Internet of UAVs Based Remote Health Monitoring: An Online eHealth System

Peiran Dong, Xiaojie Wang, Shupeng Wang, Yongjian Wang, Zhaolong Ning, and Mohammad S. Obaidat

Abstract

The recent COVID-19 pandemic has brought significant challenges to the traditional healthcare industry. A novel eHealth system is required to cope with infectious and chronic diseases. This article proposes an online eHealth system to monitor patients and provides edge computing services based on the Internet of Unmanned Aerial Vehicles (UAVs). In order to minimize the health monitoring latency and guarantee the resource utilization efficiency of UAVs, the Lyapunov optimization method is utilized to decompose the long-term optimization problem into a series of instantaneous optimization problems. Then the decomposed subproblem is formulated as a minimum cost maximum flow problem by constructing a bipartite graph that maps medical analysis requests to target UAVs. Extensive experimental results demonstrate the effectiveness of our system. Finally, system analyses illustrate that the robustness and scalability of our eHealth system is favorable, and our system can provide agile edge computing services for dispersed patients.

Introduction

The recent pandemic of Corona Virus Disease 2019 (COVID-19) has caused huge life and economic losses [1]. Its characteristics of extremely contagious and short incubation period have brought significant challenges to traditional healthcare systems. Direct contact between medical staff and patients increases the risk of infections, and surging numbers of patients can overload healthcare infrastructure. In addition, patients with chronic diseases need long-term continuous healthcare monitoring. Frequent medical treatment can cause unnecessary monetary expenditure and waste of medical resources. Therefore, a remote eHealth system is needed to facilitate effective and safe treatment.

By leveraging smart sensors, pervasive Internet of Things (IoT) devices are driving the development of modern eHealth. Patients can be quarantined if necessary and monitored through mobile edge computing (MEC) servers or unmanned aerial vehicles (UAVs), which are able to provide sufficient resources for sensors to process the monitored raw data [2]. Then the analyzed result is transmitted to the healthcare center (e.g., hospital). To design such a system, the following challenges need to be addressed.

Freshness of Medical Information

The most critical issue of remote eHealth is to guarantee the freshness of the monitored medical information. Ideally, sensors monitor fresh medical information continuously [3]. However, real-time monitoring is still impractical due to the limitation of wireless channels. In such cases, the monitored information is transmitted to nearby UAVs or MEC servers periodically. The remote eHealth system needs to schedule wireless communication resources to update the medical information of all patients in time.

Load Balance among UAVs

Without the restriction of roads and buildings, UAVs can be deployed dispersed in the urban area. However, since remote health monitoring enables free movements of patients, the distribution of patients is difficult to predict [4]. Sensors always upload medical information to the nearest UAV to process the monitored raw data; thus, UAVs in different zones may receive distinct amounts of medical information, where a few UAVs are overloaded and others are idle. The remote eHealth system needs to achieve cooperative offloading to balance the computation load of all UAVs.

Trade-off between Latency and Queue Stability

In order to keep the queue stability of UAVs and achieve load balance, each UAV is able to undertake limited workloads, and excessive information processing requests need to be migrated to adjacent UAVs. On one hand, migration allows information offloaded to UAVs with sufficient computation resources to relieve the burden of overloaded UAVs. On the other hand, multihop transmission incurs extra communication latency, and the request processing latency can exceed the deadline. Thus, the remote eHealth system needs to address the trade-off between latency and queue stability.

Robustness and Scalability

High mobility enables UAVs to provide agile edge computing services for patients. With this advantage, the topology of the Internet of UAVs

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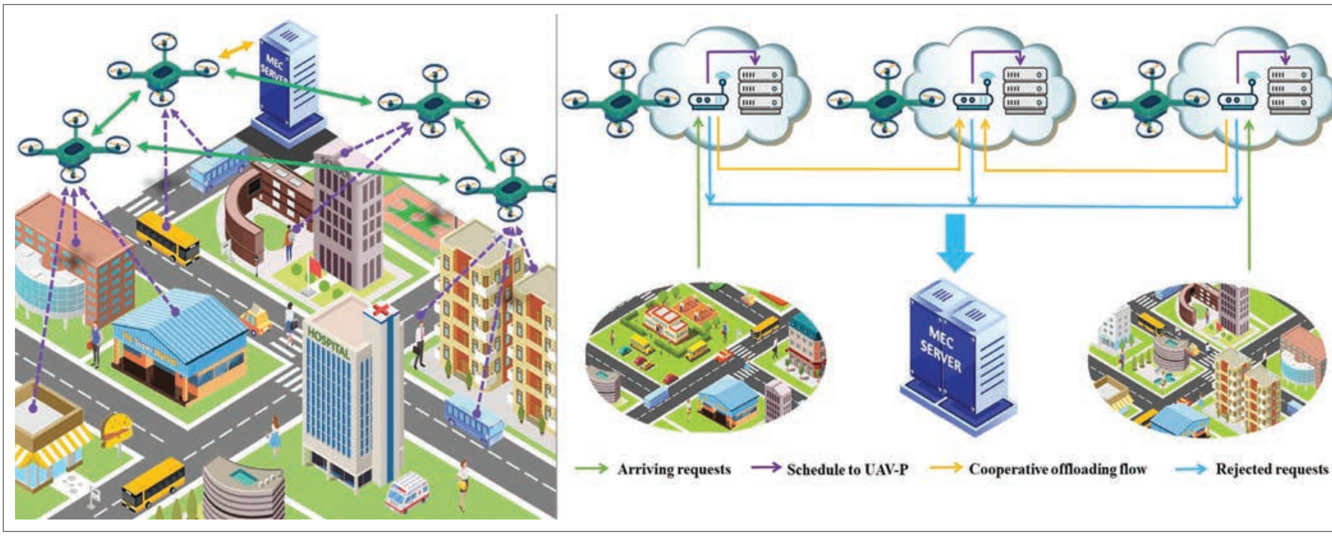

FIGURE 1. Online eHealth system for remote health monitoring.

is unstable, that is, both the number of UAVs and the connected communication edges are time-varying. In addition, UAVs may fail to provide services due to power limitation. Correspondingly, additional UAVs should be delivered to share computation loads. To cope with the dynamic network topology, the eHealth system needs to be robust and scalable, and the time complexity of the online request scheduling algorithm should not be increased with the expansion of the network scale.

In order to address the above-mentioned challenges, this article concentrates on the cooperative offloading, medical information processing, and transmission for the remote eHealth system. The optimization problem is formulated to minimize the average execution latency of medical analysis requests. Since the decision variables in the long-term optimization problem are coupled, the Lyapunov optimization algorithm is utilized to decompose the formulated problem into a series of instantaneous optimization problems. Then we solve each sub-problem in three steps: request admission, request scheduling, and queue update. The main contributions of this article can be summarized as follows:

- Based on the Internet of UAVs, this article proposes an online eHealth system for remote health monitoring. The system is robust and scalable, and can provide agile edge computing services.
- By utilizing the Lyapunov optimization technique, the formulated long-term latency minimization problem is decomposed into a series of instantaneous optimization problems.
- An improved shortest augmenting path algorithm is developed to solve the formulated minimum cost maximum flow problem, where constraints of UAVs are carefully addressed.

The rest of this article is organized as follows. The following section overviews the online eHealth system. Then the optimization problem is formulated. Following that, we propose the online scheduling algorithm. Performance results are then presented. Finally, this article provides system analysis and conclusions.

Overview of the Online eHealth System

Figure 1 illustrates a sketch of the online eHealth system for remote health monitoring. By equipping smart body sensors, patients are able to receive treatment without direct contact with doctors. Specifically, health monitoring has little impact on the physical health of patients. They are distributed randomly in our considered urban area. In order to process the arriving medical analysis request, multiple UAVs are deployed to provide timely and efficient edge computing services. Compared to traditional MEC servers on the network edge, UAVs outperform in three aspects. First, the deployment of UAVs is flexible and not restricted by roads and buildings. Second, the network of UAVs is decentralized, and offloading scheduling can be implemented in a distributed manner. Third, the mobility of UAVs enables eHealth systems to cope with emergencies (e.g., plagues), where abundant edge computing resources are needed in a short time. However, traditional fixed MEC servers cannot satisfy the above requirements. We assume that wireless transmission is privacy-protected and all UAVs are trusted. Since the analyzed medical report by UAVs is sent to healthcare centers (e.g., hospitals), the mobility of patients does not affect the transmission process.

Medical Information Analysis Requests

Sensors collect raw data and upload the medical information to UAVs regularly. Let the monitored data be timestamped when they are collected. After receiving medical information analysis requests, UAVs decide whether the requests are processed by themselves or offloaded to peers. Finally, the medical analysis report is sent to the medical center for expert diagnosis. The main focuses of remote healthcare monitoring are medical information freshness and privacy-protected transmission. In this article, we concentrate on the former, while trusted offloading for the eHealth system is considered in our future work. We utilize age of information (AoI) [5] to measure the freshness of medical information. From the perspective of the medical center, AoI depicts how old the medical information is since it was monitored. While the medical center does not receive new medical analysis reports from UAVs, the AoI value increases linearly with time, indicating that the existing information about the corresponding patient becomes old. As soon as the medical center receives new reports, the AoI value updates instantaneously. In our proposed remote eHealth system, the AoI value is numerically equal to the request execution latency, including information transmission, queueing, and processing latency. Intuitively, good AoI performance can be achieved by minimizing the average request execution latency while stabilizing the queue of UAVs [3]. In summary, the online eHealth system guarantees that UAVs are not overloaded, and the medical information can be delivered promptly and regularly, benefiting both network operators and patients.

Queues of UAVs

UAVs are responsible for information transmission and request processing. There are two queues for each UAV, that is, front-end transmission queue (UAV-T) and back-end processing queue (UAV-P), where UAV-T schedules the arriving medical information analysis requests, and UAV-P processes the dispatched requests from UAV-T. Other requests are transmitted to peers through cooperative offloading.

At the beginning of time slot *t*, the remaining medical information analysis requests in UAV-T are scheduled; that is, some requests are dispatched to UAV-P, and some are offloaded to peers. At the end of slot *t*, new requests from patients or other UAVs arrive, and the UAV decides whether to accept and put them in UAV-T or not. This process is similar to [6].

MEC Servers

Although this article constructs a remote eHealth system based on the Internet of UAVs, traditional MEC servers are still necessary for two reasons. First, since the physical size of UAVs is limited, the storage and computation capabilities are correspondingly constrained. Rejected medical analysis requests can be offloaded to MEC servers. Much existing research on MEC-based energy harvesting [7, 8] can guarantee the stable power supply of MEC servers. Second, the Internet of UAVs is often constructed for a dedicated employment, for example, health monitoring of patients infected with COVID-19. Thus, other patients can move out of the wireless communication range of UAVs. In order to update their medical information in time, body sensors can choose the nearest MEC server as a backup option.

Latency Minimization Problem Formulation

This section formulates the latency minimization problem for the remote eHealth system. Constraints are first specified. Then the Lyapunov optimization method [9] is utilized to decouple the long-term optimization problem into a series of time-instantaneous optimization subproblems, which are reduced to a minimum cost maximum flow (MCMF) problem [10].

Constraints of the Latency Minimization Problem

With the objective of minimizing request execution latency, there are three constraints for the optimization problem:

- The monitored raw data by sensors are atomic and cannot be divided, that is, we do not consider partial offloading for the remote eHealth system. Each medical information analysis request can only be scheduled to one UAV or MEC server to process.
- The length of UAV-T queues cannot exceed the threshold; that is, the storage capability of UAVs is limited. Excessive requests are offloaded to MEC servers.
- The length of UAV-P queues cannot exceed the threshold; that is, the computation resources of UAVs are limited. We do not assign priorities to different patients, and all requests in the UAV-P queue share computation resources equally. The higher the number of requests, the higher the resource utilization efficiency. Correspondingly, the average processing rate decreases.

Lyapunov-Based Problem Decomposition

There are two challenges to solve the latency minimization problem. First, request scheduling variables are coupled in the long-term optimization problem. The scheduling decision in the current time slot affects the decision in the next slot by updating UAV-T and UAV-P queues. Second, there is a trade-off between computation resource utilization efficiency and the average processing rate. Both factors influence the request execution latency.

In order to resolve the above-mentioned challenges, an online eHealth scheduling OHS) method is developed by utilizing Lyapunov optimization. First, a quadratic Lyapunov-drift function is defined to capture the changes of UAV-T and UAV-P in each time slot. Then the optimization objective (i.e., request execution latency) is incorporated with the Lyapunov-drift function by minimizing the obtained Lyapunov-drift-plus-penalty function. Three main reasons motivate us to formulate the latency minimization issue by a Lypapunov optimization problem:

- The long-term optimization problem is decomposed into a series of time-instantaneous optimization problems. Correspondingly, scheduling variables over continuous time slots are decoupled, facilitating problem-solving processes.
- The Lyapunov-drift-plus-penalty function is strictly positive correlated to the original optimization objective. In addition, a tunable parameter is added as the coefficient of the penalty, weighting the importance on the request execution latency.
- To minimize the Lyapunov-drift-plus-penalty function, the Lyapunov-drift function and the request execution latency need to be jointly minimized. Based on the definition, the changes of both UAV-T and UAV-P are minimized, keeping UAV-T and UVT-P stable over continuous time slots. Then the computational resource utilization efficiency of UAVs can be guaranteed.

By minimizing the upper bound of the Lyapunov-drift-plus-penalty function, OHS can minimize the request execution latency while guaranteeing

There are two challenges to solve the latency minimization problem. First, request scheduling variables are coupled in the long-term optimization problem. The scheduling decision in the current time slot affects the decision in the next slot by updating UAV-T and UAV-P queues. Second, there is a trade-off between computation resource utilization efficiency and the average processing rate. Both factors influence the request execution latency.

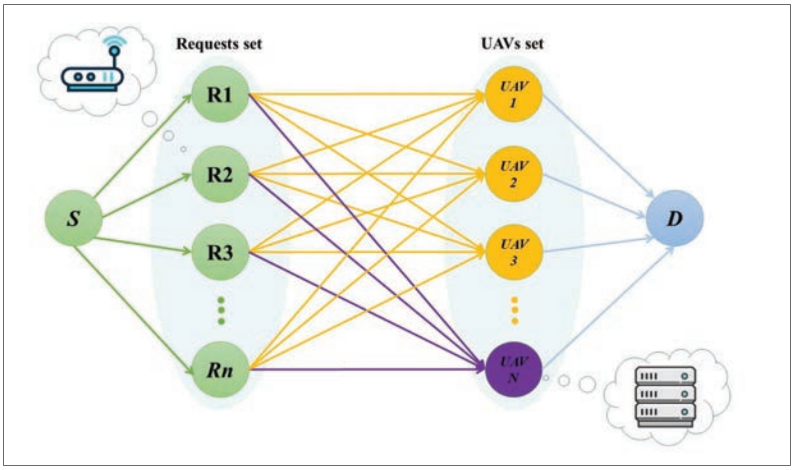

FIGURE 2. Request flow network for online eHealth system.

the stability of UAV-T and UAV-P queues. The performance gap can be derived theoretically [11].

Minimum Cost Maximum Flow Problem Formulation

Consider a time-instantaneous request scheduling problem for a remote eHealth system with the three constraints formulated above. The problem can be reformulated into an MCMF problem with several constraints.

Figure 2 illustrates the request flow network for an online eHealth system. Source node S, denoting one UAV, connects to all requests that need to be scheduled in the current time slot, where the capacity and cost of the green edges in Fig. 2 are set to 1 and 0, respectively. Then requests and all available UAVs constitute a fully connected diagram. Since each request can only be scheduled to one UAV for processing, the capacity of the yellow edges in Fig. 2 between each request and UAV is set to 1. In addition, the cost of the edge equals the Lyapunov-drift-plus-penalty function defined above. Specifically, the purple edges in Fig. 2 indicate that requests are sent to the UAV-P queue without cooperative offloading. Correspondingly, there is no extra transmission latency for this type of scheduling. Finally, UAVs connect to virtual sink node D, where the cost of the blue edges in Fig. 2 is set to 0. Considering the limitation of storage and computation capabilities of UAVs, the capacity of the edge between each UAV and node D is no larger than the remaining capacities of both UAV-T and UAV-P queues. In such cases, the three constraints illustrated above are satisfied. Minimizing the cost of the flow network is equivalent to minimizing the Lyapunov-drift-plus-penalty function, and maximizing the flow in the eHealth network guarantees the utilization efficiency of computation resources of UAVs.

In existing offloading scenarios, MEC servers need to send task results back to users, and backhaul transmission latency needs to be considered. However, in the eHealth system, UAVs transmit medical analysis results to the hospital rather than patients. In addition, the communication between UAVs and the hospital is independent of patients. Thus, we ignore the latency of resulting backhaul transmission. To solve that issue, our model can easily be extended by setting the cost of the edges between UAVs and the virtual sink node D (blue edges in Fig. 2) to the corresponding backhaul transmission latency.

Online eHealth Scheduling Algorithm

Our proposed OHS algorithm consists of three steps: request admission, request scheduling, and queue update.

Request Admission

When a medical analysis request arrives at one UAV, the UAV needs to decide whether and where to process the request. Generally, there are two decision variables for each request: admission and scheduling variables. Previously, the instantaneous request scheduling problem was formulated into an MCMF problem. Before solving this problem, the request admission variable needs to be decided.

We propose a simple rule to control request admission decisions. For each UAV, a newly arrived request is admitted when the length of the UAV-T queue does not reach the threshold; otherwise, it is rejected to enter the UAV-T queue to avoid system overload. Those rejected requests are offloaded to MEC servers.

Note that the request admission procedure can be aggregated into a request scheduling procedure by adding the MEC server as an optional processing platform in the constructed request flow network. Specifically, in Fig. 2, an MEC server is added into the UAV set. The cost of edges between requests and the MEC server is set to the accumulation of transmission and computation latency. The weight is set to the computation capability of the MEC server. However, two reasons motivate us to separate request admission and scheduling procedures. First, we mainly utilize UAVs to provide edge computing services, and MEC servers are merely backup options. When UAVs are overloaded, excessive requests are offloaded to MEC servers. Second, adding an MEC server into the request flow network increases the time complexity of our proposed OHS algorithm. Furthermore, to compute the accurate edge weight, the synchronization of UAVs and MEC servers leads to extra communication costs.

Request Scheduling

In each time slot, UAVs perform the Improved Shortest Augmenting Path ISAP) algorithm [12] to obtain the maximum flow and minimum cost of the remote eHealth network. The upper bound of time complexity for the ISAP algorithm is $O(E^2V)$, where variables E and V denote the number of edges and nodes in the constructed flow graph, respectively. Although the time complexity is a quadratic function of the number of edges, two characteristics guarantee the efficiency of the ISAP algorithm. First, our constructed flow graph is sparse, where edges between the source node and requests as well as that between UAVs and sink nodes do not need to update when the shortest augmented path is found. Second, we consider an extreme case in which the sets of requests and UAVs constitute a fully connected bipartite graph. However, due to the accumulation of transmission costs, the hops of cooperative offloading are usually restricted to a small number in reality. In such cases, the number of edges in our constructed flow graph decreases significantly. This characteristic not only guarantees the scalability of our designed eHealth system, but also provides an efficient UAV deployment strategy, that is, deploying multiple small-scale Internet of UAVs to cover different areas instead of a whole large network. Specifically, this ensures that the request set and the UAV set in Fig. 2 constitute a complete bipartite graph; that is, any two UAVs in a small-scale Internet of UAVs can communicate within the maximum number of hops.

For example, let the maximum hop of cooperative offloading be 3. The number of requests and UAVs are represented by variables M and N ($N > 3$), respectively. Each UAV is directly connected to n UAVs on average, which is much smaller than N. Then the number of effective edges can be represented by $\min\{3Mn, NM\}$. Correspondingly, the time complexity is $O(9n^2M^2(M + 3n + 2))$. Due to the limitation of storage capability, each UAV schedules a limited number of requests (i.e., M is small). In summary, the ISAP algorithm can be efficiently executed in an online manner. In addition, note that the time complexity in reality is independent of the number of UAVs. With the expansion of the eHealth network, the consumed time of our method for each UAV has little change.

After request scheduling, requests transmitted through each UAV node to the sink node are offloaded to the corresponding UAV for processing. The virtual sink node can also be viewed as the medical center. The communication between UAVs and the medical center is beyond the scope of this article; thus, the results of transmission latency are omitted.

Queue Update

At the beginning of time slot t, UAVs schedule some requests in UAV-T queues to UAV-P queues for processing. The remaining requests are offloaded to other UAVs. At the end of time slot t, UAV-T queues admit requests from cooperative offloading and nearby patients. UAV-P queues receive workloads from UAV-T queues. In the next time slot, UAV-T and UAV-P queues update correspondingly.

Performance Evaluation

We utilize the Electroencephalography (EEG) dataset, recording the brain state information of patients, in [13] to evaluate our proposed OHS algorithm. Various brain diseases such as epileptic seizures can be monitored by analyzing EEG time series data. Each medical information analysis request consists of 4096 samples of EEG data. The data size of each request is between [560, 747] kB. The bandwidth for communication between sensors and UAVs is set to 0.5 MHz. Our proposed OHS algorithm is compared to the following two methods.

Source Destination Pair Matching (SDM) Algorithm [14]: It is a Gale-Shapley-based centralized matching algorithm. Each request is matched up with one target UAV. Under the premise of underload, each UAV is able to admit multiple requests.

Independent eHealth Monitoring (IHM) Algorithm: Without cooperative offloading, UAVs provide MEC services independently. All overloaded burden is sent to nearby roadside units (RSUs).

Figure 3 shows performance results in terms of the average request execution latency. In Fig. 3a, the latency decreases with the increasing number of

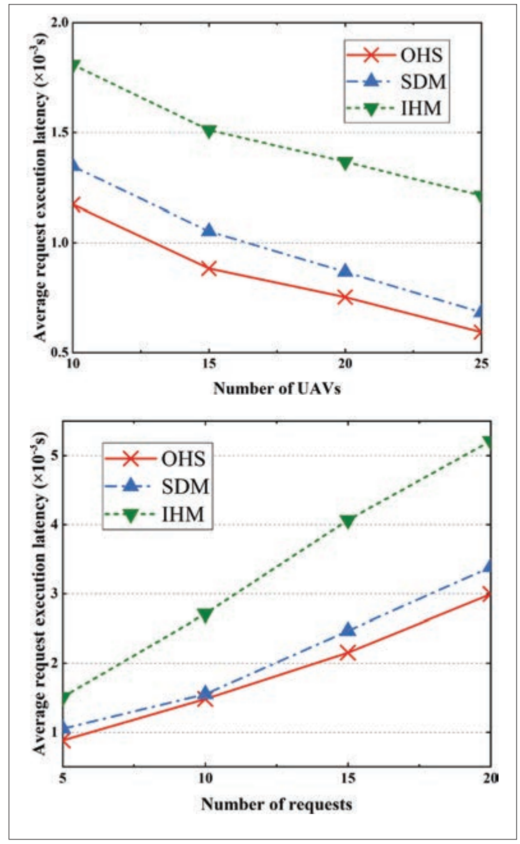

FIGURE 3. Performance evaluations in terms of the average request execution latency: a) Number of UAVs, b) Number of requests

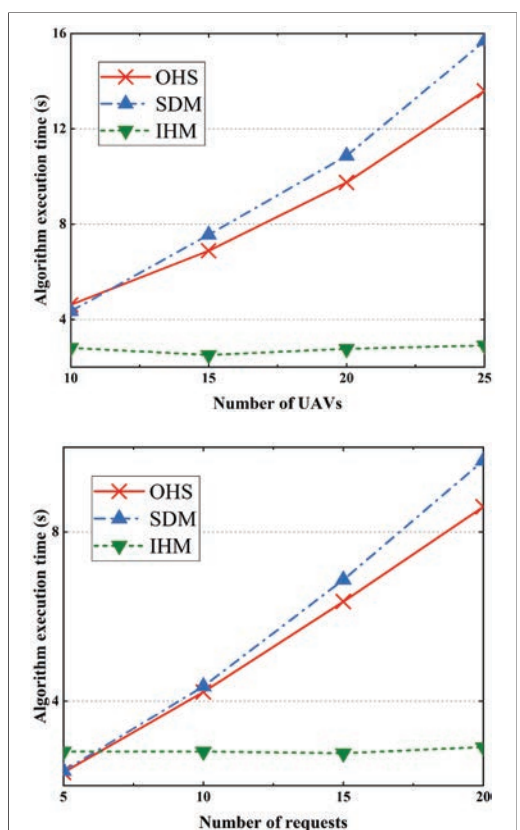

FIGURE 4. Performance evaluations in terms of the number of RSUs: a) Number of active miners, b) Block size, c) Latency, and d) Throughput.

Due to the limitation of storage capability, each UAV schedules a limited number of requests, that is, M is small. In summary, ISAP algorithm can be efficiently executed in an online manner. In addition, note that the time complexity in reality is independent of the number of UAVs. With the expansion of the eHealth network, the consumed time of our method for each UAV has little change.

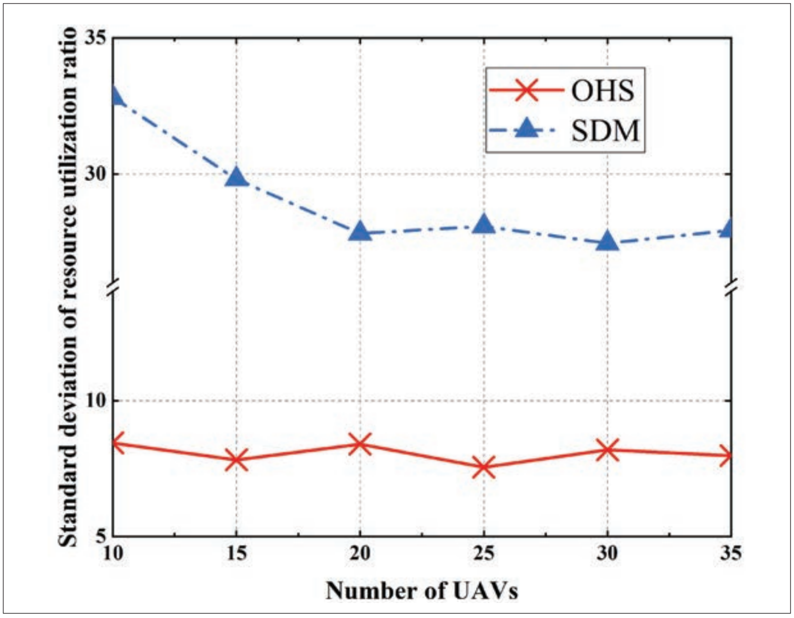

FIGURE 5. Uploading delay in BS based on NOMA and OFDM, respectively.

UAVs. This is because more computation resources can be utilized to process medical analysis requests, and the queue latency and the computation latency decrease correspondingly. With cooperative offloading, the performance of our proposed OHS algorithm is 47 percent better than that of the IHM method. In Fig. 3b, when the number of requests increases, the computation burden of UAVs aggravates, and the average request execution latency increases. Since both OHS and SDM algorithms derive asymptotically optimal solutions, the performance of the OHS and SDM algorithms is similar.

Performance trends of the algorithm execution time are illustrated in Fig. 4. For the IHM method, UAVs provide edge computing services independently. The time of MFMC flow construction and policy iteration process is saved. Thus, the execution time of the IHM method is lower than that of the other two algorithms. When the number of UAVs or requests is small, the OHS and SDM algorithms consume almost the same time to schedule the arriving requests. Then, with the increase of the network size or computation burden, the algorithm execution time of the SDM algorithm increases faster than that of the OHS algorithm. This is because the SDM algorithm constructs a fully connected bipartite graph between requests and all UAVs. The policy iteration process consumes much time to converge.

In Fig. 5, the resource utilization efficiency of UAVs is evaluated by comparing the standard deviation of the resource utilization ratio (the ratio of occupied queue length and total queue length). It can be observed that the standard deviation of the SDM algorithm is approximately 2.5 times higher than that of the OHS algorithm. This is because the SDM algorithm maps requests to UAVs with the objective of minimizing the request execution latency and does not consider the queue stability of UAVs. This result demonstrates that our proposed OHS algorithm can reach load balance, and the resource utilization efficiency of UAVs can be guaranteed.

System Analysis

This section analyzes the robustness and scalability of our remote eHealth system, and discusses its ability to provide agile edge computing services.

Robustness

Without stable power supply, UAVs may fail to provide edge computing services. Let variable N denote the number of UAVs. Our system is tolerant to $n(n < N)$ UAV failures with a well-designed queue threshold. In ideal circumstances, no UAV can fail. Then we set the queue threshold to the true capability of UAV-T and UAV-P queues, making full use of the storage and computation capability of UAVs. However, in reality, when UAVs fail, their received requests need to be migrated to guarantee that all patients' medical information can be updated in time. Thus, adequate storage and computation resources need to be reserved in advance; that is, the queue threshold is set to be lower than the true capacity to cope with UAV failures.

In order to accommodate requests on n failed UAVs while improving resource utilization efficiency, the queue threshold is an n-dependent function. Let f denote the ratio of the designed queue threshold and the true capacity. Taking UAV-P queues as an example, the workloads in n failed UAVs can be computed by nf. Correspondingly, the residual resource capacity in other UAVs can be represented by $(N - n)(1 - f)$. To accommodate requests in n failed UAVs, the residual resource capacity should be no less than the workloads in them. Thus, the range of ratio f can be derived, and the robustness of our system can be guaranteed. Note that the smaller ratio f is, the more robust the system is. However, the resource utilization efficiency of UAVs is low, and the trade-off between system efficiency and robustness needs to be carefully addressed.

Scalability

As mentioned before, the time complexity of our developed OHS algorithm is a function of the number of scheduled requests and that of cooperative UAVs. When UAV-T and UAV-P queues are stable, the number of scheduled requests during each time slot is relatively constant. Thus, the time complexity mainly depends on the number of cooperative UAVs. Ideally, when a new UAV joins the remote eHealth system, each UAV needs to add M offloading edges to the original flow graph. The graph update operation for one edge is not complicated and does not influence other edges.

Actually, the expansion of the UAV network by adding a new member merely affects UAVs within their cooperative offloading ranges. In a large health monitoring network, those affected UAVs merely account for a small percentage of total UAVs. In summary, the scalability of our system is strong.

Agile Edge Computing

Since the distribution of patients is difficult to predict, traditional edge computing servers are empirically deployed, resulting in unbalanced loads. Due to the mobility of patients, the communication between body sensors and RSUs may be interrupted. Although emerging techniques, such as dynamic service migration, are proposed to solve this problem, the migration cost puts an extra burden on the eHealth system. With the advantage of high mobility and self-organization, UAVs can provide agile edge computing services, known as the paradigm of follow me at the edge [15]. In particular, when a sudden outbreak of an infectious disease exists (e.g., COVID-19), UAVs can be accurately scheduled to a patient isolation area for health monitoring and online treatment services.

Conclusion

This article focuses on the latency and stability issues of remote health monitoring, and constructs the online eHealth system based on the Internet of UAVs to provide edge computing services for patients. By considering the constraints of storage and computation capability of UAVs, the long-term latency minimization problem is formulated. In order to guarantee the resource utilization efficiency of UAVs, a Lyapunov-drift-plus-penalty function is constructed to keep the stability of service queues. After that, the original optimization problem is reformulated into an MCMF problem, where constraints are addressed by appropriately setting the edge weights. Numerical results based on an EEG dataset illustrate that our eHealth system can achieve satisfactory performance on request execution latency minimization. In addition, our proposed OHS algorithm is able to balance computation loads of UAVs. System analyses demonstrate that our system is robust and scalable. Agile edge computing services can be provided for patients. Privacy protection and secure transmission will be considered in our future work.

Acknowledgments

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Biographies

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Numerical results based on an EEG dataset illustrate that our eHealth system can achieve satisfactory performance on request execution latency minimization. In addition, our proposed OHS algorithm is able to balance computation loads of UAVs. System analyses demonstrate that our system is robust and scalable. Agile edge computing services can be provided for patients.