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The QoE Driven Transmission Optimization Based on Cognitive Air Interface Match for Self-Organized Wireless Body Area Network

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ABSTRACT This paper studied the optimization of air interface (AI) allocation in self-organized wireless body area network (WBAN), for the quality of experience (QoE) of wireless data transmission between patients' body base station and the medical surveillance network (MSN). To improve the spectrum efficiency, the partial overlapping channel (POC) is adopted for the cognitive AI, which could adjust its wireless channel according to the environment. In the same time, the heterogeneous QoE of patients is also taken into consideration to optimize the network. A two-layer game model and the corresponding learning algorithm have been proposed for the AIs' channel choosing and body base stations' AI choosing in a distributed way, to realize the optimized and stable match between AI and patient's transmission demand. The theoretic analysis for the equilibrium of the game and the convergence of the proposed algorithm is carried out. Simulation experiment results shows that the proposed two-layer game model and learning algorithm could effectively improve the QoE of WBAN, along with the fairness.

INDEX TERMS Medical surveillance network, wireless body area network, quality of experience, partial overlapping channel, spectrum efficiency, game theory.

I. INTRODUCTION

Nowadays, the researches and applications on internet of things (IoT) are drawing much attention [1]. As an important part of the IoT on the health care, the medical surveillance network (MSN) and the wireless body area network (WBAN) is currently one of the important research hotspots [2]–[8]. It can be applied to real-time monitoring and family health care in hospitals and has wide application prospects and huge market potential.

Wireless body area network is a communication system that is placed on people's body for healthy monitoring and obtaining human health signals, as shown in Figure 1. The WBAN would be constituted by some micro sensors which can be moved. The sensors in WBAN almost could communicate with others, especially with the body station. Some typical early applies are mainly to successive monitor and data obtaining of chronic diseases and the health data of people, in order to present an approach of automatic control therapy. With the maturity and development of technology, the wireless body area network in the future can also be widely applied to consumer electronics, entertainment, sports, environmental intelligence, animal husbandry, ubiquitous computing, military or safety and other fields.

With the WBAN, the information exchange between the personal sensing system and the MSN should be guaranteed. The monitors need to upload their monitoring data to the MSN timely through the patients' base station, which would be call as the WBAN body user in the MSN in this paper (Figure 2). To reduce the energy consumption of the body user and improve the throughput, the air interfaces (AIs) are

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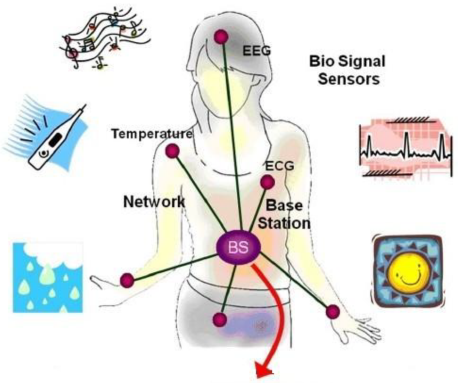

FIGURE 1. The illustration of wireless body area network.

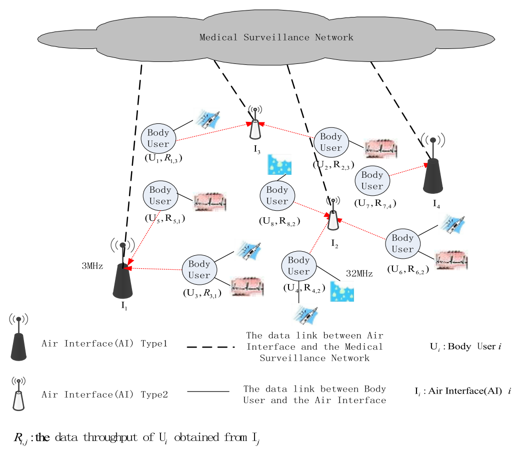

FIGURE 2. The air interface based data exchange between heterogeneous body users and medical surveillance network.

usually provided to relay the data transmission between the body user and MSN.

To our best knowledge on the related existing works, there are two issues should be studied further in depth. The one is that the spectrum utility of AIs is not so efficient by using traditional orthogonal channel, the other one is that the heterogeneous QoE demands of different patients have not been taken into consideration seriously in the AI allocation.

With the first issue, the use of POC has been adopted in some researches for wireless networks. In order to improve the spectrum efficiency, authors in [9] proposed a partial overlapping channel to further improve the spectrum efficiency. The main feature of partial overlapping channels was that the band division between each channel is no longer completely separated, but can be partially overlapping. Traditionally, this division has led to the non-orthogonal nature of the channel and complicated the system interference. However, its advantage is also obvious that the spectrum efficiency would be relatively high. In reference [9], [10], the effectiveness of network throughput was improved by using partial overlapping channel, and the influence of channel distance on interference is analyzed. In reference [11], the channel interference of 802.11b was theoretically modeled, and the application of POC was simulated. In reference [12], on the basis of the predecessors, the user distance analysis was added, and the access problem of some overlapping channels was extended to a larger scale network, which enriched the interference analysis using some overlapping channels. With the AIs, the use of POC would also improve the performance of business data transmission. The main problem that needs to be studied is that how to overcome the weakness of the partial overlapping channel access technology in multi-user interference.

With the second issue about different patients' monitoring requests, the differences in the types of business and traffic of various body base stations in the WBAN are obvious. With some specific body user, the chosen of AI would be based on its own data transmission demand, along with the wireless environment and neighboring users' AI chosen.

Related works have been done to solve the communication relay optimization problem [13]–[18]. In addition, Some important works is about the resource allocation related to game theory [16], [19], [23]–[26], [28], [30]. However, most of existing works paid attention to the capacity-oriented optimization, the QoE of different users were ignored. In fact, there exists gap between the capacity-oriented optimization and the QoE optimization, especially for the WBAN which serves different patients. For example, with a limited temperature data transmission requirement, the further improvement of transmission capacity would be nonsense for the patient's QoE. However, if the transmission resource was allocated to this patient user, the QoE of other serious patients who need online heart monitor would be affected. As a result, the QoE of the whole WBAN would not be well enough, even with a good network capacity. In our opinion, the ultimate purpose of network optimization would be the improvement of quality of experience (QoE) of the patients, which is closely related with the data transmission demands.

Base on the analysis on the related work, The main challenges this paper aims to solve is summarized as follow:

a. How to overcome the weakness of the partial overlapping channel access technology in multi-user interference.

b. How to realize the optimal match between patients' heterogeneous data transmission requirements and heterogeneous AI spectrum resource in a self-organizing way.

In this paper, we study the QoE oriented AI allocation distributed optimization in WBAN, along with using POC technology to improve the spectrum efficiency. The aim is to improve users' QoE, by dynamically optimizing users' AI choices according to their own monitor data transmission request and dynamically optimizing AIs' channel selection according to the requirements of connected users.

The motivation of this study is to solve the quality-oriented wireless connection in self-organized wireless body area network (WBAN), which is an important issue in the WBAN. With the heterogeneous data transmission requirements of different patients, the wireless connect should also be optimized, to meet the requirements with limited spectrum resources. In addition, the movement of patients requires the self-organization of the wireless connection, which is also one of the features of WBAN. This work aims to achieve the optimization on the spectrum resource allocation for the heterogeneous data transmission requirements of different patients, under the self-organizing architecture. We would like to improve the development of WBAN on the network flexibility and patients' quality of experience.

We aim to develop the distributed choosing scheme, which could make the WBAN adapts the dynamically deployment of body users and the unstable wireless surroundings. The main contribution of this paper is summarized as follow:

Firstly, the QoE analysis of the WBAN users is done, by comprehensive considering the AI's location and channel competing of AIs, and user's requirements etc.

Secondly, the two-layer game model of the distributed AI matching is constructed, the rules of matching and user utility functions are constructed, and the equilibrium of the game is analyzed.

Thirdly, the QoE oriented distributed AI matching algorithm is proposed to achieve QoE optimization, while achieving the stability of system.

The novelties of this paper is summarized as follow:

In aspects of system model:

a. Optimizing the QoE of patients rather than the throughput.

b. Considering the partial overlapping channel access technology for the WBAN.

c. Considering the heterogeneous data transmission requirements of different patients.

In aspects of methodologies:

d. Proposing the two-layer game model and the equilibrium of the game is analyzed.

e. Proposing the QoE oriented distributed AI matching algorithm which is proposed to achieve QoE optimization, while achieving the stability of system.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a WBAN connecting to the MSN as in the Figure 2. The WBAN consists of N body users and M AIs. Body users upload the sensors' data to the MSN through the AIs. The AIs are considered to be limited cognitive, which can adjust the working wireless channel from the available set of POC according to the environment. Figure 3 shows the comparison between the POC channel and orthogonal channel.

Importantly, the heterogeneous requirements of different body users are considered. With different patient, the sensors on the patients would be not the same, which cause the different data traffic of the body users. The transmission requirements should be heterogeneous. For example, the data transmission requirement of the temperature sensor would be obviously different with the heart monitor sensor. Body users are randomly deployed and would choose AIs based on their own decisions.

Denote $\mathbf{S_{CH}} = \{1, 2, \ldots, L\}$ as the set of the POC channels, $\mathbf{S_U} = \{U_1, U_2, \ldots, U_n, \ldots, U_N\}$ is the set of the

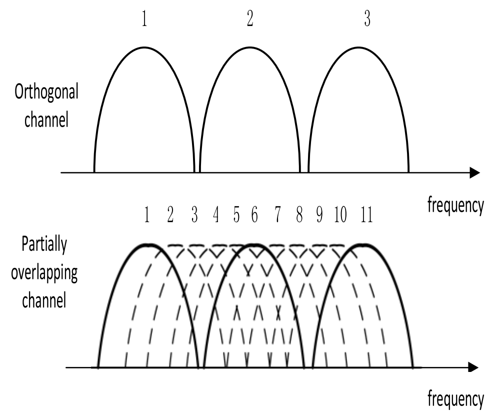

FIGURE 3. The orthogonal channel and partially overlapping channel.

WBAN users, $S_I = \{1, 2, \ldots, M\}$ represents the set of AIs, $\mathbf{B} = [B_1, B_2, \ldots, B_N]$ is the bandwidth vector of POC channels, $\mathbf{R_{max}} = \left[R^1_{max}, R^2_{max}, \ldots, R^M_{max}\right]$ is the max throughput need vector of users, $c_{max} = [c_1, c_2, \ldots, c_M]$ is the QoE parameter vector of users.

Under the condition of using POC shown in figure. 3, the interference between users depends on not only position distance, but also the channel distance, defined as $\vartheta_{ij} = \left|ch_i - ch_j\right|$. For example, if the central frequency of channel is f_c, the bandwidth is 44MHz, the power distribution would be [12]:

$$p(f) = \begin{cases} 0\text{dB}, |f - f_c| \leq 11\text{MHz} \\ -30\text{dB}, 11\text{MHz} < |f - f_c| \leq 22\text{MHz} \\ -50\text{dB}, |f - f_c| > 22\text{MHz} \end{cases} \quad (1)$$

With user i and user j, the interference power would be:

$$H(f) = \int p_i(f) \cdot p_j(f)\, df \quad (2)$$

Obviously, the more the channel distance, the smaller the interference. According to [21], the interference compute could be carried out as follow:

$$H\left(\delta_{ij}\right) = \begin{cases} 1, & \vartheta_{ij} = 0 \\ 0.605, & \vartheta_{ij} = 1 \\ 0.305, & \vartheta_{ij} = 2 \\ 0.108, & \vartheta_{ij} = 3 \\ 0.012, & \vartheta_{ij} = 4 \\ 0, & \vartheta_{ij} \geq 5 \end{cases} \quad (3)$$

Define the neighbor as the users in the interference range:

$$\mathcal{J}_i = \left\{j \in \mathbf{S_U} : d_{ij} \leq d_\tau\right\}, \quad \forall i \in \mathbf{S_U}. \quad (4)$$

where d_τ represents the position distance threshold. With use i, the interference would be computed by considering both the position distance and channel distance:

$$I_i = \sum_{j \in \mathcal{J}_i} p_j H\left(\vartheta_{ij}\right) d_{ij}^{-\alpha}, \quad \forall i, j \in \mathbf{S_U}. \quad (5)$$

According to [22], the throughput of user n through the AI m based on the decode-and-forward model would be:

$$R^1(n,m) = \frac{B}{2}\log_2\left(\min\left\{\begin{array}{l}1+SNR(n,m)\\ ,1+SNR(n)+SNR(m)\end{array}\right\}\right), \quad (6)$$

where $SNR(n,m)$ represents the signal-to-noise-ratio (SNR) from user n to AI m, $SNR(n)$ represents the SNR from user n to the MSN, $SNR(m)$ represents the SNR from AI m to the MSN.

$$SNR(n,m) = P_n \chi_{m,n} \zeta_{m,n}^{-\omega_{m,n}} / (\sigma^2 + I_n), \quad (7)$$

where P_n is the transmission power of user n, $\zeta_{m,n}^{-\omega_{m,n}}$ is the path gain, σ^2 is the variance of white Gaussian noise. $\zeta_{m,n}$ is the distance between user n and AI m, $\omega_{m,n}$ is the path loss exponent between user n and AI m, and $\chi_{m,n}$ is the instantaneous random component of the path loss.

The throughput of user n through the AI m based on the direct transmission model would be:

$$R^2(n) = B\log_2(1+SNR(n)), \quad (8)$$

With the AIs, the resource mechanism would be adopted to allocate the resource. To be simplify, it is assumed that time division multiple access protocol is adopted. Then the AIs on the same channel would equally share the transmission resource. To meet the transmission requirement of users, the AIs would choose the proper channel to work on.

With the user, the following condition should be meet:

$$\sum\nolimits_{m\in \mathbf{S}_\mathrm{I}} \psi_{nm} \le 1, \quad \forall n \in \mathbf{S}_\mathrm{U}$$
$$\text{s.t. } \psi_{n,m} = \begin{cases}1, & \text{if n connects with m}\\ 0, & \text{else}\end{cases} \quad (9)$$

According to the above analysis, the throughput of user would be:

$$R_n = \sum\nolimits_{m\in \mathbf{S}_\mathrm{I}} \frac{R^1(n,m)}{|AI^l|}\psi_{n,m}\mu_{n,m} + \frac{R^2(n)}{|U^2|}\left(1-\sum\nolimits_{m\in \mathbf{S}_\mathrm{I}}\psi_{n,m}\right), \quad (10)$$

where $|AI^l|$ represents the number of AIs working on channel l, $|U^2|$ represents the number of users working on the direct transmission model. AI m allocates a period of time μ_{nm} to the user n, and $0 \le \mu_{nm} \le 1$.

To evaluate the QoE precisely, the computing of QoE is defined as follow [23]:

$$q_i = 5 - 5\cdot e^{-\frac{c_i R_i}{R_{\max}^i}}, \quad \forall i \in \mathbf{S} \quad (11)$$

where R_i is the user i's throughput. $R_{\max}^i$ is the max throughput the user needs, which reflects the heterogeneous transmission requirements of different users. c_i is the sensitive parameter to the throughput of user i.

Obviously, the capacity optimization would not be equal to QoE optimization. The complex of the problem is that the relationships between QoE and throughput are heterogeneous for different users. In this scenario, the AI choosing of user U_8 would be based on its data transmission requirement, affected by the distribution of AIs and other users, the channel qualities, the channel choosing of AIs, and the AI choosing of other users.

There are two optimization aims need to be obtained. First, the result of users' AI choosing and AIs' channel choosing is likely to be stable, which means the network would be stable status. Second, the QoE of users in the WBAN would be improved, i.e.,

With the users, the optimization would be choosing the proper AI to improve its QoE:

$$a_m^* = \arg\max q_m \quad (12)$$

With the network, the optimization would be how to improve the total QoE of the network:

$$\mathbf{P}: \max q_{net} = \sum_{m\in \mathbf{S}_U} q_m. \quad (13)$$

The exhaustive search algorithm could achieve the best result. However, the computation complexity is too high to carry out in practical scenarios. For example, when N = 6 and M = 50, the possible users' AI choosing would be $6^{50} = 8.0828 \times 10^{38}$. Considering the possible channel choosing of AIs, the candidate action space would be huge. Importantly, the flexibility of the central controlled is not appropriate to the WBAN, where the topology and patients' requirement vary all the time. The desired method should be with executable complexity and environment adaptive flexibility.

III. THE QOE ORIENTED TWO-LAYER MATCHING GAME

Based on the above analysis, a QoE oriented two-layer matching game (QoETLMG) is proposed to deal with the AI allocation optimization problem.

Definition 1: We define the QoETLMG as:

$$G = \{S_U, S_I, S_{CH}, \Psi, u_n, u_m, a_n \subset A_U, a_m \subset A_I\} = \begin{cases} G_{up} = \{S_I, S_{CH}, \Psi, u_m, a_m \in A_m \subset A_U\} \\ G_{low} = \{S_U, S_I, \Psi, u_n, a_n \in A_n \subset A_I\}\end{cases} \quad (14)$$

where S_I is the set of AIs, S_U is the set of users, Ψ is the relationship graph of the WBAN, among which $N_{m,n} \subset \Psi$ is the connectivity relationship between I_m and user U_m. user n could connect to I_m if $N_{m,n} = 1$, otherwise, $N_{m,n} = 0$. $A_U = A_1 \otimes A_2 \otimes \ldots \otimes A_N$ is the set of strategy profiles of all the users, $A_I = A_1 \otimes A_2 \otimes \ldots \otimes A_M$ is the set of strategy profiles of all the AIs, where $\otimes$ is the Cartesian product, A_n is the available strategy set of user n. A_m is the available strategy set of AI m. For simplification, the users and AIs in the game are called player. Define $\aleph_m$ is the set of body users which are related to the action of player m:

$$\aleph_m = \left\{i \in \mathbf{S}_\mathrm{U} : if N_{m,j} = 1, N_{i,j} = 1, \forall j \in \mathrm{S}_\mathrm{I}\right\} \quad (15)$$

TABLE 1. The QoEDDMA Algorithm.

Begin: $t = 0$; each body user randomly chooses an AI, and each AI works on a channel randomly;

Loop1: up-layer action updating:

Step 1: Status information acquisition:

(1) Environmental information acquisition.

(2) AI utility calculations.

Step 2: channel choosing updating:

(1) Determination of action updating AI: The randomly selected AI updates the channel choosing action, while others remain unchanged in this iteration.

(2) channel choosing:

$$a_m(t+1) = \arg\max_{a_m \in A_m} u_m(a_m, a_{-m} \mid t). \quad (16)$$

Loop2: low-layer action updating:

Step 2.1: **Status information acquisition:**

(1) Environmental information acquisition.

(2) Information exchange: Each body user interacts with its chosen AI.

(3) User utility calculations: Each user computes its utility.

Step 2.2: **AI choosing updating:**

If the QoE of user is not good enough, it would re-choose AI according to the following rule:

$$R_n > R_n^{\max} \Rightarrow u_n = 1, \text{ or}$$
$$(n,m) \succ (n,j) \text{ if } u(n,m) > u(n,j) \quad (17)$$

If there is no AI could be connected with, or all the AIs had refused this user, the user would transmit data to the MSN directly without AI.

Step 2.3: **User selection:**

AIs order the users that require transmission assist according to the follow rule:

$$(n,m) \succ_m (i,m) \text{ if } \alpha_n u(n,m) > \alpha_i u(i,m) \quad (18)$$

Step 2.4: **Transmission resource allocation:** the AI allocates transmission resource to the connected users according to their requirement.

End loop2: all the users' AI choosing would not be changed again.

Step 3: Data transmission:

The users upload the sensors' data to the MSN through the chosen AI. The status of the WBAN would be refreshed.

End loop1: all the AIs' working channel would not be changed again.

Denote the action of player m as, $a_m \in A_m, u_m$ is the utility function of player m, and $u_m(a_m, a_{-m})$ denotes the player m's utility when action a_m is adopted by m and a_{-m} is the action profile of other players. The utility of users is defined as $u_n = q_n$. The optimal utility of AI is defined as $a_m(t+1) = \arg\max_{a_m \in A_m} u_m(a_m, a_{-m}|t)$.

IV. THE QOE ORIENTED DISTRIBUTED DYNAMIC MATCHING ALGORITHM

In this section, the QoE Oriented Distributed Dynamic Matching Algorithm (QoEDDMA) is proposed to realize the optimal match between AIs and users according to the QoE improve need. Then, the stability of the WBAN system is analyzed.

Compared with traditional studies in which the resource would be fixed and the decision of AI can only be acceptation or refusing, the transmission resource could be allocated dynamically, according to the requirement. In addition, the transmission resources of AIs are also dynamic based on their channel choosing updating. To optimize the heterogeneous QoE, in the proposed algorithm, the AI's action has taken into consideration of QoE parameter for the business data.

Theorem 1: The proposed algorithm could achieve the stable status of WBAN, the AI allocation, user's transmission allocation and AIs' working channel would be stable after the algorithm converges.

Proof: The proof of the theorem 1 would be based on the theory in [24] and [25]. The $u(a_m, a_{-m})$ would be a non-increasing function. Then, the up-layer game $G_{up} = \{S_I, S_{CH}, \Psi, u_m, a_m \in A_m \subset A_U\}$ could be modeled a congestion game [24]. According to [24], the up-layer game $G_{up} = \{S_I, S_{CH}, \Psi, u_m, a_m \in A_m \subset A_U\}$ has at least one Nash equilibrium (NE), which is defined as follow:

Let $\mathbf{a} = \{a_1, a_2, \ldots, a_M\}$ represents the actions of users, and $\mathbf{a}^* = \{a_1^*, a_2^*, \ldots, a_M^*\}$ would be a pure strategy NE if and only if no user could increase its utility by choosing other actions, i.e.,

$$u_m(a_m^*, a_{-m}^*) \geq u_m(a_m, a_{-m}^*)$$
$$\forall m \in S_I, \quad \forall a_m \in A_m, \; a_m \neq a_m^* \quad (16)$$

To obtain the NE state, the proposed algorithm adopts the best response (BR) channel selection method in up-layer action updating, which can converge to a pure NE point in finite iterations among AIs [24].

With the matching game for the low-layer action updating in the proposed algorithm, the stable matching [25] would meets the related matching condition in the algorithm. If the transmission requirement of user n is met, it would not change its AI selection decision. Otherwise, it would look for other AI according to the following standard:

$$\mu_{nm}\psi_{nm} + \sum\nolimits_{i \in S_U \setminus n} \mu_i \psi_{im} \leq 1$$
$$\text{s.t. } \mu_{nm} = R_n^{\max}/R_n, \quad \psi_{im} = 1$$
$$i \in \{\mathrm{S_U} | (i,m) \succ_m (n,m)\} \quad (17)$$

If no AI could meet the requirement, it would make the best choice for the current state:

$$\max \left(1 - \sum\nolimits_{i \in S_0 \setminus n} \mu_i \psi_{im}\right) \cdot R_n$$
$$\text{s.t. } i \in \{\mathrm{S_U} | (i,m) \succ (n,m)\} \quad (18)$$

Based on the matching rule in [26], users accepted by AI would not be replaced by other ones, which means the optimal AI could be decided. Then the users can achieve to the stable matching result.

When the stable status is obtained in the matching model, each AI would choose working channel based on the utilities of users connected. When the AI has got the need resource, i.e., $u_m = \sum_{i \in S_U} \psi_{im}$ It means that related users' QoE would be good enough, then the AI's channel selection decision would hold. According to the congestion game [24], the working channel of AIs would be stable after the action updating. Hence, the Theorem is proved.

V. SIMULATION RESULTS AND DISCUSSION

In order to verify the correctness and validity of the proposed AI choosing method, the Matlab simulation was carried out. The topology of the scenario would be generated randomly. In the course of simulation, the topology, and the number of users would be changed to verify the performance under different condition. Without loss of generality [16], [27], the related parameters are set as follow: the path loss exponent is 2 [25]. The number of POC channel 8, and the bandwidth vector is $[1, 2, 4, 6, 8, 10, 16, 32]MHz$. The number of AIs is 10. The noise power spectral is -170 dBm/Hz, the data transmission power of users and AIs is 23dBm and 30dBm respectively. To simulate the heterogeneous patients' data transmission requirement, the maximal transmission requirement would be varying between 5-20 Mbps, and the QoE parameter would be varies between 1-5.

The simulation was carried out mainly from the following aspects: the convergence of the algorithm, individual user's QoE, the WBAN network QoE, and the fairness of the users.

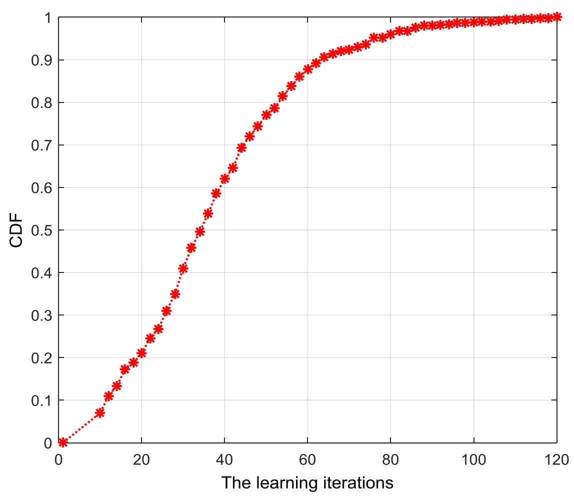

FIGURE 4. **The convergence of the proposed algorithm (20 body users).**

The above figure 4 shows the convergence of the proposed algorithm. It can be seen from the result that the proposed approach could achieve the convergence after the learning and action updating course. The cumulative distribution function (CDF) is shown.

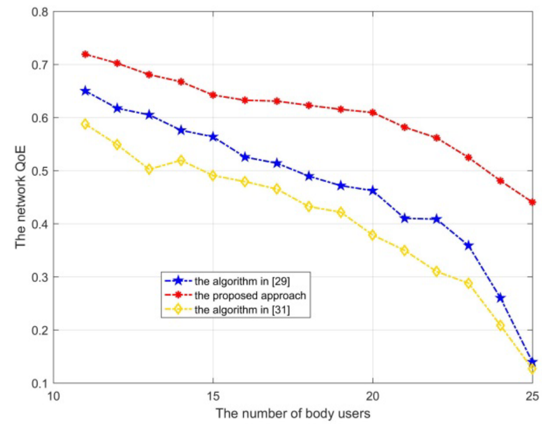

FIGURE 5. **The network QoE comparison between different approaches.**

The above figure 5 shows the network QoE level variation along with change of body users, by using different approaches. It can be seen from the result that the proposed approach could achieve better QoE level compared with approach adopted in [28]. The advantage of the proposed approach is more obvious under heavy load condition (more users). The explanation for this result is that the approaches in [28] are not QoE oriented optimization, the throughput-oriented optimization is not accord with the network QoE under heterogeneous users' demand condition. Allocating communication resource to users which had been satisfied with current would be resource waste, bring QoE performance decrease especially when other users need more resource to meet their requirement. The proposed approach could realize the rational resource allocation according to the heterogeneous requirement, and improve the QoE level.

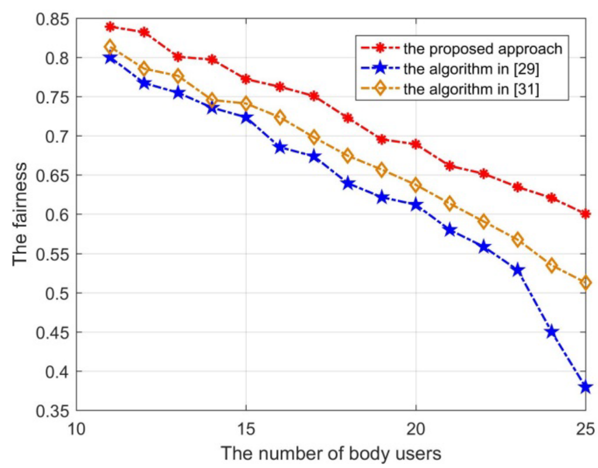

FIGURE 6. **The fairness comparison between different approaches.**

The above figure 6 shows the comparison on fairness of users. The standard of fairness adopts the model in [29], which has been widely adopted. It can be seen from the result that the proposed approach could achieve better fairness performance compared with existing approach. The explanation for this result is that the approaches in [28] do not taken fairness into consideration, while the proposed matching algorithm could improve the fairness from both resource allocation perspective and random choosing and refusing perspective.

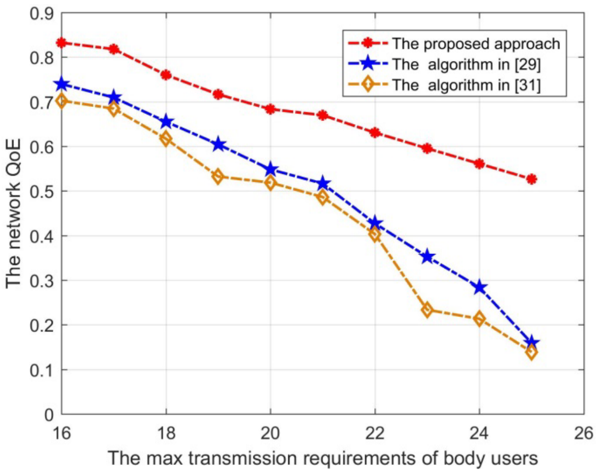

FIGURE 7. The network QoE comparison under changing requirement condition.

The above figure 7 shows the performance comparison between different approaches under the changing requirement condition. The data transmission request of different users would be random and the changing range would be heterogeneous too, that aims to depict heterogeneous patients' demand. It can be seen from the result that the proposed approach could achieve better QoE performance compared with existing approaches. The explanation for this result is that the proposed matching algorithm could realize the optimal resource allocation according to practical requirement of users. The throughput orient algorithm could not adapt to the requirement changing well.

VI. CONCLUSION

In this paper, the optimization of AI allocation in self-organized WBAN for QoE of heterogeneous patients was studied. The QoE analysis of the WBAN users is done, by comprehensive considering the AI's location and channel competing of AIs, and user's requirements etc. Then the two-layer game model of the distributed AI matching was constructed, the rules of matching and user utility functions are constructed, and the equilibrium of the game was analyzed. At last, the QoE oriented distributed AI matching algorithm is proposed to achieve QoE optimization, while achieving the stability of system. The simulation results show that the proposed approach could improve the WBAN QoE level, along with the fairness of users.

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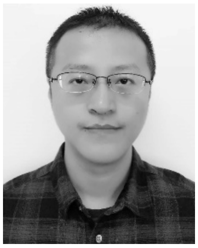

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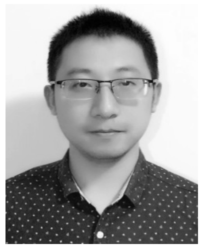

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