MULTIMEDIA COMMUNICATIONS TECHNICAL COMMITTEE
https://mmc.committees.comsoc.org

MMTC Communications - Frontiers

Vol. 15, No. 2, March 2020

CONTENTS

SPECIAL ISSUE ON *Data Transmission for IoT: Challenges, Algorithms, and Applications*

Guest Editor: Bin Tan and Rui Wang
Jinggangshan Univeristy, Tongji University, China
tanbin@jgsu.edu.cn

Nowadays, billions of mobile and IoT devices are connected to the Internet, generating zillions Bytes of data, specially the video data at the network. This special issue of Frontiers focuses on data transmission for IoT, including challenges, algorithms, and applications in wireless networks. These three research directions have received great attentions from both academia and industries. Various research groups all around the world are currently working on these topics. We invited three papers from three distinguished research groups. The main contributions are summarized as follows.

The first paper is about nergy Harvesting based Data Uploading for Internet of Things. The authors proposed proposed a novel data uploading mechanism, especially for large amount IoT devices, which increases the spectrum utilization a lot by incorporating the data uploading scheduling with energy state forecasting.

The second paper of the issue focuses on the real-time problem of the IoT systems. It described the basic concepts of real-time systems and the IoT, and then puts forward the concept of real-time IoT and lists the basic elements of the real-time IoT.

In the third paper, issues related the multimedia communication are discussed. It provides approach on how to reduce the overhead and transmit the analog data more robust. The proposed scheme adopts CDF 9/7 to perform decorrelation transform and BCS to resist channel noise.

Bin Tan (tanbin@jgsu.edu.cn) received her M.S. degree from Wuhan University, China, in 2008 ; and the Ph.D. degree in 2017 from Tongji University, China, all in computer science. From Jan. 2017 to May. 2017, she was a visiting Ph.D. student at the Department of Information Engineering and Computer Science of University of Trento. Since Fall 2003, she has been with the College of Electronics and Information Engineering, Jinggangshan University, where she is currently an associate professor. Dr. Tan serves as a chair for the Multimedia Communications Technical Committee :(IVCTIG) Intelligent Video Coding and Transmission. Her research interests include video transmission, joint source and channel coding, and machine learning in wireless networks.

Rui Wang (ruiwang@tongji.edu.cn) received his Ph.D. degree in 2013 from Shanghai Jiao Tong University, China. From Aug. 2012 to Feb. 2013, he was a visiting Ph.D. student at the Department of Electrical Engineering of University of California, Riverside. From Oct. 2013 to Oct. 2014, he was with the Institute of Network Coding, the Chinese University of Hong Kong as a post- doctoral research associate. From Oct. 2014 to Dec. 2016, he was with the College of Electronics and Information Engineering, Tongji University as an assistant professor, where he is currently an associate professor. Dr. Wang is currently an associate editor of the journal of IEEE Access and editor of IEEE Wireless Communications Letters.

Energy Harvesting based Data Uploading for Internet of Things

Gaofei Sun[1], Xiaoshuang Xing[1], Xiangpin Qin[1], Xiujian Fan[1]
[1]*Changshu Institute of Technology*
gfsun@cslg.edu.cn

1. Introduction

Data uploading and transmission mechanism or scheme for energy harvesting IoT devices are already proposed by organizations and companies in recent decades [1-6]. Along with the 5G network evolution, novel protocols for IoT devices, NB-IoT, EMTC, are proposed for catering different requirements, such as high data rate and lower delay, or low data rate and tolerable delay in specific scenarios [7-11]. However, there still leave several obstacles to be solved as follows: First, the coverage of given mechanism cannot be perfect anywhere, thus it is not sensible for IoT devices to rely on specific access technology only. Second, the direct link from IoT devices to cellular base-station is not suitable for information fusion, and also bring large information redundancy and privacy issue [12]. Practically, for monitoring the environment in a given area, the acquired information from several deployed devices can be fused locally to derive the key information about the circumstance, and thus only the key information needs to be uploaded [13-18]. Third, the existed mechanisms mainly focus on data transmission process, but ignore the joint design with energy state of IoT devices. Without enough energy, devices cannot perform the data uploading, and thus waste the valuable spectrum allocated to.

Related Work

For data uploading, the well investigated scheme is the harvest-then-transmit protocol [8-10]. In [8], the joint optimization problem of down-link RF energy harvesting and up-link information transmission is studied based on time division multiple access (TDMA), and thus a common-throughput metric is proposed to address the doubly near-far problem. Further, the work in [8] extended this protocol by incorporating user cooperation, and work in [10] proposed a low complexity iteration algorithm to achieve a similar throughput as in [8]. However, these work main focused on the fairness among multiple users, and sacrificed system throughput to a certain extent. Therefore, work in [15-16] aim to achieve system throughput maximization by optimal power allocations. To achieve this goal, only part of users is scheduled for data transmission in given time and frequency blocks, while other users are arranged for energy harvesting. In [17-18] the authors studied the data uploading scheme that can maximize the energy efficiency. By exploring nonlinear fractional programming and Lagrange dual decomposition, an iterative algorithm is proposed to achieve better performance in average energy efficiency and system performance. However, all the above mentioned schemes are centralized that perform well in small-scale network. With the increasing number of users in the network, the computation complexity of these centralized scheme will become intractable. To accommodate with the data uploading requirements of the large number of users/devices, the multi-tier network structure has been proposed in [19–21] without considering the energy harvesting capabilities of the users. Devices are divided into groups, and a device is selected as the gateway AP within each group. The devices inside the same group may transmit their data to the gate way AP while the gateway AP can merge the information of the group and decide the accessing strategy to decrease the data flow in the backbone networks and improve the spectrum efficiency.

Contributions

In our scheme, IoT devices select the appropriate AP for distributive data uploading, and APs acted as a controller to schedule devices' uploading and ensure the spectrum efficiency inside APs. To our knowledge, our work proposed a novel data uploading mechanism, especially for large amount IoT devices, which increases the spectrum utilization a lot by incorporating the data uploading scheduling with energy state forecasting. The main contributions are as follows: (i) IoT devices are heterogeneous in data pattern and uploading requirement, and thus the proposed algorithms are suitable for applications in real environment. (ii) The energy state of IoT devices are incorporating into the data uploading process, we depicted the data uploading demand of devices as urgency function, which well reflect devices' requirement. (iii) A central slot utilization and also a distributive AP selection algorithm for IoT devices are proposed, to achieve the joint optimization on data uploading and energy harvesting.

2. System Model and Problem Formulation

The system model consists 3 layers: The IoT devices, Access Points, and the backbone infrastructures. Each device is equipped with short range communication module for data uploading, such as WiFi, or BLE4.0, also cognitive access. Therefore, devices may select the proper AP for data uploading according to its requirement and communication load.

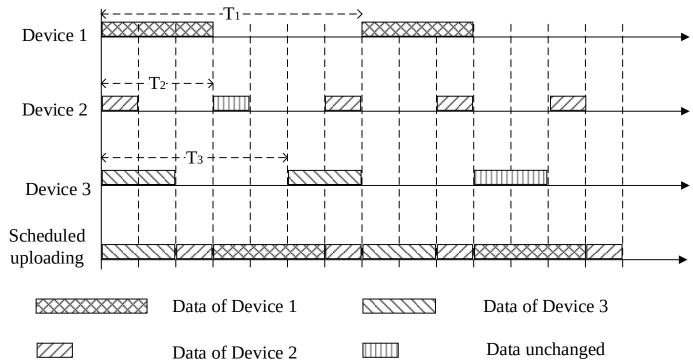

Figure 1: The data frame with 3 IoT devices.

The data frames with 3 IoT devices are depicted in Figure 1. We consider that there are M IoT devices and N APs in given area, which denote as $\mathrm{M} = \{1,\cdots,i,\cdots,M\}$ and $\mathrm{N} = \{1,\cdots,j,\cdots,N\}$, and characterize IoT device $i, i \in \mathrm{M}$ with following parameters: data volume s_i, data uploading period t_i, and energy state e_i. Further, we divide each device's energy state into $K+1$ states from empty energy to full energy, $\xi^i_{k_1,k_2}, k_1, k_2 \in [0,K]$ means the probability that the energy state of device i changes from state k_1 to state k_2, and denote the required energy for finishing data upload as e^r_i. Hence, we omit the accuracy on acquired data, and model the data transition as a Markov chain, thus define the data transition matrix for device i as

$$\Gamma_i = \begin{bmatrix} \gamma^i_{1,1} & \gamma^i_{1,2} & \cdots & \gamma^i_{1,L_i} \\ \gamma^i_{2,1} & \gamma^i_{2,2} & \cdots & \gamma^i_{2,L_i} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma^i_{L_i,1} & \gamma^i_{L_i,2} & \cdots & \gamma^i_{L_i,L_i} \end{bmatrix} \tag{1}$$

Here, $\gamma^i_{m,n}$ represents the probability of transferring from state $m, m \in [1, L_i]$ to state $n, n \in [1, L_i]$. We classify these devices into groups as $\{\mathrm{M}_1,\cdots,\mathrm{M}_j,\cdots,\mathrm{M}_N\}, \mathrm{M}_j \cap \mathrm{M}_k = \phi, \forall j,k \in [1,N]$. Hence, we incorporate depth κ as a metric for measuring the available remaining slots for data uploading. From a given time stamp $t=0$ to relatively large time stamp $t=T$, we denote device i's data in each period as $\mathbf{d}_i = \{d^1_{i,j}, d^2_{i,j},\cdots,d^{n_i}_{i,j}\}, n_i \cdot t_i \le T \le (n_i+1)\cdot t_i$ once it selected AP j for uploading. Here, $d^k_{i,j}, k \in [1,n_i]$ denotes a serial of slots begin with $t = t_i \cdot (k-1)+1$ and end with $t = t_i \cdot (k-1+s_i)$, that is $|d_{i,j}| = s_i$. By considering the possible uploading in next κ periods, the data uploading slots can be changed, such as $d^2_{i,j}$ changed from $[t_i+1, 2\cdot t_1]$ to $[t_i+1+\Delta t, 2\cdot t_1+\Delta t]$. Hence, the derived data sequence of device i is denoted as $\mathbf{d}_i$. Note that, the data sequence's transformation is affected by other devices who selected identical AP, thus the new data sequences $\mathbf{d}_1, \mathbf{d}_2, \cdots, \mathbf{d}_{M_j}$ have already no collusion between each other's uploading from AP j. Therefore, the optimization problem can be denoted as

$$\max_{\kappa,\mathbf{d}_1,\mathbf{d}_2,\cdots,\mathbf{d}_M} \frac{\sum_j \sum_{i,i\in \mathrm{M}_j} |\mathbf{d}_i|}{T} \tag{2}$$

With the constraints

$$\mathbf{d}_m \cap \mathbf{d}_n = \phi, \forall m,n \in [1, \mathrm{M}_j], j \in [1,N] \tag{3}$$

Therefore, this optimization problem needs an iterative process of two parts: devices select the proper AP for data uploading, the scheduling of data for devices who access the same AP.

3. Data uploading scheduling under an identical AP

Device $i, i \in \mathrm{M}$ would upload its data under conditions: enough energy, that is $e_i \geq e_i^r$, and data changed compared with previous period, that is $d_i \neq d_i^{-1}$. Therefore, we derive the data uploading probability as.

$$P_i^S = (\sum_{i=1}^{K+1} \pi_i^e \sum_{e_k \geq e_i^r, k \in [1, K+1]} \xi_{i,k}) \cdot (\sum_{i=1}^{L_i} \pi_i^d \sum_{j \neq i} \gamma_{ij}^i). \tag{4}$$

Thus, we derive the urgency function for devices in M_j as

$$U_i(T_i, n_i, d_i^{-1}, d_i, e_i) = f(s_i, T_i) \cdot \sum_{k=1}^{\kappa} \theta(n_i + k \cdot T_i) U_i(n_i + k \cdot T_i), \tag{5}$$

here $\theta(n_i + k \cdot T_i)$ is a decreasing factor refer to number of slots, which reflect the inaccuracy of $U_i(n_i + k \cdot T_i)$. The energy state e_i^1 can be divided into two cases: First, $\overline{e}_i \geq e_i^{req}$, thus no matter whether device i obtain energy outside the sensing can be performed with probability 1; Second, $\overline{e}_i < e_i^{req}$, whether device i performs the data sensing depending on obtaining energy to achieve the minimum energy e_i^{req}. Based on analysis above, we derive the expression of $U_i(n_i)$ as in equation (6).

$$U_i(n_i) = \begin{cases} \sum_{j \neq d_i} \gamma_{d_i, j}^i & , \overline{e}_i \geq e_i^{req}, \\ \sum_{j = e_i^{req}}^{K} \xi_{\overline{e}_i, j}^i \cdot \sum_{j \neq d_i} \gamma_{d_i, j}^i & , \overline{e}_i < e_i^{req}. \end{cases} \tag{6}$$

4. AP selection among IoT devices

Basically, we proposed a metric for IoT devices, for facilitating their selection among APs. Fortunately, the actual data uploading probability $A_i^s, i \in \{1, M\}$ can be used as a metric to measure the data uploading performance of APs. Suppose that device i selects AP j randomly at the beginning, then perform its data uploading through AP j. After a certain time T_s, each AP broadcasts its slot utilization probability as $\Theta_1, \cdots, \Theta_N$. At the same time, data uploading probability P_i^s and actual data uploading probability $A_{i,j}^s$ of device $i, i \in M$ are derived by device i. The expected actual data uploading probability $\tilde{A}_{i,k}^s, k \in \{1, N\}, k \neq j$ *is*

$$\tilde{A}_{i,k}^s = (1 - \Theta_k)(1 + \frac{s_i \ln(1 - P_i^s)}{T_i}). \tag{7}$$

Therefore, device i will calculate the data utilization vector $\tilde{A}_{i,1}^s, \cdots, \tilde{A}_{i,N}^s$ when APs broadcast their slot utilization $\Theta_1, \cdots, \Theta_N$, except for its current selection, that is AP j. It is apparently that the best AP to be selected is $\max_k \tilde{A}_{i,k}^s$. The variable ò is a minimal positive number, which avoids the ping-pong effect between APs selections.

5. Results and Discussion

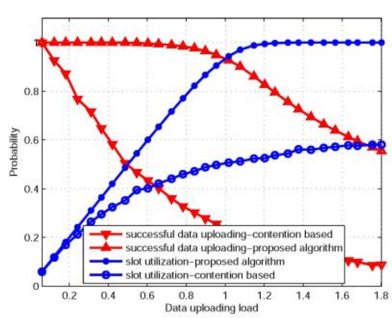

Figure 2: performance with different urgency functions.

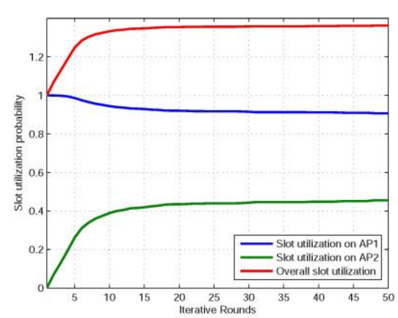

Figure 3: The slot utilization probabilities derived by 50

rounds

Slot utilization: In Fig. 2, we compared the performance with different urgency functions. We take random selection among 9 devices for transmission as a benchmark scheme for comparison, which depicted as red curve. It is observed that the class C devices with short period time have the lowest successful transmission rate, about 55%.

AP selections: The slot utilization probabilities derived by 50 rounds are depicted in Fig. 3. Here, the blue curve indicates the slot utilization of AP 1 decreases due to the departure of IoT devices. Meanwhile, the green curve increases as the number of devices gradually increased. Besides, the selection of IoT devices on APs steadied in less than 20 rounds, which indicates our proposed algorithm has a well convergence performance.

6. Concluding Remarks and Future Directions

In this work, we analyze the scenario that how to schedule the data uploading of multiple energy harvesting enabled IoT devices among multiple APs. Firstly, a multi-layer data uploading process is proposed, that devices access the proper AP for data uploading and APs relay devices' data through different network access technologies. Secondly, a low complexity slot allocation algorithm is proposed for devices who select the identical AP, the urgency function of devices ensure that the uploading period, data length, remaining slots are considered and achieve the fairness among devices; Thirdly, a distributive AP selection algorithm is proposed, and thus can achieve the stable selection among devices. Finally, the simulation results indicate that our proposed algorithms well balance the data uploading requirements and also afford multiple access choices in heterogeneous networks with low cost and complexity.

References

1. M. R. Palattella, M. Dohler, A. Grieco, G. Rizzo, J. Torsner, T. Engel, L. Ladid, Internet of Things in the 5G era: enablers, architecture, and business models . IEEE J. Sel. Areas Commun. 34(3), 510-527 (2016)

2. Z. Cai, X. Zheng, A Private and Efficient Mechanism for Data Uploading in Smart Cyber-Physical Systems. IEEE Trans. Netw. Sci. Eng., 1–1 (2018)

3. X. Lu, P. Wang, D. Niyato, D. I. Kim, Z. Han, Wireless networks with RF energy harvesting: a contemporary survey. IEEE Commun. Surv. Tutor. 17.2, 757-789 (2015)

4. T. Shi, S. Cheng, Z. Cai, Y. Li, J. Li, Exploring Connected Dominating Sets in Energy-Harvest Networks. IEEEACM Trans. Netw. 25(3), 1803-1817 (2017)

5. Q. Chen, H. Gao, Z. Cai, L. Cheng, J. Li, in Book Energy-Collision Aware Data Aggregation Scheduling for Energy Harvesting Sensor Networks.

Energy-Collision Aware Data Aggregation Scheduling for Energy Harvesting Sensor Networks, (2018), pp. 117–125

6. K. Pouya, et al., Wireless energy harvesting for the Internet of Things. IEEE Commun. Mag. 53(6), 102-108 (2015)

7. Y. Gang, C. K. Ho, Y. L. Guan, Dynamic resource allocation for multiple-antenna wireless power transfer. IEEE Trans. Sig. Process. 62(14), 3565-3577 (2014)

8. H. Ju, R. Zhang, Throughput maximization in wireless powered communication networks. IEEE Trans. Wirel Commun. 13(1), 418-428(2014)

9. L. Liu, R. Zhang, K. Chua, Multi-Antenna Wireless Powered Communication with Energy Beamforming. IEEE Trans. Commun. 62(12), 4349–4361 (2014)

10. Q. Sun, et al., A low-complexity algorithm for throughput maximization in wireless powered communication networks. arXiv preprint arXiv:1403.3665 (2014)

11. Q. Gao, T. Jing, X. Xing, X. Cheng, Y. Huo, D. Chen, Simultaneous energy and information cooperation in MIMO cooperative cognitive radio systems. (IEEE Wireless Communications and Networking Conference (WCNC), New Orleans, 2015), pp. 351–356

12. Z. He, Z. Cai, Q. Han, W. Tong, L. Sun, Y. Li, An energy efficient privacy-preserving content sharing scheme in mobile social networks. Personal Ubiquit. Comput. 20(5), 833-846 (2016)

13. T. Shi, S. Cheng, Z. Cai, L. Li, in The 35th Annual IEEE International Conference on Computer Communications(INFOCOM2016). Adaptive connected dominating set discovering algorithm in energy-harvest sensor networks

14. H. Ju, R. Zhang, User cooperation in wireless powered communication networks. available online at arXiv:1403.7123

15. W. Wang, L. Li, Q. Sun, J. Jin, in 2013IEEE78thVehicularTechnology Conference(VTCFall). Power Allocation in Multiuser MIMO Systems for Simultaneous Wireless Information and Power Transfer (IEE, Las Vegas, 2013), pp. 1–5

16. K. Huang, E. Larsson, Simultaneous information and power transfer for broadband wireless systems. IEEE Trans. Sig. Process. 61(23), 5972-5986 (2013)

17. D. W. K. Ng, E. S. Lo, R. Schober, in Proc. IEEE WCNC, Shanghai, China. Energy-efficient resource allocation in multiuser OFDM systems with wireless information and power transfer, (2013), pp. 3823-3828

18. Q. Sun, L. Li, J. Mao, Simultaneous information and power transfer scheme for energy efficient MIMO systems. IEEE Commun. Lett. 18(4), 600-603 (2014)

19. D. Niyato, D. I. Kim, P. Wang, L. Song, in 2016 IEEE International Conference on Communications(ICC). A novel caching mechanism for Internet of Things (IoT) sensing service with energy harvesting, (Kuala Lumpur, 2016), pp. 1–6

20. J. Kim, J.-W. Lee, in Proc.IEEE 3rd ICUFN Dalian, China. Energy adaptive MAC protocol for wireless sensor networks with RF energy transfer, (2011), pp. 89-94

21. P. Nintanavongsa, M. Y. Naderi, K. R. Chowdhury, in Proc. IEEE INFOCOM-Mini Conf. Medium access control protocol design for sensors powered by wireless energy transfer, (Turin, Italy, 2013), pp. 150-154

Study on Real-time IoT Systems

Bo YUAN, De-ji CHEN, Dong-mei XU, Ming CHEN
Department of Computer Science and Technology, Tongji University, Shanghai 201804, China
China Electronics Standardization Institute, Beijing 100007, China
Chinesisch-Deutsche Hochschule for Angewandte Wissenschaften, Tongji University, Shanghai 201804, China
yuanbo@tongji.edu.cn; dejichen@tongji.edu.cn

1. Introduction

Today smart embedded devices are connected to the Internet; the Internet of Things (IoT) links together devices and applications that were previously isolated. In addition, embedded devices with real-time properties (e.g., strict timing and safety requirements) require a guaranteed interaction between the cyber and physical worlds. These devices are used to monitor and control physical systems and processes in many domains, e.g., manned and unmanned vehicles (including aircraft, spacecraft, unmanned aerial vehicles(UAVs), self-driving cars). critical infrastructures, and process control systems in industrial plants. Smart systems are embedded systems which include sensing, actuation and control. Smart systems are the gateway to a smart society. Billions of smart devices and systems will make up the IoT.

A real-time system is a special kind of computer system. Its design and development are different from conventional computer systems. The disciplines involved are a real-time OS, embedded development process, etc. Multitasking is a main service provided by the real-time OS. The scheduling algorithm is applied in many IoT applications, and developers use a real-time OS in the application development of IoT [1]. A real-time IoT system is first an IoT system; we could study it under the guidance of the IoT Reference Architecture (IoT-RA) document ISO/IEC 30141. To some extent, any IoT system exhibits real-time aspects as it interacts with the physical world. We use the term "real-time IoT" to indicate IoT systems that are also real-time systems, i.e., they operate under timing constraints. Likewise, we need to pay special attention to real-time IoT systems and many of its important aspects are not sufficiently described in the IoT-RA. As a matter of fact, some categories of real-time IoT systems, such as industrial IoT (IIoT) systems [2] and cyber-physical systems (CPS) [3], have drawn no less interest. [4] explored the CPS research topics are related to the emerging IT trends and investigated how industries have implemented CPS technologies. [5] proposes a potential framework of CPS systematically. This is partly because many IoT practitioners choose to ignore real-time aspects and consider IoT simply as an extension of the Internet.

2. Conceptual Model

A new method for energy-saving and emission-reduction (ESER) life cycle assessment (LCA) based on the Internet of Things (IoT) and bill of material (BOM) is proposed in [6]. A four-layered structure (i.e., perception access layer, data layer, service layer, and application layer), the ESER LCA system is based on the IoT and the BOM is designed and presented, as well as the key technologies and the functions in each layer. In [7], the author proposes a novel, IoT-aware, smart architecture for automatic monitoring and tracking of patients, personnel, and biomedical devices within hospitals and nursing institutes. A real-time information capturing and integration architecture of the Internet of Manufacturing Things (IoMT) is presented to provide a new paradigm by extending the techniques of IoT to the manu facturing field [8]. Based on the IoT-RA in the IEC standard 30141, we define our conceptual model.

Figure 1 is the conceptual model of a real-time IoT system. First, a real-time IoT system is still an IoT system. Its conceptual model is extended from that of the six-domain model. A typical real-time IoT system is a system of systems. The subsystem operates independently. As an IoT subsystem, the edge subsystem also includes some elements of other domains. Timing constraints are the major characteristics of an RT-IoT system.

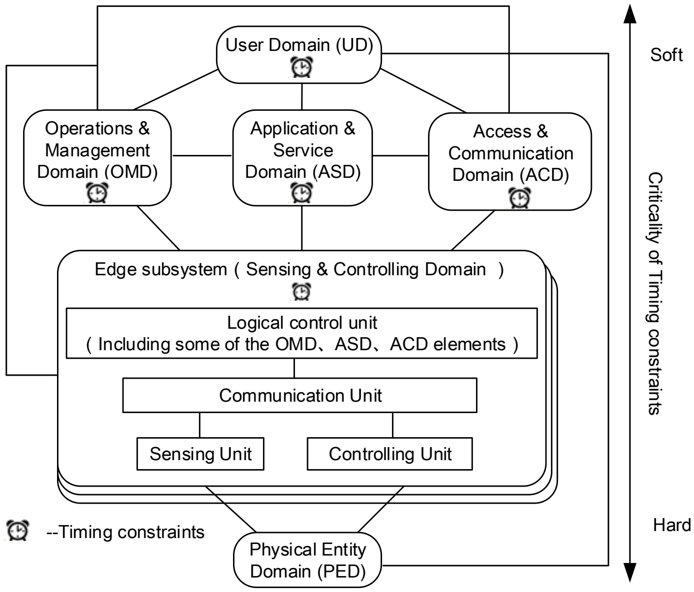

Figure 1 The conceptual model of a real-time Internet of Things (IoT) system.

Each domain, each functional component must have a sense of time. Their local clock must be synchronized with a single master clock in the system. In addition, the timing constraints can be defined and satisfied. This SCD interacts directly with the physical world, and usually involves hard real-time. The criticality of timing constraints softens as we move farther away from the PED.

IIoT systems are typical real-time IoT systems. The II Consortium has published many test-beds (http://www.iiconsortium.org/test-beds.htm). They are very representative of real-time IoT systems. There are also hard real-time IoT systems in smart homes. For example, if smoke detectors are part of an IoT system, it must be a real-time system. When fire breaks out, the smoke detector must send out the alarm information to people within the area and to firefighters and police in distant places, and relevant firefighting equipment must be activated.

3. Time View

Figure 2 is the time view of an RT-IoT system. The components of a real-time IoT system should have a common understanding of the clock, although the precision may differ. Due to the high bandwidth requirements and stringent delay constraints of multi-user wireless video transmission applications, ensuring that all video senders have sufficient transmission opportunities to use before their delay deadlines expire is a longstanding research problem.

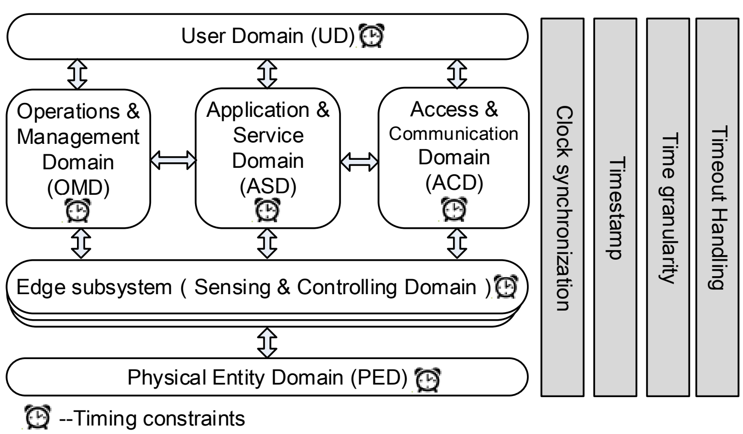

Figure 2 Time view of a real-time Internet of Things (IoT) system.

3.1 Clock Synchronization

In an RT-IoT system, all functional components must have a clock. The clocks are synchronized to a single master clock. The master clock may or may not be synchronized to the global standard time. There may be different synchronicity and/or a drifting rate among different clocks, but together, the whole system meets the timing constraints.

3.2 Timestamp

Any task of an RT-IoT system is likely to be under strict timing constraints, so it is necessary to specify the time of completion of each step in a process, such as sensing, control, transmission and computing. Therefore, a timestamp mark is needed in the output results of each unit to clarify the processing of each step. This is a necessary condition for realizing the RT-IoT system.

3.3 Time Granularity

Different IoT system can have different time granularity. A driverless car must react to external events in microseconds, whereas a smart building adjusts room temperature in minutes. Within an RT-IoT system, the actuator may act in milliseconds, but the self-diagnostics routine could run intermittently in the background.

3.4 Timeout Handling

Although an RT-IoT system must finish all tasks within the deadlines, more often than not, a individual task might miss the deadline. One major feature of a real-time system is its component handling timeouts. The result could be rolling back the modification, opening a relief valve, or rebooting the system.

5. Conclusion

We discussed mainly the real-time problem of the IoT systems. First we described the basic concepts of real-time systems and the IoT, and then puts forward the concept of real-time IoT and lists the basic elements of the real-time IoT. The challenge of the IoT as a real-time system and the necessity of its framework are analyzed, and the research result of the international researchers on the real-time property of the Internet of Things are mentioned. The IoT is an area of great importance to all governments and enterprises. It has a bright future, but there are many challenges on the road to maturity and success, especially in real-time aspects. Though difficult, it is rich in scientific challenges for research. The research results produced will greatly promote the development and application of IoT.

References

[1] W. Saad, M. Bennis, and M. Chen, "A Vision of 6G Wireless Systems: Applications, Trends, Technologies, and Open Research Problems", *arXiv preprint arXiv:1902.10265*, 2019.

[2] Hossain MS, Muhammad G, 2016. Cloud-assisted industrial internet of things (iiot) lc enabled framework for health monitoring. *Computer Networks*, 101(4):192-202.

[3] Lin F, Shu S, 2010. A review on cyber-physical systems. *Journal of Tongji University*, 38(8):1243-1248.

[4] Jin, H. K. ,2017. A review of cyber-physical system research relevant to the emerging it trends: industry 4.0, iot, big data, and cloud computing. *Journal of Industrial Integration & Management, 02*(3), 1750011.

[5] Yang Lu, 2017. Cyber physical system (cps)-based industry 4.0: a survey. *Journal of Industrial Integration and Management, 02*(03), 1750014.

[6] Tao F, Zuo Y, Xu LD, et al., 2014. Internet of things and bom-based life cycle assessment of energy-saving and emission-reduction of products. *IEEE Transactions on Industrial Informatics*, 10(2):1252-1261.

[7] Catarinucci L, de Donno D, Mainetti L, et al., 2015. An iot- aware architecture for smart healthcare systems. *IEEEInternet of Things Journal*, 2(6):515-526.

[8] Zhang Y, Zhang G, Wang J, et al., 2015. Real-time information capturing and integration framework of the internet of manufacturing things. *International Journal of Computer Integrated Manufacturing*, 28(8):811-822.

Analog Images Communication Based on Block Compressive Sensing

Min Wang
School of Mathematics and Computer Science, Gannan Normal University,China
wangmin@gnnu.edu.cn

1. Introduction

Since digital image/video transmission technologies include quantization and entropy coding, it lacks of scalability and robustness. Especially, when the quality of channel below a certain threshold, these traditional image/ video systems suffer high bit error which will result in the received images/videos appear mosaic.

Recently, analog visual transmission has attracted considerable attention owing to its graceful performance degradation for various wireless channels. Jakubczak et al [1] firstly proposed a cross-layer analog visual communications system called SoftCast which skips the conventional quantization and entropy coding, and changes the network stack to act like a linear transform. Subsequently, a lot of research work based on the framework of softcast are emerged [2-6]. However, these work reconstruct images with the help of size information. Undoubtedly, this will increases the overhead of the system.

Compressive sensing (CS) is a novel sampling theory that challenges the traditional data acquisition. It states that an n-dimensional signal $x \in R^n$ having a sparse or compressible representation can be reconstructed form m linear measurements even if $m \ll n$. A few work are on wireless visual communications based on CS [7,8]. These work use the entire image as input of CS encoder. To save memory storage and reduce computation time, references [9,10] introduce block compressive sensing (BCS) to implement wireless image transmission system.

In this paper, we propose an another analog image communication framework named CSCast, based on block compressive sensing. CSCast consists of discrete wavelet transform, power scaling, compressive sampling and analog modulation. We adopt the Cohen Daubechies Feauveau 9/7 (CDF 9/7) wavelet transform to de-correlation for input images signal. In power allocation, we set scaling factor $\alpha = -\frac{1}{4}$ to achieve good performance. And, we adopt block compressive sensing [11] to encode DWT coefficients, and use compressive reconstructed algorithm named CS-SPL-DCT [12] to decoding. Simulations show that the performance of CSCast better than Softcast in all SNR range, and better than Cactus in high SRN range.

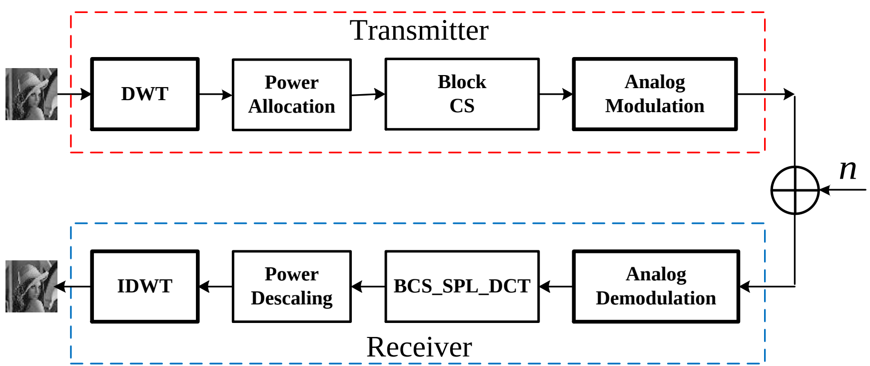

Figure 1 System framework of CSCast.

2. System Design

Fig.1 shows the system framework of CSCast. Transmitter of this system includes discrete wavelet transform (DWT), power allocation, compressive sampling, and analog modulation. Receiver performs contrary operators of transmitter, includes analog demodulation, compressive sensing decoding, power descaling and invert discrete wavelet transform (IDWT). From the framework of CSCast, we can find that our proposed system is different from Softcast. In Softcast, 2-dimensional discrete cosine transform (DCT) and power scaling are performed in the transmitter, and power descaling and 2-dimensional discrete cosine invert transform (IDCT) transforming are performed in the receiver. It is should be note that power scaling and power descaling in CSCast are only multiply a factor on corresponding blocked coefficients.

(1)Transmitter

In transmitter of CSCast, we adopt the Cohen Daubechies Feauveau 9/7 (CDF 9/7) wavelet transform to de-correlate for an input image, and set the decomposition layer number $L = 5$.

$$X_{dwt} = f_{dwt}(X, L) \tag{1}$$

where X is the input image signal, X_{dwt} is the discrete wavelet coefficients. Next, If we use analog modulation to send these discrete wavelet coefficients, the energy carried by each coefficient determines its anti-noise ability in wireless channel. In other word, power allocation directly affects the quality of reconstructed image at the receiver. Assume that discrete wavelet coefficients are divided into N blocks, and the coefficient of power allocation in each block is calculated by

$$g_i = C(\sigma_i^2)^{\alpha}. \tag{2}$$

where $\sigma_i^2, \mathrm{i} = 1,2,\ldots,\mathrm{N}$ is the variance information of *i'th* block, C is a constant number to ensure all allocated powers satisfy the constraint of total transmitting power, and α is a power scaling factor. Through experiments evaluting, our proposed schemes achieve the best performance when$\alpha = -\frac{1}{4}$. After power allocation, we get the signals

$$X_{pa} = G * X_{dwt} \tag{3}$$

where G is a power allocation matrix which consists of different sub-matrics, and the elements of each sub-matrix are all g_i, * is dot product operator on matrix. Next, our proposed system performs compressive sampling. Assume that the dimension of the block sensing matrix Φ_{B} are $\mathrm{B}^2\mathrm{R} \times \mathrm{B}^2$, and the measurement vector of *i'th* block is given by

$$X_{CS_i} = \Phi_{\mathrm{B}} X_{B_i} \tag{4}$$

where $X_{B_i}$is reshaped vector from the *i'th* DWT block, and Φ_{B} is an orthonormalized independent identically distributed (i.i.d) Gaussian matrix.

(2)Receiver

After through the additive white Gaussian noise (AWGN) channel, the the receiver gets signals $Y_{CS} = X_{CS} + \boldsymbol{n}$, where $\boldsymbol{n}$ is a noise vector whose entries obey i.i.d. Gaussian variables. The operators performed at receiver are as follows. Firstly, we use BCS_SPL_DCT CS reconstruction method [12] to reconstruct blocks coefficients Y_{B_i}. Secondly, according to the g_i transmitted from sender, the system performs power descaling, i.e., $Y_{dwt_i} = Y_{B_i}/g_i$. Finally, receiver performs invert discrete wavelet transform $\hat{X} = f_{idwt}(Y_{dwt}, -L)$ to reconstruct image.

3. Simulation Results

In this section, we use peak signal-to-noise ratio (PSNR) to assess image quality between our proposed scheme and other reference schemes. The first reference scheme is Softcast [1] which is the most typical joint source and channel coding based scheme. The second reference scheme is Cactus [3] based on Softcast. Cactus is the state of the art analog visual communication schemes without using side information. In this simulation, we choose *boat*, *lena*, *cameraman* and *peppers* as test images. For fair comparison, we set the compression ratio $R = 1$ in experiments. Given a fixed image, all schemes transmit the same size of data.

In our simulation, we find that the size of isn't affect the performance of CSCast given a scaling factor α. We further evaluate the performance of CSCast according to different α. Fig. 2 shows the performance comparison result. We can observe that CSCast achieves the best performance when $\alpha = -\frac{1}{4}$.

Table 1 gives out the PSNR performance comparison among different schemes on test images. The bold numbers are the best performance of test images at a SNR. Fig.3 shows the average PSNR performance comparison results. We can observe that the performance of CSCast and Cactus better than Softcast. With the increasing of SNR, the gain of CSCast over Softcast is increase, while the gain of Cactus over Softcast is decrease. When SNR > 12 dB, the performance of CSCast better then Cactus. Specially, when SNR = 25 dB, CSCast achieves a maximum gain 1.8 dB over Cactus, and achieves a maximum gain 2.03 dB over Softcast, respectively.

In Softcast and Cactus, it needs to transmit the power scaling factors with reliable digital method. Since the DCT block size is 8×8 in the two schemes, there are 64 metadata per image. In CSCast, we use CDF97 with level $L = 5$ to de-correlate. There are only 16 metadata sent to receiver by using digital method. In addition, receiver needs generate the measurement matrix from a pseudo random number which can be negotiated with transmitter. Therefore, CSCast only needs 17 metadata while others schemesneed 64 meatdata. Comparing to SoftCast and Cactus, CSCast can save about 75% overhead.

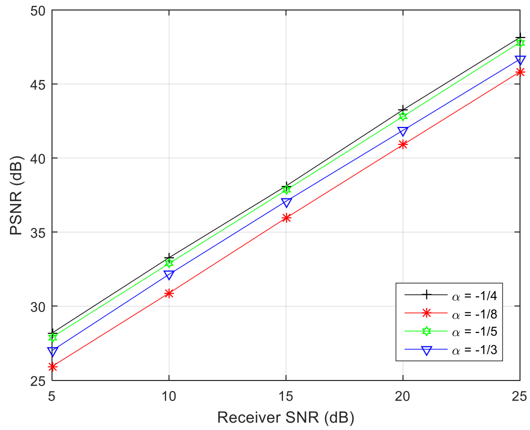

Fig.2 PSNR comparison among different α.

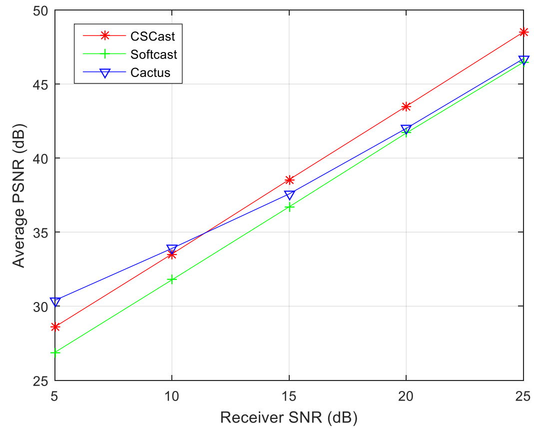

Fig.3 Average PSNR comparison among different schemes.

Table 1. Performance comparison among reference schemes.

Images	Schemes	5 dB	10 dB	15 dB	20 dB	25 dB
Boat	CSCast	29.3029	34.3619	**39.4057**	**44.3888**	**49.3655**
	SoftCast	27.9161	32.8640	37.8047	42.7524	47.5299
	Cactus	**30.9983**	**34.5501**	38.1904	43.0946	47.6810
Cameraman	CSCast	26.3936	31.1772	36.1703	**41.1463**	**46.0907**
	SoftCast	25.0142	29.7584	34.7358	39.7218	44.5371
	Cactus	**29.4773**	**32.8349**	**36.5414**	40.2382	44.6729
Lena	CSCast	28.2160	33.1329	**38.2140**	**43.1397**	**48.1949**
	SoftCast	26.3322	31.3363	36.1510	41.0875	45.9312
	Cactus	**29.5158**	**33.2710**	37.0620	41.2568	46.4771
Peppers	CSCast	30.4984	**35.4353**	**40.3915**	**45.3343**	**50.3805**
	SoftCast	28.2635	33.1763	38.1407	43.2035	47.8751
	Cactus	**31.5800**	34.9598	38.5314	43.4345	47.9992

4. Conclusion

We present an analog images communications system called CSCast which adopts CDF 9/7 to perform decorrelation transform and BCS to resist channel noise. We give out the appropriate value of power scaling factor. According to our analysis, comparing with schemes based on Softcast, CSCast can save about 75% overhead. Simulation shows that the performance of CSCast outperforms over Softcast in all SNR range, and better than Cactus in high SNR range.

References

[1] Szymon Jakubczak and Dina Katabi. A cross-layer design for scalable mobile video. In Proceedings of the 17th Annual International Conference on Mobile Computing and Networking, MobiCom '11, pages 289-300, New York, NY, USA, 2011. ACM.

[2] Xiao Lin Liu, Wenjun Hu, Qifan Pu, Feng Wu, and Yongguang Zhang. Parcast: Soft video delivery in mimo-ofdm wlans. In Proceedings of the 18th Annual International Conference on Mobile Computing and Networking, Mobicom '12, pages 233-244, New York, NY, USA, 2012. ACM.

[3] F. Wu, X. Peng, and J. Xu. Linecast: Line-based distributed coding and transmission for broadcasting satellite images. IEEE Transactions on Image Processing, 23(3):1015-1027, March 2014.

[4] Hao Cui, Zhihai Song, Zhe Yang, Chong Luo, Ruiqin Xiong, and Feng Wu. Cactus:A hybrid digital-analog wireless video communication system. In Proceedings of the 16th ACM International Conference on Modeling, Analysis & Simulation of Wireless and Mobile Systems, MSWiM '13, pages 273-278, New York, NY, USA, 2013. ACM.

[5] J. Wu, J. Wu, H. Cui, C. Luo, X. Sun, and F. Wu. Dac-mobi: Data-assisted communications of mobile images with cloud computing support. IEEE Transactions on Multimedia, 18(5):893-904, May 2016.

[6] H. Liu, R. Xiong, X. Fan, D. Zhao, Y. Zhang, and W. Gao. Cg-cast: Scalable wireless image softcast using compressive gradient. IEEE Transactions on Circuits and Systems for Video Technology, 29(6):1832-1843, June 2019.

[7] S. Xiang and L. Cai. Scalable video coding with compressive sensing for wireless videocast. In 2011 IEEE International Conference on Communications (ICC),pages 1-5, June 2011.

[8] H. Chen, A. Wang, and X. Ma. An improved wireless video multicast based on compressed sensing. In 2013 Ninth International Conference on Intelligent Information Hiding and Multimedia Signal Processing, pages 582-585, Oct 2013.

[9] A. S. Yami and H. Hadizadeh. Visual attention-driven wireless multicasting of image using adaptive compressed sensing. In 2017 Artificial Intelligence and Signal Processing Conference (AISP), pages 37-42, Oct 2017.

[10] X. Ming, T. Shu, and X. Xianzhong. An energy-effcient wireless image transmission method based on adaptive block compressive sensing and softcast. In 2017 International Conference on Security, Pattern Analysis, and Cybernetics (SPAC), pages 712-717, Dec 2017.

[11] Lu Gan. Block compressed sensing of natural images. In 2007 15th International Conference on Digital Signal Processing, pages 403-406, July 2007.

[12] S. Mun and J. E. Fowler. Block compressed sensing of images using directional transforms. In 2010 Data Compression Conference, pages 547-547, March 2010.

Min Wang received the B.S. degree in Computer Science and Technologies from Nanchang University, Jiangxi, China, in 2003. He received the M.S. degrees in computer science from Graduated University of Chinese Academy Science, and Shenyang Institute of Computing Technology of Chinese Academy Science, China, in 2009. He received the Ph.D. degrees in computer science from Tongji University, Shanghai, China, in 2015. He is an Associate Professor in Gannan Normal University, China. His research interests include wireless communication and machine learning.