Near-Far Computing Enhanced C-RAN for Wireless Big Data Processing

Lianming Zhang, Kezhi Wang, Du Xuan, and Kun Yang

Abstract

With the increasing popularity of user equipments, the corresponding UE generated big data (UGBD) is also growing substantially, which makes both UEs and current network structures struggle to process those data and applications. This article proposes a near-far computing enhanced C-RAN (NFC-RAN) architecture that can better process big data and its corresponding applications. NFC-RAN is composed of near edge computing (NEC) and far edge computing (FEC) units. NEC is located in the remote radio head, which can quickly respond to delay-sensitive tasks from the UEs, while FEC sits next to a baseband unit pool, which can do other computation-intensive tasks. Task allocation between NEC and FEC is introduced in this article. Also, WiFi indoor positioning is illustrated as a case study of the proposed architecture. Moreover, simulation and experiment results are provided to show the effectiveness of the proposed task allocation and architecture.

Introduction

With the increasing popularity of user equipments (UEs) such as smartphones and handheld devices, more and more resource-hungry applications like high definition video gaming and virtual reality applications are developing and coming into play in our mobile devices. Due to limited resources in UEs, it is very difficult for them to compute the resource-intensive applications. Moreover, UE generated big data (UGBD) is growing accordingly, which poses big challenges to the existing mobile devices and wireless networks [1].

Mobile edge computing (MEC) [2] and offloading techniques [3] have been proposed to enable UEs to send their tasks to their corresponding virtual machines. In this case, UEs’ experience will be increased substantially, and their battery life will be prolonged greatly. By taking advantage of cloud technology, wireless networks have also recently undergone a revolution [4, 5]. The cloud radio access network (C-RAN) has been proposed [6], moving most of the signal processing tasks previously done in special hardware to the cloud. In it, baseband unit (BBU) pools. In this architecture, remote radio heads (RRHs) can be distributed easily according to requirements. In C-RAN, we can dynamically and easily adjust and allocate computing resource to wireless communications. Previous studies [7, 8] have proposed placing MEC resources next to the BBU pool to better provide service to UEs. However, due to the transmission latency and limited bandwidth in fronthaul, the above architecture may not be beneficial for delay-sensitive tasks and big data applications.

Moreover, the studies in [9] investigated big data applications in wireless communications and showed that it is not easy to process those data in wireless networks due to the required large amount of computation resource. Reference [10] proposed a big data computing architecture for smart grid analytics. Some key technologies to enable big-data-aware wireless communication for smart grid were investigated in that paper. Reference [11] showed that most applications require very short response times, which is typically composed of two parts: transmission (i.e., communication) and processing (i.e., computation).

To better process big data applications, we propose a near-far computing enhanced C-RAN (NFC-RAN) architecture by extending the C-RAN enhanced with mobile cloud [8] with another layer of cloud computing, called near edge computing (NEC). In comparison with the mobile cloud in [8], which is referred to as far edge computing (FEC), NEC is deployed in the RRHs, that is, much closer to UEs. Also, in this article, we introduce how we allocate different tasks between NEC and FEC, as proper allocation affects the performance of whole networks and the experience of the user significantly [12].

Furthermore, in this article, we use indoor positioning [13, 14] as an example to showcase the benefits of the proposed network architecture. To fulfill indoor positioning effectively, a large amount of wireless data concerning signal strength of positioning beacons needs to be collected, transmitted, and processed. Also, unlike outdoor positioning where the distance is usually measured in terms of tens of meters, indoor positioning techniques require to capture movement at a level of no more than 2–3 m. This requires a very short response time when processing the above-mentioned large amount of information, and the corresponding processing has to be conducted promptly in order to show a walker’s current position in real time.

Lianming Zhang is with Hunan Normal University; Kezhi Wang is with Northumbria University; Xuan Du is with the University of Essex; Kun Yang is with the University of Essex and with the University of Electronic Science and Technology of China.
The remainder of the article is organized as follows. We describe the proposed NFC-RAN architecture on top of the popular C-RAN and present various tasks involved in indoor positioning. Then the big data nature of the indoor positioning problem is discussed. We generalize the task allocation issue in NFC-RAN into an optimization problem covering both the computation and communication aspects. Also, simulation results are given in this section. We then introduce the indoor positioning as a case study to illustrate our proposed architecture. Also, experimental results are reported. Finally, concluding remarks are given.

**NFC-RAN Architecture and Its Application to Indoor Positioning**

**NFC-RAN Architecture**

Our proposed NFC-RAN is shown in Fig. 1. NFC-RAN is composed of the BBU pool, which is responsible for most of the signal processing tasks, and RRHs, which are in charge of sending and receiving data to and from UEs. RRHs can serve as the access points, which can be distributed closer to UEs as required. Also, RRHs are connected to the BBU pool through a high-speed fronthaul link. To support wireless big data processing, similar to [8], we propose to have FEC located next to the BBU pool. If FEC decides to execute a task for UEs, FEC will send all the task data to RRHs through wireless channel first, and then RRHs will forward the data to FEC via the fronthaul link. This may not be beneficial for delay-sensitive tasks or tasks involving big transmission data. Thus, in addition to FEC, we propose to have the NEC located in each RRH as well. NEC can respond to UEs’ requests much faster due to its closer geographic location. In this architecture, UE does not have to send the data all the way to the central cloud (i.e., FEC). This can not only save the bandwidth for fronthaul, but also reduce the response time for the tasks.

However, NEC may not have enough computational resource to process requests from all the UEs from its serving premises. Some delay-tolerant tasks that require more computation can be forwarded to FEC instead. Thus, it is important to identify whether the tasks from UEs are delay-tolerant, computation-intensive, or both, and then allocate them to FEC and NEC accordingly. Next, we analyze the big data tasks involved in indoor positioning.

**Tasks Involved in Indoor Positioning**

Outdoor positioning has been widely used in real life thanks to Global Positioning System (GPS) technology [15]. However, GPS does not work indoors, but demands on finding indoor locations are high, as people spend most of their time indoors rather outdoors. Much effort has been made for indoor positioning, especially regarding techniques that do not involve much effort for initial deployment of positioning beacons. Due to the wide spread of WiFi hotspots (technically access points or APs), WiFi has become a cost-effective option for indoor positioning. WiFi-assisted indoor positioning works in the steps below.

First, WiFi APs’ signal fingerprints, which are typically composed of received signal strength (RSS), are collected against a particular physical indoor location (also known as a reference point). Then, after some signal processing in the cloud, those (RSS, location) pairs are stored in a database, which can be referred to as a signal fingerprints database (SFD).

Second, one can repeat the first step until all the designated locations are traversed. This procedure can be called the site survey, which is conducted offline.

Then, during the online positioning stage, the UE, which must show its current location, collects the current RSS of the WiFi signal in the surrounding area and then compares the RSS with the data in the SFD. To this end, the location with the best-matched fingerprint can be considered as the UE’s current location. The software architecture and the corresponding tasks of this widely used fingerprint-based indoor positioning are depicted in Fig. 2.

To make positioning more accurate and efficient, extra procedures are introduced, such as signal pattern processing to clean out and correct wrong fingerprints. Also, as RSS may change along with the changing indoor environment, to reflect in the signal pattern database on the positioning server, feedback is also applied in Fig. 2.

In summary there are two types of tasks. The first are non-real-time or delay-tolerant tasks that have long-term effects on the system such as signal pattern collection, processing, and map generation. The other type is real-time or delay-sensitive tasks that are more concerned with end users’ positioning or display, such as instantaneous signal fingerprint collection, location display, and signal pattern matching. The non-real-time tasks can run remotely on FEC, whereas the real-time tasks have to be executed on NEC to ensure fast response action. The experimental results later show the effectiveness of NEC in improving the accuracy of location.

**Wireless Big Data Involved in Indoor Positioning**

To have an estimate of how many WiFi signals are needed for indoor positioning, certain tests are carried out in our experimental site (i.e., the fifth floor of the Network Centre Building on the Col-
The software architecture and the corresponding tasks in WiFi assisted indoor positioning.

![Diagram of software architecture and tasks](image)

**Figure 2**

The pie chart in Fig. 3 shows the percentage of observed APs with different appearance frequency, which reveals that 5 GHz channels may be less crowded, and weak signals in 5 GHz are more likely to be observed than the signals in 2.4 GHz.

Figure 3 also shows that approximately 600 observations are collected within 25 s, which means that about 25 APs are observed every second on average. For each AP, a large amount of information has to be collected, such as MAC address, RSS, working frequency, and timestamp, amounting to at least 8 bytes. Thus, a stream of data of more than 200 B/s is generated. When the number of UEs or APs increases, the amount of data just for the purpose of indoor positioning will increase significantly. Note that this is a stream of data which is generated constantly and continually. Thus, it is nearly impossible for UEs to process tasks with huge amounts of data. The only way is to offload the corresponding tasks to the cloud (i.e., NEC and FEC). Next, we introduce how we allocate the tasks to NEC and FEC in our proposed architecture.

**Task Allocation in NFC-RAN for Wireless Big Data**

**System Model**

To better describe the task allocation algorithms, we assume that there are $M$ RRHs, each of which, $j = 1, 2, ..., M$, forms a small cell that can support $N_j$ UEs, as shown in Fig. 1. Also, assume each UE employs the orthogonal channel to transmit its data, and there is no interference between them. We assume each UE is only served by its nearest RRH, which is predefined by its geographical position and signal strength.

We denote UE $i = 1, 2, ..., N$ in the coverage of the $j$th RRH as $i$th UE, which has a task $U_{ij} = (F_{ij}, D_{ij}, T_{ij})$, where $F_{ij}$ (in cycles) describes the computation requirement of this task, $D_{ij}$ (in bits) denotes the data required to be transmitted to NEC or FEC, and $T_{ij}$ (in seconds) is the delay requirement in order to satisfy the UE’s quality of service. We assume there is one FEC next to the BBU pool with huge computation capacity $F_{ij}^{FEC}$ (in cycles per second), and it can be allocated to any UE in any cell. We also assume each RRH has a small NEC with limited computation capacity $F_{ij}^{NEC}$ (in cycles per second).

Also, we assume that the tasks cannot be executed in UEs, as UEs may not have enough processing capacity, and thus UEs can either offload the tasks to FEC or NEC. We define the indication parameters (i.e., $a_i, b_j, \forall i \in N, \forall j \in M$) to indicate where the task should be executed ($a_i = 1$ denotes that the task is executed by FEC, whereas $b_j = 1$ denotes that the task is executed by the $j$th NEC). On the other hand, if $a_i = b_j = 0$, it means this task can be executed by neither the NEC nor the FEC, and thus it has to be delayed to the next time slot.

If NEC decides to execute the task for the $i$th UE, it will allocate the CPU capacity $F_{ij}^{NEC}$ to the UE, which needs to send its data through a wireless channel to the $j$th RRH with data rate $\frac{D_{ij}}{T_{ij}}$. In this case, a task with a large amount of data $D_{ij}$ (big data application) does not have to send all the data to the central cloud through the fronthaul link. On the other hand, if the task requires a huge amount of calculation (computation-intensive application), NEC may not be able to...
complete this task, due to its limited computation capacity, i.e., $F_E^{j}$. Then UE has to send all the data to the central cloud (i.e., FEC).

If FEC decides to execute the task for UE, it will allocate the CPU capacity $r_{ij}^{FE}$ to the $j$th UE. In this case, UE should first send its data to the $j$th RRH with wireless data rate $r_{ij}^{W}$, and then RRH will forward the data to FEC with fronthaul transmission data rate $r_{ij}^{F}$. Also, as the computation capacity of FEC is not infinite, but constrained by the capacity of the physical machine (i.e., $F_E^{j}$), some UEs may still not be able to complete the tasks. Moreover, if UEs decide to send the task to FEC, the capacity of fronthaul has to be taken into account. Thus, we assume the capability of the $j$th fronthaul as $R_j$.

We model the task allocation problem as follows:

$$\begin{align*}
\mathcal{P}: \max & \sum_{a_{ij}, b_{ij} \in \mathcal{J}, \mathcal{F}} \sum_{a_{ij}, b_{ij} \in \mathcal{M}} (a_{ij} + b_{ij}) \\
\text{subject to:} & \quad C_1: a_{ij} \left( \frac{D_{ij}^{W}}{r_{ij}^{W}} + \frac{D_{ij}^{F}}{r_{ij}^{F}} + \frac{F_{ij}^{FE}}{r_{ij}^{FE}} \right) \leq T_{ij} \\
& \quad C_2: b_{ij} \left( \frac{D_{ij}^{W}}{r_{ij}^{W}} + \frac{F_{ij}^{NE}}{r_{ij}^{NE}} \right) \leq T_{ij} \\
& \quad C_3: \sum_{a_{ij} \in \mathcal{J}, \mathcal{F} \in \mathcal{M}} a_{ij} f_{ij}^{FE} \leq F_{ij}^{FE} \\
& \quad C_4: \sum_{b_{ij} \in \mathcal{J}, \mathcal{F} \in \mathcal{M}} b_{ij} f_{ij}^{NE} \leq F_{ij}^{NE} \\
& \quad C_5: \sum_{a_{ij} \in \mathcal{J}, \mathcal{F} \in \mathcal{M}} a_{ij} + b_{ij} \leq 1
\end{align*}$$

(1)

where we aim to maximize the successful rate of all the offloading tasks by deciding where the tasks should be executed. In other words, we try to accommodate as many tasks in the cloud as possible. In the above problem, $C_1$ and $C_2$ denote that the task has to be completed in a certain amount of time by FEC or NEC, respectively; $C_3$ and $C_4$ denote that the computation resources are limited in FEC and the $j$th NEC, respectively; $C_5$ is the constraint for the $j$th fronthaul; and $C_6$ and $C_7$ can not only show where each task should be executed, but also make the problem feasible. The above problem may be modified as the multi-dimension multi-choice 0-1 knapsack problem (MMKP), which can be solved effectively by using a heuristic algorithm.

**Simulation Results**

We assume that there are $M = 5$ RRHs, each of which forms a small cell. In each cell, there are $N$ UEs, each of which has a task to be completed. For each task, we assume the latency requirement is 3 s. We assume that other parameters are randomly assigned from the sets indicated on the left of Fig. 4.

On the right of Fig. 4, we show the relation between task successful rate vs. the number of offloading tasks. The task successful rate or the task completion rate is defined as the ratio of the number of completions to the overall offloaded tasks. We compare the new NFC-RAN and the traditional C-RAN architecture only with FEC. The number of UEs is set from 10 to 50 in each of the 5 cells. Also, to compare fairly, $r_{FE}$ is set to $10^7$ GHz for traditional C-RAN.

One can see that with the increase of the number of offloading tasks, the successful rate decreases. This is because the cloud has limited computation resource, and some tasks may be dropped or delayed to the next time interval. Our proposed NFC-RAN outperforms the traditional C-RAN with FEC, as NFC-RAN supports not only FEC but also NEC, which is much closer to UEs. This structure is beneficial to the delay-sensitive tasks and therefore can increase the overall tasks' successful rate. In the next section, we use indoor positioning as a case study to show the benefit of NFC-RAN.

**Case Study: Indoor Positioning**

This section uses indoor positioning as a case study, and we assume that the task allocation is predetermined, namely, all the offline tasks and feedback tasks (refer to Fig. 2) are executed at FEC, whereas the online computation tasks are executed at NEC. The experiments are carried out to show the performance improvement of positioning by using NFC-RAN architecture.

| Parameter | Description | Value |
|-----------|-------------|-------|
| $D_{ij}$ | Communication resource required (bits) | 1M–1G |
| $F_{ij}$ | Computation resource required (cycles) | 1M–1G |
| $r_{ij}^{W}$ | Wireless data rate (bits/s) | 1G–10G |
| $r_{ij}^{F}$ | Fronthaul data rate (bits/s) | 1G–10G |
| $f_{ij}^{NE}$ | Computation allocation from NEC (cycles/s) | 1G–10G |
| $f_{ij}^{FE}$ | Computation allocation from FEC (cycles/s) | 100G–1000G |
| $R_j$ | Fronthaul capacity (bits/s) | $10^3$ G–$10^4$ G |

**FIGURE 4** Simulation parameters setting (left) and simulation result (right).
**Experimental Setup**

We set up our testbed on the fifth Floor of the Network Centre Building of the University of Essex, where the experiments were conducted. The map of the environment is depicted on the left of Fig. 5. The site is covered by about 60 wireless APs of Aruba mounted on the ceiling. Each physical AP may generate multiple SSIDs, which means many more APs are observed by UEs. The circle on the right of Fig. 5 indicates the location of the UE.

**Experimental Results**

Two experiments were conducted. In the first one, most of the online tasks, such as fingerprint matching, are offloaded to and conducted by NFC-RAN, whereas in the second experiment, UE itself executes most of the tasks. We compare these two cases in Fig. 6, where in Fig. 6a we show the cumulative distribution function (CDF) of location errors for both cases.

One can see that our proposed NFC-RAN-assisted system shows better location accuracy than the UE-based one. The percentage of accuracy within 1 m is approximately 70 percent in the NFC-RAN assisted system, which doubles the percentage of the UE-based approach (35 percent). In 90 percent of positioning results, the NFC-RAN-assisted and UE-based systems provide accuracy of 3 m and 5 m, respectively. Through comparison of the location errors when the CDF is 100 percent, it is apparent that the maximum error distance of the UE-based system is almost 7.5 m, whereas the NFC-RAN-assisted system can decrease it to 4.5 m. The major reasons why NFC-RAN architecture outperforms the UE-based one are two-fold. First, the processing capacity of UE cannot compare with that of the NFC-RAN system, which is composed of much more powerful computation resource. The high computation capacity in NFC-RAN can process more patterns (big data applications) and execute more comprehensive tasks. Second, the proposal of NEC, which brings computation closer to the UE, can quickly calculate and execute tasks for the UE, such as signal pattern matching tasks. However, the UE-based positioning approach may lead to a situation where the produced location result by UE is sometimes out of date, thus resulting in worse location accuracy.

In Fig. 6b, we show the overall energy consumption on UE when NFC-RAN deals with computation or UE itself conducts computation. From Fig. 6b, we can see that UE will save a lot of energy on the NFC-RAN assisted situation, as most of the tasks are offloaded from UE to NFC-RAN. This is particularly important for a practical indoor positioning system as the positioning process may incur a large amount of data and therefore drain the UE’s battery quickly.

**Conclusions**

In this article, we have proposed NFC-RAN architecture, which can facilitate wireless big data processing. NFC-RAN is composed of NEC and FEC.
where FEC is located next to a BBU pool, which can provide a large amount of computational resource to UEs, while NEC, located in RRHs, can quickly respond to delay-sensitive applications. Also, task allocation in NFC-RAN for wireless big data is illustrated, and indoor positioning, as a case study, is exemplified to show the benefit of the proposed architecture. Future work will focus on how to allocate and execute the tasks dynamically, including in the NEC, FEC, and UE itself. Also, more efficient task allocation algorithms for wireless big data will be investigated.

ACKNOWLEDGMENTS

This work was supported in part by the Natural Science Foundation of China (Grant Nos. 61620106011, 61372389, and 61372191), the U.K. EPSRC NIRVANA project (EP/L026031/1), the EU Horizon 2020 ICIRRUS project (GA-644526), and the EU FP7 Project CROWN (GA-2013-610524). We also would like to thank Dr. Yuansheng Luo for very useful discussion.

REFERENCES

[1] S. Bi et al., “Wireless Communications in the Era of Big Data,” IEEE Commun. Mag., vol. 53, no. 10, Oct. 2015, pp. 190–99.
[2] M. Patel et al., “Mobile Edge Computing White Paper,” ETSI, 2014.
[3] S. Kosta et al., “Thinkair: Dynamic Resource Allocation and Parallel Execution in the Cloud for Mobile Code Offloading,” Proc. IEEE INFOCOM 2012, Mar. 2012, pp. 945–53.
[4] M. Peng et al., “Recent Advances in Cloud Radio Access Networks: System Architectures, Key Techniques, and Open Issues,” IEEE Commun. Surveys & Tutorials, vol. 18, no. 3, 2016, pp. 2282–2308.
[5] J. Wu et al., “Da-CRAN: A Data-Assisted Cloud Radio Access Network for Visual Communications,” IEEE Wireless Commun., vol. 22, no. 3, June 2015, pp. 130–36.
[6] China Mobile Research Institute., “C-RAN White Paper: The Road Towards Green RAN,” June 2014, http://labs.china-mobile.com/cran.
[7] K. Wang et al., “Cost-Effective Resource Allocation in C-RAN with Mobile Cloud,” 2016 IEEE ICC, May 2016, pp. 1–6.
[8] K. Wang, K. Yang, and C. Magurawalage, “Joint Energy Minimization and Resource Allocation in C-RAN with Mobile Cloud,” IEEE Trans. Cloud Computing, 2016.
[9] X. Zhang et al., “Social Computing for Mobile Big Data,” Computer, vol. 49, no. 9, Sept 2016, pp. 86–90.
[10] K. Wang at al., “Wireless Big Data Computing in Smart Grid,” IEEE Wireless Commun., vol. 24, no. 2, Apr. 2017, pp. 58–64.
[11] K. Wang et al., “Computation Diversity in Emerging Networking Paradigms,” IEEE Wireless Commun., vol. 24, no. 1, Feb. 2017, pp. 88–94.
[12] G. Nan et al., “Distributed Resource Allocation in Cloud-Based Wireless Multimedia Social Networks,” IEEE Network, vol. 28, no. 4, July 2014, pp. 74–80.
[13] X. Du and K. Yang, “A Map-Assisted WiFi AP Placement Algorithm Enabling Mobile Device Indoor Positioning,” IEEE Systems J., 2016.
[14] X. Du et al., “An AP-Centred Indoor Positioning System Combining Fingerprint Technique,” 2016 IEEE GLOBECOM, Dec 2016, pp. 1–6.
[15] G. Xu et al., “A Survey for Mobility Big Data Analytics for Geolocation Prediction,” IEEE Wireless Commun., vol. 24, no. 1, Feb. 2017, pp. 111–19.

BIographies

LIAOWANG ZHANG (zlw@hunnu.edu.cn) is currently a professor in the College of Information Science and Engineering of Hunan Normal University, China, and leads the Key Laboratory of Internet of Things Technology and Application there. He received his Ph.D. degree from the School of Information Science and Engineering of Central South University, China, and his M.Sc. and B.Sc. degrees from the Department of Physics of Hunan Normal University. His main research interests include computer networks, software-defined networking, edge computing, complex networks, and network calculus. He completed a two-year postdoctoral fellowship in complex networks at the School of Computer Science and Engineering of South China University of Technology. He manages research projects funded by various sources such as the National Natural Science Foundation of China and companies. He has published more than 100 papers.

KEZHI WANG (kezhi.wang@northumbria.ac.uk) received his Ph.D. degree from the University of Warwick, United Kingdom, in 2015. He was a senior research officer at the University of Essex, United Kingdom. Currently he is a lecturer in the Department of Computer and Information Sciences, Northumbria University, United Kingdom. His research interests include mobile cloud computing and wireless communications.

Du Xuan [S] (duxuan@essex.ac.uk) received his B.Eng. degree in computing and electronics in 2013 from the School of Computer Science & Electronic Engineering, University of Essex, and is currently pursuing a Ph.D. degree in computing systems engineering. His research interests include indoor positioning, the Internet of Things, and mobile computing. He is involved in research projects funded by various sources such as UK EPSRC and EU H2020.

KUN YANG (SM’08) (kunyang@essex.ac.uk) received his Ph.D. degree from the Department of Electronic & Electrical Engineering of University College London (UCL), United Kingdom, and M.Sc. and B.Sc. from the Computer Science Department of Jilin University, China. He is currently a Chair Professor in the School of Computer Science & Electronic Engineering, University of Essex, leading the Network Convergence Laboratory. He is also an affiliated professor at the University of Electronic Science and Technology of China. Before joining the University of Essex at 2003, he worked at UCL on several European Union (EU) research projects for several years. His main research interests include wireless networks and communications, data and energy integrated networks, and computation-communication cooperation. He manages research projects funded by various sources such as UK EPSRC, EU FP7/H2020, and companies. He has published more than 100+ journal papers. He serves on the Editorial Boards of both IEEE and non-IEEE journals. He is a Fellow of IET (since 2009).

Future work will focus on how to allocate and execute the tasks dynamically, including in the NEC, FEC, and UE itself. Also, more efficient task allocation algorithms for wireless big data will be investigated.