HealthEdge: Task Scheduling for Edge Computing with Health Emergency and Human Behavior Consideration in Smart Homes

Haoyu Wang†, Jiaqi Gong*, Yan Zhuang†, Haiying Shen†, John Lach*

†Department of Computer Science, University of Virginia, Charlottesville, VA 22904, USA
*Department of ECE, University of Virginia, Charlottesville, VA 22904, USA
{hw8c, jgong, yz8bk, hs6ms, jlach}@virginia.edu

***Abstract*—Nowadays, a large amount of services are deployed on the edge of the network from the cloud since processing data at the edge can reduce response time and lower bandwidth cost for applications such as healthcare in smart homes. Resource management is very important in the edge computing since it is able to increase the system efficiency and improve the quality of service. A common approach for resource management in edge computing is to assign tasks to the remote cloud or edge devices just according to several factors such as energy, bandwidth consumption, and latency. However, the approach is insufficiently efficient and falls short in meeting the requirements of handling health emergency when being applied in smart homes for healthcare. Possible health emergency needs immediate attention and different health tasks have different priorities to be processed. In this paper, we propose a task scheduling approach called *HealthEdge* that sets different processing priorities for different tasks based on the collected data on human health status and determines whether a task should run in a local device or a remote cloud in order to reduce its total processing time as much as possible. Based on a real trace from five patients, we conduct a trace-driven experiment to evaluate the performance of *HealthEdge* in comparison with other methods. The results show that *HealthEdge* can optimally assign tasks between the network edge and cloud, which can reduce the task processing time, reduce bandwidth consumption and increase local edge workstation utilization.**

I. INTRODUCTION

Although the integration of smart Internet of Things (IoT) and cloud computing enables many applications, completely moving all the computing tasks to the cloud is inefficient in several scenarios. For instance, when the bandwidth is limited and response time requirement is strict, uploading the data to the cloud for processing may incur longer response time and occupy large portion of the bandwidth. A study reported that the bandwidth demand nearly double each year [1], which would even increase the response time. Fortunately, since the IoT devices become increasingly powerful nowadays, the data processing can be executed at the edge of networks, namely the edge computing [2]. By allowing the computation near the data source and avoid unnecessary data movement, edge computing gains several benefits, e.g., providing efficient network operation and fast service delivery to ensure the quality of service and improve the user experience [3]. Therefore, recently, an increasing amount of services are pushed back to the edge of the network from the cloud to reduce response time and lower bandwidth cost.

Meanwhile, the healthcare domain starts to leverage edge computing to improve healthcare services. The healthcare platform deployed in a smart home enables utilizing sensors and mobile devices, and scaling data storage and processing power, for different kinds of healthcare analysis. It enables the sharing of analytical results and accessing to the processing and storage infrastructure with reduced response time and optimized resource utilization [2]. For example, in a standard healthcare scenario, assisted persons are monitored by many different sensors gathering data and processing the data in edge workstations (i.e., servers) or the private cloud data center managed by the hospital. The doctors can diagnose and make decisions with these data processing results. Computing tasks on processing the collected data facilitate inferring complex human behaviors [4], [5] Also, this healthcare platform provides an infrastructure for large-scale data analysis for health in communities, public and global.

In edge computing, resource management plays an significant role for assigning tasks (that are generated by local devices) to the remote cloud (the central of the network) or local servers/devices (the edge of the network). A common approach for resource management in edge computing is to assign tasks to the remote cloud or local servers according to several factors such as energy, bandwidth consumption and latency. These methods can be generally classified into three categories based on their goals: (1) reducing energy consumption (e.g., [6]), (2) improving system throughput (e.g., [7], [8]), and (3) reducing task completion time (e.g., [9]).

In this paper, as in Figure 1, we consider the resource management in the healthcare platforms in smart homes between the network edge (e.g., smart home sensors) and the central of the network (e.g., the private cloud data center). Specifically, we propose a task scheduling approach called *HealthEdge* that sets different processing priorities for different tasks based on the collected data on human health status, and determines whether a task should run in a local device or a remote cloud in order to reduce its total processing time as much as possible.

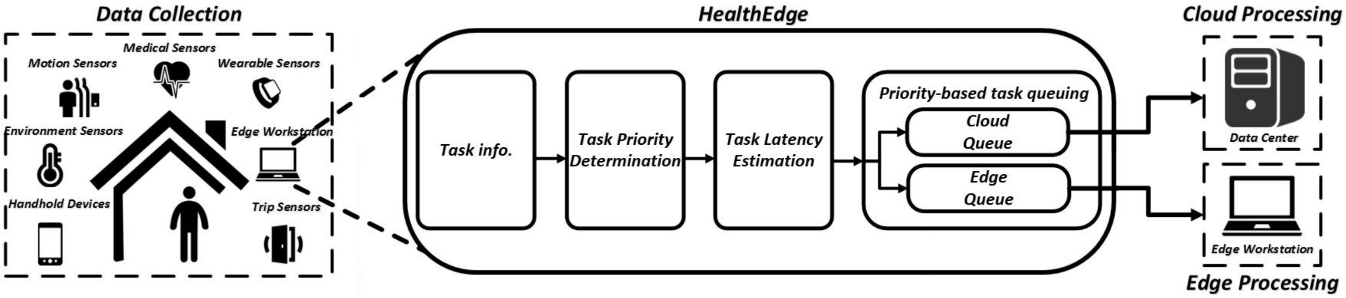

Fig. 1: The overview of *HealthEdge*, which consists of three major components: task priority determination, latency estimation and priority-considered task queuing.

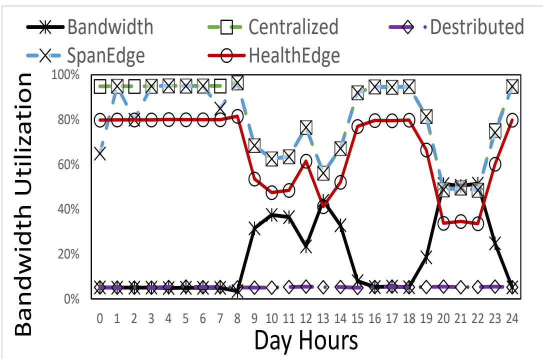

Fig. 2: Bandwidth utilization.

In *HealthEdge*, the system architecture is separated into two tiers, where the private cloud data center is in the first tier, the network edge including sensors and edge workstations are in the second tier. All the tasks are generated by the sensors and then the tasks will be transferred to the edge workstation.

II. Performance Evaluation

In this section, we evaluate the performance on network bandwidth utilization for all the methods which include *Distributed*, *Centralized* and *Spanedge* [10]. We attempt to check if the methods use most of the available bandwidth, leaving little bandwidth to users for daily use and hence adversely affecting user experience. In Figure 2, we show the average bandwidth utilization at each hour per day per smart home from the one-month trace. *Bandwidth* means the average bandwidth utilization by the user's family excluding the bandwidth utilization for the health systems. We can see that the bandwidth utilization varied a lot over time. From 9:00 to 14:00 and 20:00 to 23:00, the bandwidth utilization is almost 50% on average. In order to provide better user experience, a task assignment method should limit the network bandwidth usage and leave enough bandwidth to users for daily use. *HealthEdge* assigns the tasks based on their dataset size and predicted available bandwidth at that time. Its total utilization is from 85% to 90%. *HealthEdge* can avoid the problems of *SpanEdge* and *Centralized*. That is, *HealthEdge* leaves a certain amount of bandwidth to users for daily use, it constrains network cost and won't cause network congestion which enable to complete tasks timely.

III. Conclusion

In this paper, we propose a priority-based task queuing method that enables emergency tasks to be processed earlier. Meanwhile, it avoids delaying waiting tasks according to the task waiting time and processing time. Further, *HealthEdge* predicts human behaviors and hence available resources for each server and its bandwidths to the cloud. based on which it estimates the data transmission latency, queuing latency and computing latency to predict the total processing time of a task in each edge workstation and the private cloud data center. Finally, *HealthEdge* assigns the task to the destination with the shortest estimated processing time. We construct a trace-driven simulation to evaluate the performance of *HealthEdge* in comparison with other methods. The experimental results demonstrated that *HealthEdge* can optimally assign tasks to significantly reduce task total processing time, especially for some emergency tasks.

IV. Acknowledgment

This research was supported in part by U.S. NSF grants ACI-1719397 and CNS-1733596, and Microsoft Research Faculty Fellowship 8300751.

References

[1] D. Gilstrap. Ericsson mobility report. *Ericsson*, 2013.
[2] W. Shi and S. Dustdar. The promise of edge computing. *Computer*, 2016.
[3] M. Patel, B. Naughton, C. Chan, N. Sprecher, S. Abeta, and A Neal. Mobile-edge computing introductory technical white paper. *Journal of Mobile-edge Computing (MEC) industry initiative*, 2014.
[4] D. Spruijt-Metz and W. Nilsen. Dynamic models of behavior for just-in-time adaptive interventions. *Journal of Pervasive Computing*, 2014.
[5] W. T. Riley, D. E. Rivera, A. A. Atienza, W. Nilsen, S. M. Allison, and R. Mermelstein. Health behavior models in the age of mobile interventions: are our theories up to the task? *Translational behavioral medicine*, 2011.
[6] A. Rudenko, P. Reiher, G. Popek, and G. Kuenning. Saving portable computer battery power through remote process execution. *Proc. of SIGMOBILE*, 1998.
[7] E. Cuervo, A. Balasubramanian, D. Cho, A. Wolman, S. Saroiu, R. Chandra, and P. Bahl. Maui: making smartphones last longer with code offload. In *Proc. of Mobile systems, applications, and services*, 2010.
[8] M. Aazam and E. Huh. Fog computing micro datacenter based dynamic resource estimation and pricing model for iot. In *Proc. of AINA*, 2015.
[9] D. Huang, P. Wang, and D. Niyato. A dynamic offloading algorithm for mobile computing. *Trans. on Wireless Communications*, 2012.
[10] H. P. Sajjad, K. Danniswara, A. Al-Shishtawy, and V. Vlassov. Spanedge: Towards unifying stream processing over central and near-the-edge data centers. In *Proc. of SEC*, 2016.