 5 continuous turns or the maximum number of iterations is reached

3: output P_i^{opt} ;

4: else goto step 1;

5: end if

This algorithm is implemented in the body coordinator, which is supposed to be more powerful devices compared with the body sensors. Each time the sensor node transmits the sensing data to the body coordinator, it piggybacks its transmission power value in the packet. The coordinator measures current SINR and calculates optimal transmission power for the sensor node to use in the next time slot. This optimal transmission power value is piggybacked in the acknowledgement packet back to the sensor node. Therefore, this algorithm incurs very little overhead.

5.2 Cost Coefficient Setting Discussion

(1) *Coefficient setting adaptive to the transmission environment*: When the transmission environment is favorable, the cost coefficient should better be assigned a small value, allowing the users to enjoy good QoS. On the other hand, if the transmission environment is hostile, the cost coefficient should better be assigned a large value to improve the system robustness. Actually, if the cost coefficient is not large enough under heavy traffic load condition or not small enough under light traffic load condition, a user may suffer from oscillation, i.e., being turned off and turned on repeatedly. Therefore, it is desirable that the cost coefficient takes a value adaptive to the transmission environment. A simple measure of the transmission environment by user i is R_i/G_{ii}. So k_i can take the form as:

$$k_i = kR_i / G_{ii}, \tag{15}$$

where k is a constant which can be assigned by the system.

(2) *Coefficient setting adaptive to the energy allowance*: For nodes with less residual energy, the cost of increasing the transmission power should be larger than those with more residual energy. Thus, it is desirable that the cost coefficient takes a value adaptive to the energy allowance. A simple measure of the energy allowance of user i is E_i^{ini} / E_i^{res}, where E_i^{res} and E_i^{ini} are the residual energy and initial energy of node i. So k_i can take the form as:

$$k_i = kE_i^{ini} / E_i^{res}, \tag{16}$$

(3) *Combined coefficient setting*: To achieve adaptiveness to both transmission environment and energy allowance, we only have to combine (15) and (16) to get the following setting:

$$k_i = kR_iE_i^{ini} / G_{ii}E_i^{res} . \tag{17}$$

6. Simulation Results

In this section, we evaluate the performance of the proposed UQoS-PCA with different cost coefficient settings. We also implement the power control game algorithm (PCGA) proposed in [5] for comparison.

6.1 Simulation Environment

We setup the simulation in a 5m×5m square area, where 6 WBANs are generated. For each WBAN, one body sensor node is either attached on or implanted inside the human body and it directly communicates with its body coordinator on the body surface. The location of the body coordinators are shown in **Fig. 3**. The distances between the sensor nodes and their own coordinators are listed in **Table 1**. For simplicity, we assume the distances between one sensor node and other coordinators are the distances between corresponding two coordinators. Channel gains are calculated based on the channel model specified in the standard draft of WBAN channel models [24]. A typical path loss model is:

$$PL(d_{ji})[dB] = P_0[dB] + 10n\log_{10}(d_{ji}/d_0) + N\,, \tag{18}$$

where d_{ji} is the distance between node j and node i's coordinator, P_0 is the path loss at the reference distance d_0, n is the path loss exponent, N is a normally distributed variable with standard deviation σ_N. According to the CM3 (the channel model based on measurements that cover frequencies of 950-956 MHz) defined in [24], P_0=-23.5dB, d_0=1mm, n=2.88, σ_N=11.7. The channel gain from node j to node i's coordinator is easily obtained as:

$$G_{ji} = 10^{-\frac{PL(d_{ji})[dB]}{10}}\,. \tag{19}$$

We assume that different types of traffic are transmitted in each WBAN, which are characterized by different sigmoid utility functions. Respective parameters are listed in **Table 2**. Judging from the settings of the parameters α and β, we assume that WBAN 1 and 2 carry medical traffic, and WBAN 3 and 4 carry multimedia traffic, while WBAN 5 and 6 carry best effort traffic. The range of the transmission power is $[0, 10^{-3}]$ W. The number of iterations is set to 20 in all the simulations. The purpose of the simulations is to show the performance of the proposed algorithm under different parameters and different cost coefficient settings. The comparison with existing algorithm is also conducted to show the superiority of the proposed algorithm in terms of QoS and power efficiency.

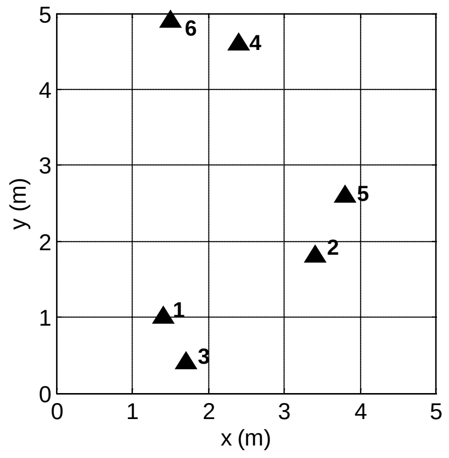


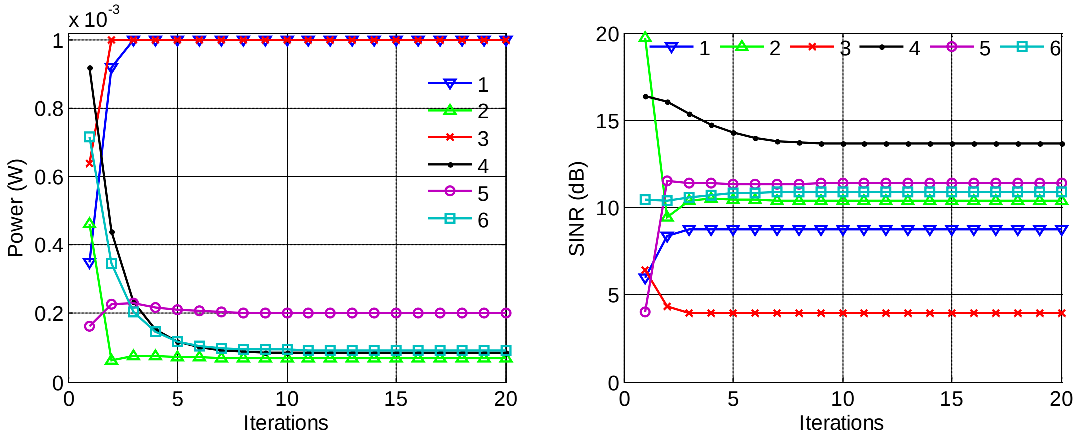
Fig. 3. A network of 6 WBANs.

Table 2. Parameter settings of the 6 WBANs.

WBAN No.	1	2	3	4	5	6
$d_{i,i}$ (m)	0.35	0.25	0.5	0.3	0.45	0.4
α	1.35	1.45	0.66	0.76	0.9	1.05
β (dB)	7	6	12	13	9	8

6.2 Simulation Results

We first implement UQoS-PCA with fixed cost coefficient k=10 for all WBANs. **Fig. 4** plots the evolution of the power and SINR for all WBANs. We observe from the figure that the power and SINR converge very quickly in a few iterations though starting with random initialization. As the cost coefficient is set to a small value, the weight of the power consumption is smaller than that of the utility. Consequently, the power levels of the WBANs can be relatively high. Taking the pair WBAN 1 and WBAN 3 for example, they both reach the maximum transmission power. But WBAN 3 cannot meet the SINR target of 12dB. Nevertheless, WBAN 1 will not reduce its transmission power to mitigate the interference to WBAN 3 because it carries medical traffic and its performance requirement is more rigid than WBAN 3. For WBAN 2 and 5, the target SINR of WBAN 5 is larger than that of WBAN 2 and the sensor in WBAN 5 is farer to its coordinator, so WBAN 5 adopts a higher transmission power. They both meet their respective target SINRs. WBAN 4 and 6 also reach their respective target SINRs of 13dB and 8dB.

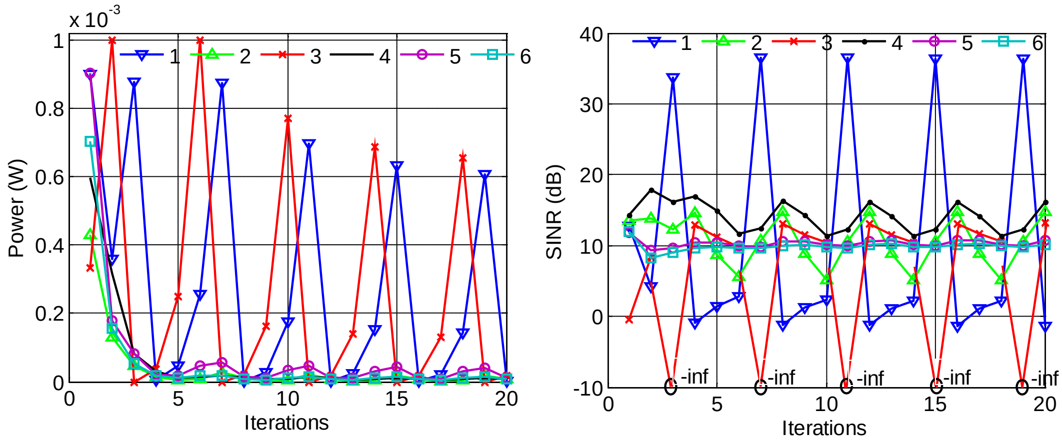


(a) Evolution of the power (b) Evolution of SINR

Fig. 4. Evolution of the power and SINR using UQoS-PCA with fixed cost coefficient k=10.

In the second simulation, we increase the cost coefficient to 1000 for all WBANs. The results are shown in **Fig. 5.** As the cost coefficient is set to a large value, the weight of the power consumption is greater than that of the utility, which discourage the WBANs to use a high transmission power. As pointed out in Theorem 1, only if $\forall i \in M$, $p_i > \dfrac{R_i \beta_i}{G_{ii}}$, there exists a NE for the power control game. Obviously, this condition cannot be satisfied under current scenario. Therefore, the NE cannot be reached. We can see from **Fig. 5** that the transmission powers of WBAN 2, 4, 5, 6 are all set to very low values and their respective

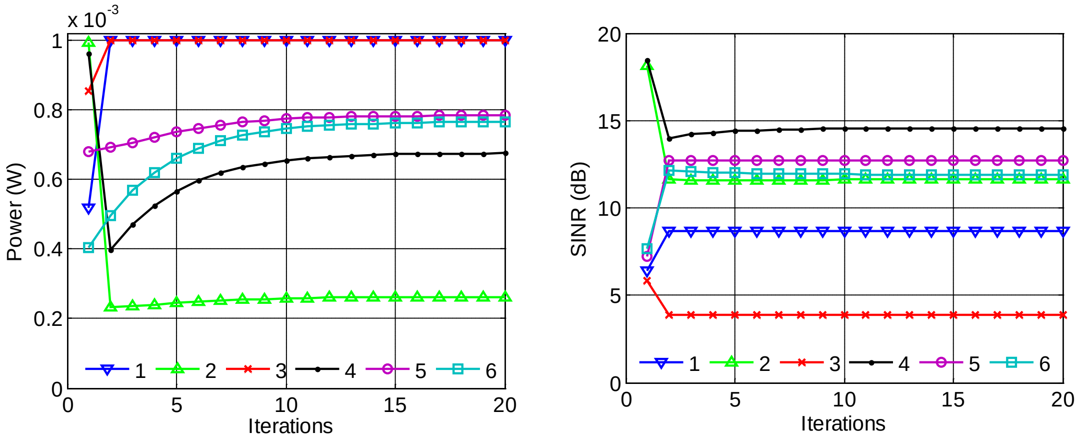
SINR performances are unstable. On the other hand, WBAN 3 is frequently set to a high transmission power and turned off, and WBAN 1 also suffers from severe oscillation. To avoid this problem, we will adopt adaptive cost coefficient in the following simulation.



(a) Evolution of the power (b) Evolution of SINR

Fig. 5. Evolution of the power and SINR using UQoS-PCA with fixed cost coefficient k=1000.

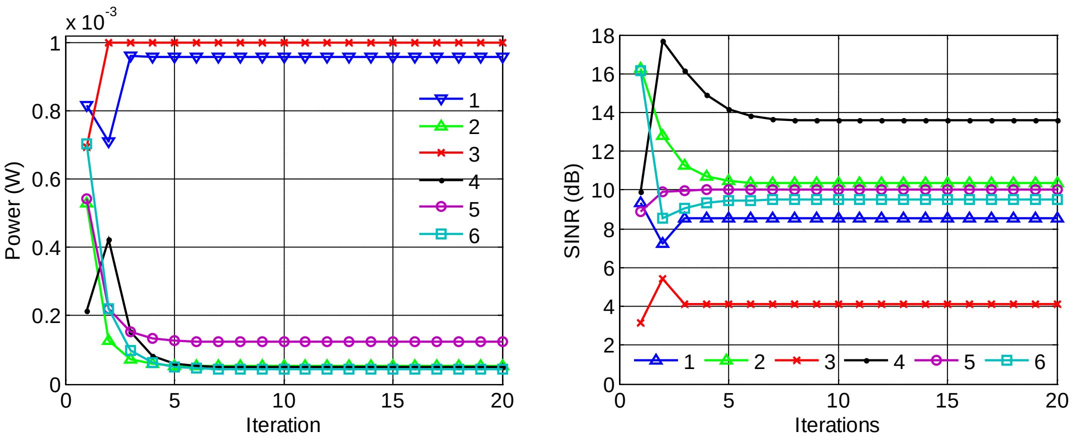
In the third simulation, we use an adaptive cost coefficient given by (15), where k is set to 1000 for all WBANs. As shown in **Fig. 6**, the power and SINR converge very quickly in a few iterations for all WBANs and the transmission powers of all the WBANs are set to relatively high values. Even though k is assigned a large value, as the transmission environment is favorable, the value of R_i/G_{ii} will be small, which can adjust the final cost coefficient k_i. Thus, this scheme achieves transmission environment adaptiveness.



(a) Evolution of the power (b) Evolution of SINR

Fig. 6. Evolution of the power and SINR using UQoS-PCA with adaptive cost coefficient by (15), k=1000.

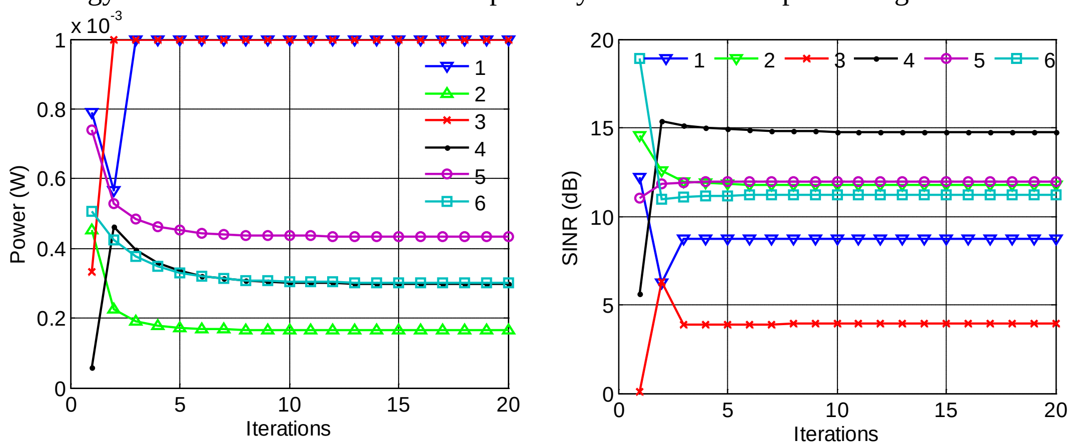
In the fourth simulation, we use an adaptive cost coefficient given by (16), where k is set to 10 for all WBANs and the values of E_i^{ini} / E_i^{res} for the 6 WBANs are set to 50, 1.5, 5, 2, 30 and 50, respectively. The results are shown in **Fig. 7**. As pointed out in the previous section, the cost of increasing the transmission power should be larger for nodes with less residual energy than those with more residual energy. Taking the pair WBAN 1 and WBAN 3 for example, the residual energy of WBAN 1 is much less than that of WBAN 3, so WBAN 1 adopts a smaller transmission power. However, the residual energy of WBAN 5 is much less than that of WBAN 2, but WBAN 5 still adopts a higher transmission power. This is because the target SINR of WBAN 5 is larger than that of WBAN 2. Thus, WBAN 5 has to sacrifice energy for guaranteed performance.



(a) Evolution of the power (b) Evolution of SINR

Fig. 7. Evolution of the power and SINR using UQoS-PCA with adaptive cost coefficient by (16), k=10.

In the fifth simulation, we use combined cost coefficient given by (17), where k is set to 1000 for all WBANs and the settings of E_i^{ini} / E_i^{res} are the same as in the fourth simulation. **Fig. 8** shows the results. This scheme achieves adaptiveness to both the transmission environment and energy allowance. We will show its superiority in the final comparison figures.



(a) Evolution of the power (b) Evolution of SINR

Fig. 8. Evolution of the power and SINR using UQoS-PCA with adaptive cost coefficient by (17), k=1000.

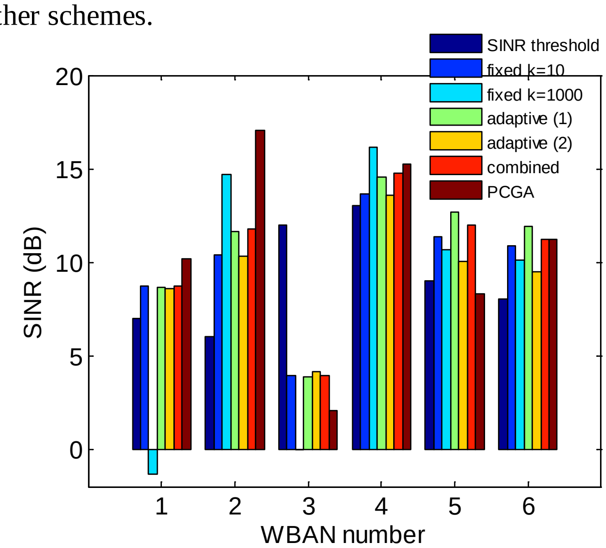
Finally, in **Fig. 9** we compare the SINR performance, the system utility and the power consumption of different power control schemes, i.e., our proposed UQoS-PCA with different cost coefficient settings and PCGA proposed in [5]. Different from the sigmoid utility function adopted in our proposed UQoS-PCA, the utility function in PCGA is defined as $U_i(SINR_i)=\log(SINR_i)$, which characterizes the maximum achievable data rate given by Shannon channel capacity formula. Then the system utility defined in PCGA is:

$$SU_{PCGA}=\sum_{i=1}^{m}\log(SINR_i)\,, \tag{20}$$

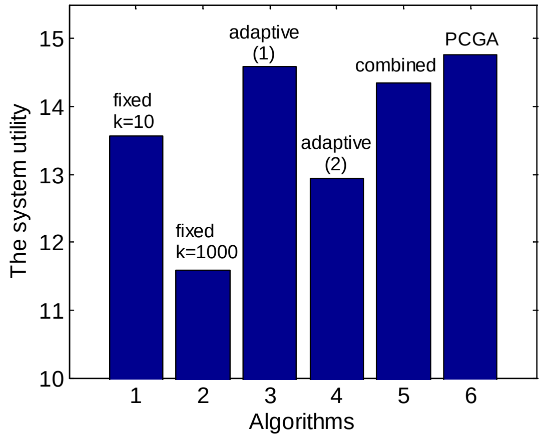
while the system utility defined in our proposed UQoS-PCA is:

$$SU_{UQoS-PCA}=\sum_{i=1}^{m}\frac{1}{1+e^{-\alpha_i(SINR_i-\beta_i)}}\,. \tag{21}$$

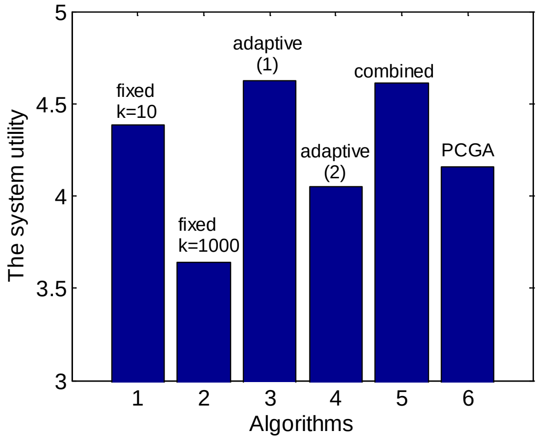
In the following simulation, we measure the system utility according to the above two definitions for all the schemes. In **Fig. 9(a)**, there are in total 6 groups of bars, where the *i*th group corresponds to the *i*th WBAN. In each group, the first bar represents the SINR threshold, i.e., the minimum SINR required. The remaining bars represent the SINR performances of UQoS-PCA with fixed k=10, with fixed k=1000, with cost coefficient adaptive to the transmission environment, with cost coefficient adaptive to the energy allowance, with combined cost coefficient and PCGA, respectively. The empty bar in the third group is due to the turned-off of the transmission power. In **Fig. 9(b)** and **Fig. 9(c)**, the 6 bars represent the achieved system utility computed by Eq. (20) and (21), respectively. In **Fig. 9(d)**, the 6 bars represent the total power consumption of the six different power control schemes. From **Fig. 9(b)**, we observe that PCGA achieves the largest system utility. This is because in PCGA, the objective is to maximize the system utility defined by Eq. (20), which indicates the data rate. PCGA only tries to maximize the data rate while minimizing the power but does not consider diverse QoS requirements of different WBANs. Therefore, based on the system utility defined by Eq. (21), PCGA cannot achieve a satifying performance, as shown in **Fig. 9(b)**, while our proposed UQoS-PCA with cost coefficient adaptive to the transmission environment and with combined cost coefficient achieve almost equally best performance. Since UQoS-PCA with combined cost coefficient considers both transmission environment and energy allowance, the power consumption is much less than that of the UQoS-PCA with cost coefficient only adaptive to the transmission environment, as shown in **Fig. 9(d)**. In summary, we reach the conclusion that UQoS-PCA with combined cost coefficient not only guarantees QoS to most WBANs, but also reaches better tradeoff between the SINR performance and the power consumption than other schemes.



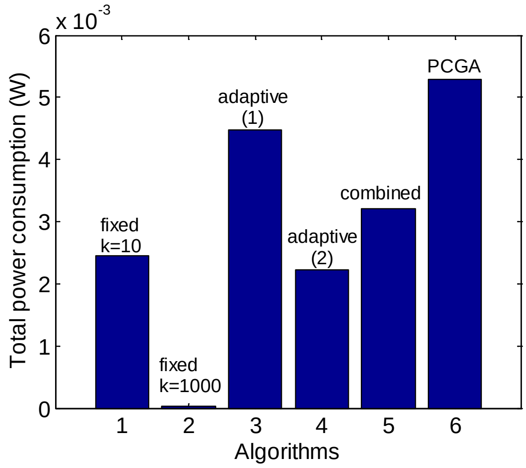
(a) Achieved SINR



(b) Achieved system utility defined by Eq. (20)



(c) Achieved system utility defined by Eq. (21)



(d) Total power consumption

Fig. 9. Comparison of the achieved SINR, the system utility and power consumption under different power control schemes.

7. Conclusion

In this paper, we study the power control problem in WBAN to reduce co-channel interference and guarantee SINR performance. To satisfy diverse QoS requirements of WBAN users, we propose to view the QoS objective as a utility function, which represents the degree of user satisfaction, while the power consumption as a cost function and then formulate the power control problem as a non-cooperative multiplayer game, in which each player tries to maximize its net utility, i.e., the utility minus the cost. The existence and uniqueness of NE in such a game are proved and the best response solution to reach the NE is derived. In order to obtain the optimal transmission power in a distributed way, we further propose a utility-based and QoS-aware power control algorithm UQoS-PCA. Tunable cost coefficient is adopted in UQoS-PCA which enables this scheme to be flexible to satisfy diverse service requirements. Simulation results show that UQoS-PCA with combined cost coefficient reaches best tradeoff between the SINR performance and the power consumption and also outperforms existing algorithm PCGA.

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