Context Recognition of Humans and Objects by Distributed Zero-Energy IoT Devices

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***Abstract*—Understanding humans and its environment is a key enabler of smart, intelligent applications and services for a future smart society. To deploy such services in our ambient environment, it is expected to fully utilize battery-less and maintenance-free IoT devices and technologies for more ambient, distributed computing. In recent years, Wi-Fi-based communications are becoming more energy-efficient, and channel state information (CSI) has the potential to sense more detailed information about the things in the real world. Besides, ambient backscatter has appeared as a promising technology for zero-energy sensing and communications. Leveraging those state-of-the-art technologies, energy harvested IoT devices for context recognition of humans and objects will be in reality. A significant challenge is how to make use of inferior, less-powerful zero-energy IoT devices to achieve processing of interest, i.e., accurate recognition of humans and objects, while a single device does not work. Therefore, we consider orchestrating distributed tiny IoT devices for both sensing and communications. Particularly, distributed machine learning in the local environment will achieve highly promising sensing in our ambient environment. In this paper, we survey the state-of-the-art technologies for zero-energy sensing and communications in the context of humans and objects sensing and recognition. Then, we address the challenges to be tackled in terms of such distributed, intelligent sensing using zero-energy devices. Finally, we introduce the concept of utilizing distributed IoT devices, followed by the statement about our ongoing work toward future zero-energy sensing and processing.**

Keywords—zero-energy IoT devices; backscatter communication; context recognition; channel state information

I. Introduction

Recently, a variety of methodologies and technologies to address the issues in smart and connected communities (S&CC) have been actively studied [1] [2]. Besides, in the context of the Internet of Things, it is said that there exist 1.5 trillion objects in the real world and that only 0.6% of the objects are connected to the Internet [3]. With a more enhanced capacity of the Internet connection of those IoT devices in future, unpredictable amount of sensing data will be generated, and more intelligent, smart data processing (such as AI) will be expected to mine significant knowledge and values from the big data. Especially, understanding humans and its environment is a key enabler of smart, intelligent applications and services for a future smart society.

To deploy such services in our ambient environment, it is expected to fully utilize battery-less and maintenance-free IoT devices and technologies for more ambient, distributed computing. In general, IoT devices spend energy for sensing, computation and communication. Sensing can be executed in the order of μW up to tens of μW. However, conventional wireless communication consumes several tens or several hundreds of mW for amplifying a radio signal. Even BLE consumes the order of mW. To this end, ultra-low power communication technologies are essential. In recent years, a new wireless communication technology called *ambient backscatter communication* [4][5][6] is being developed, which can reduce the power consumption to about 1/10,000 (about 10 μW) by utilizing radio waves in the wild such as TV and Wi-Fi. In the ambient backscatter communication, by changing the resistance values of the antenna, the device can control the radio waves that propagate in the environments. Using this feature, we can transmit 0/1 bit signals with zero-energy. Originally, the backscatter communication is a technology for RFID. RFID communicates by transmitting a continuous carrier wave from a reader and each RFID tag sends back its ID by backscattering received carrier waves. Since the carrier waves are generated externally, the RFID tag only needs to change the impedance by controlling ON/OFF of RF switch, and the controller consumes almost no power. While traditional backscatter uses continuous carrier waves, ambient backscatter uses radio signals emitted by surrounding equipment/devices. As shown in Fig. 1, recently we can combine general Wi-Fi communication with Wi-Fi-based ambient backscatter communication (for details, see Section IV.A).

If we can develop a mechanism to detect motion and environment of humans and objects (e.g. walking, stay, sit-down, object movement, temperature change, and shape change) by radio waves fluctuation using ambient backscatter technologies, it will contribute to zero-energy sensing of humans and objects. In recent years, Wi-Fi-based ambient backscatter is able to transmit and receive data in several tens

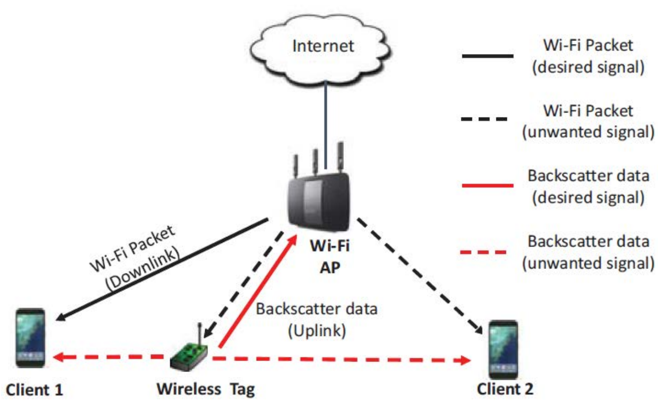


Fig. 1. Ambient Backscatter Communication[64]

of meters with several Mbps. Some recent RFID technologies enable several meters of transmission. Besides, sensing devices using only harvested energy have been investigated and developed, and they can be used for human and object sensing. We have also been developing human sensing technologies in a variety of contexts and services [7][8][9][10][11][12][13].

The context recognition technologies for humans and objects using energy-efficient or zero-energy sensors have been actively investigated and presented at top-tier ubiquitous and pervasive conferences such as *UbiComp* and *PerCom*, and published in journals such as *Pervasive and Mobile Computing* and *Proc. of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT)*. On the other hand, most of the existing sensing technologies using backscatter communication or similar zero-energy technologies are still in progress. Particularly, they are focusing on the detection of the presence of humans, etc., which is not comparable with those using powerful sensors. To complement this poor computational capability, we believe distributed processing where tiny IoT devices are united is promising. With nicely designed protocols and algorithms, we can execute even neural networks for machine learning. We have already proposed the design concept of such distributed machine learning in [7], where tiny IoT devices are operated in a distributed fashion to run Convolutional Neural Networks (CNN). We will later introduce this concept.

In this paper, we survey the technologies for context recognition of humans and objects using the state-of-the-art ambient backscatter communication technologies, channel state information (CSI) and other wireless sensing technologies. We also address issues to be discussed for distributed processing by coordination of IoT devices, each of which is energy-harvested. We consider the following plausible examples of context recognition of humans and objects that should be realized in the near future by using zero-energy IoT devices with ambient backscatter communication or some other technologies. They are, for example, (i) elderly monitoring at nursing home or their homes, (ii) activity recognition of athletes, (iii) tracking human trajectories and detecting intrusion of wild animals, (iv) construction of *sociograms* to visualize the friendship among children, (v) grasping wind and ground fluctuation of sloping lands in disasters. We are working toward context recognition that will be mandatory in our connected societies. It is also significant to deploy design and development support. The goal of this paper is to promote such research activities that contribute to ambient, zero-maintenance human and object sensing. We will discuss the issues mentioned above presenting our ongoing research on zero-energy communication and distributed sensing.

II. Related Work

Here, we survey the latest technology for ambient backscatter communication, channel state information (CSI), and human/object context recognition using IoT devices.

A. *Ambient backscatter communication*

The study of ambient backscatter communication [4][5][6] has two directions. The first direction is to borrow existing radio signals for energy harvesting communication purposes. For example, there are methods using radio signals from TV broadcasting and mobile communication [6][14], Wi-Fi signals [15][16][17], LoRa signals [18], Bluetooth signals [19] and FM broadcasting signals [20]. Ref. [14][16] address speeding up of Wi-Fi backscatter. Especially, BackFi [16] has succeeded to achieve high throughput backscatter communication using Wi-Fi signals by making an access point having the in-band full-duplex capability [21][22].

The second direction is to generate ambient backscatter packets that can be received by existing wireless communication devices such as Wi-Fi and LoRa. By replacing radio signals used in the above first direction with those emitting from a plug-in device that transmits continuous waves, it is possible to generate packets receivable by the existing radio communication devices. Ref. [23][24] have successfully generated Wi-Fi packets and LoRa packets in backscatter communication, respectively. Also, inter-technology backscatter is succeeded (e.g., the generation of Wi-Fi packets using radio signals from Bluetooth [18], and the generation of ZigBee packets using radio signals from Wi-Fi [17]). Ref. [25][26] have realized new backscatter-based communication methods such as backscatter video [25] and voice [26], NetScatter [27] supports a massive number of ambient backscatter nodes, and Ref. [28] has proposed in-band full-duplex communication between ambient backscatter nodes.

B. *Wireless Sensing*

In recent years, *wireless sensing* technology for sensing various objects by using radio waves without using sensors has attracted attention. Wi-Fi Channel State Information (CSI) is an emerging approach for wireless sensing, which is widely applicable to various types of sensing. Several works have proposed congestion estimation and people counting by feeding CSI-based features into estimation models built by machine learning and/or deep learning. For example, in [29], the feature quantity called Percentage of nonzero Elements (PEM) is defined, the magnitude of the fluctuation in the propagation path of radio waves is quantified, and the number of people in the room is estimated based on the Gray model. Also, FreeCount [30] realizes the number of people in the room by using Transfer

Kernel Learning (TKL), and achieves approximately 96% accuracy in the classification of 0 to 7 people. CSI is also used for sensing movement of various objects. Ref. [31] uses CSI to estimate state changes of everyday objects (e.g., door open/close). WiAG recognizes gestures by using CSI [32]. Similarly, Ref. [33] proposes sign language recognition by CSI and CNN. Furthermore, Ref. [34] achieves an estimation of keystrokes on laptops by learning CSI change due to the different movement of fingers for different keystrokes. Recently, CSI is also used for fall detection [35].

Backscattering RF signal is another emerging trend of wireless sensing. Printed Wi-Fi [36] is the first concept of truly battery-less sensors fabricated by a 3D printer by combining plastic and conductive filament materials. Surprisingly, the printed battery-less sensors can communicate with Wi-Fi devices by translating physical movement (e.g., the flow of water) into the backscattered Wi-Fi signal. To do this, Printed Wi-Fi leverages mechanical movements of gears, etc. and creates the change of the antenna impedance which results in the backscattered signals. To recognize and count repetitive motions such as squats and steps, Motion-Fi [37] leverages repetitive changes of RF signal from backscattering tags. To avoid interference of backscattered signals, Motion-Fi controls the frequency shift in the backscattered signals. Also, Word-Fi [38] recognizes handwriting letters by leveraging the backscattering tags developed in Motion-Fi [37].

C. *Context Recognition of Humans and Objects*

Context recognition is one of the key technologies for a future smart society. For example, various ubiquitous technologies have been proposed for elderly people [39]. The first step to support elderly people is context recognition such as activities [40], fall detection [41], daily living patterns [42], and so on. Human Activity Recognition (HAR) has attracted a large number of researchers [43]. Smartphones are used for mapping our real social networks [44]. Ref. [45] leverages wireless sensor networks for landslide monitoring and detection. Ultra-Wide Band (UWB) combined with CNN is fully exploited for animal intrusion detection which is able to classify humans and animals [46]. Ref. [47] proposes a method to infer social/organizational relationships among occupants in a building from plug load energy consumption sensors. Ref. [48] analyzes the impact of different resolutions of occupancy count profiles estimated by cameras and Wi-Fi sensors on the accuracy of building performance simulation.

III. Distributed Process on Zero-Energy IoT Devices

Here, we describe issues to be considered in the construction of zero-energy IoT devices and distributed processing on such IoT devices, and their solutions.

A. *Construction of Zero-Energy IoT Device Networks*

With the emerging progress of MEMS technology, it has become relatively easy to develop energy harvesting IoT devices. RFID tags are also used as zero-energy devices since they can harvest energy from RF emitted by RFID readers. Also, many researchers have been working on passive sensing which relies on plug-in infrastructure devices with energy supply. However, due to the limitation of energy harvesting, each IoT device has limited capabilities in terms of sensing, processing, and communication. For example, the only capability of an IoT device may be backscattering RF signal which does not require a large amount of energy. To overcome such limitations, the key is distributed processing among multiple IoT devices.

As shown in Fig. 2(a), by attaching multiple RFID tags to a human body, the skeleton of the person is captured by analyzing signals backscattered from the tags. In general, sensing capabilities of individual sensors are not so high since many of low power sensors return limited information such as the tag's ID. On the other hand, by connecting a large number of these energy harvested sensors to the network, it is possible to construct a system that estimates the movement of the skeleton with high accuracy. Furthermore, by attaching multiple RFID tags to multiple people, the spatial resolution of sensing increases to identify different targets. Another example is zero-energy sensing by backscatter-based wireless sensing. Similar to printed Wi-Fi, we may be able to translate change of temperature into the change of antenna impedance by using a bimetallic switch which changes its state (ON/OFF) according to the ambient temperature (see Fig. 2(b)). Since the change of antenna impedance can be directly captured by observing Wi-Fi signals backscattered from IoT devices, zero-energy sensing is achievable. To widen the target area of sensing, multiple IoT devices are deployed and coordinated accordingly with the assistance of infrastructure.

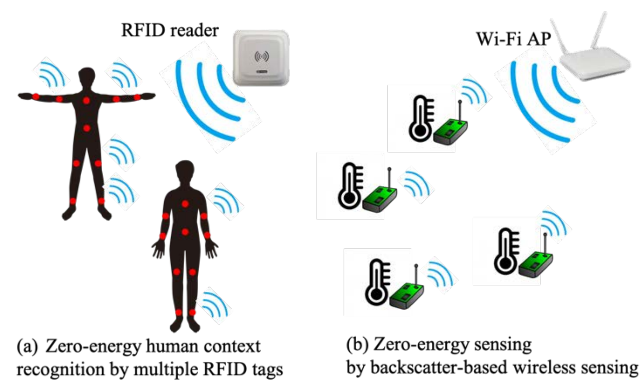


Fig. 2. Examples of Zero-energy IoT Device Networks

Besides, research and development of learning mechanisms using energy harvested sensor groups are conducted. In order to develop such zero-energy IoT device networks and/or energy harvest sensing systems, it is essential to construct networks based on a communication scheme with ultra-low power consumption such as backscatter communication.

B. *Distributed Processing on Zero-Energy IoT Device Networks*

In context recognition systems using zero-energy IoT devices, since the recognition capability of each device is not so high, there are cases where a large number of IoT devices must be arranged in a target area. In such a case, we need to consider (i) what kind of queries are to be sent to multiple IoT devices in the target area, (ii) what timing those queries should be sent, and

(iii) whether all the necessary data can be forwarded efficiently at a certain period (k times per second, for example), simultaneously. It is also important to consider a communication mechanism not to make packets from the multiple IoT devices collide each other. It is also assumed that it may be necessary to construct a mechanism for transmitting and receiving data concurrently using multiple radio channels. Meanwhile, it is troublesome for a system designer to individually designate these transmission/reception timing, channel assignment, recovery procedure when the transmission/reception errors occur in a given zero-energy IoT device network.

Therefore, if (i) the 3D map and obstacle information of a target IoT device network, (ii) the required information collection cycle, and (iii) the recovery method at the time of errors are designated, it is desirable that we can devise a mechanism to estimate the appropriate information collection mechanism, automatically generate the necessary information collection algorithm, and develop a design development support environment by using the radio wave propagation evaluation tool and network simulator together.

In recent years, research on machine learning such as deep learning has been actively conducted, and attempts to machine learning on a wireless sensor network have also begun [7][49][51][53][54][55]. Although it is conceivable to transfer all the sensing data to the cloud for machine learning, continuous transmission of sensing data from all the IoT devices to the cloud increases communication costs. The power consumption of the IoT devices can be reduced by holding their sensing data as much as possible within their own IoT devices and implementing a learning mechanism within the local IoT device network. Generally, zero-energy IoT devices are ineffective and even if they can utilize power supply mechanisms such as environmental power generation, there is a high possibility that machine learning mechanisms consisting of zero-energy IoT devices will not function well when communication load increases. Multi-layer neural networks have recently attracted a lot of attention, and Convolutional Neural Networks (CNNs) have been utilized in many domains. Since wireless sensor networks (WSNs) continuously create 2D or 3D geographical data, we can train CNNs to process such data from WSNs. For this purpose, it is desirable that we can design a distributed version of CNNs restricting wireless communication amounts among wireless sensor nodes and a neuron assignment algorithm which can naturally handle operations like convolution, pooling and backward propagation in a fully distributed manner, averaging communication and processing tasks over wireless sensor nodes.

Since we often need multiple IoT devices for context recognition of humans and objects, CNNs on WSNs can integrate ambient backscatter based direct sensing using various sensors with ultra-low power IoT devices and wireless sensing based indirect sensing using RSSI and CSI with existing wireless networks as shown in Fig. 3. Ambient backscatter and wireless sensing are complementary. Ambient backscatter can overwhelmingly reduce the energy consumption of communication. It also can directly and precisely acquire target physical information using maintenance-free sensor nodes, but time and effort for installation on humans and objects remain. On the other hand, since wireless sensing performs sensing indirectly using radio waves, it is difficult to acquire detailed physical information of the target. However, it is possible to acquire spatial information easily because of using radio waves. There is no need to install sensors on humans and objects. By combining fine detail information of ambient backscatter and super multidimensional information brought by coarse grain spatial information of wireless sensing by deep learning, it becomes possible to handle fine grain spatial information.

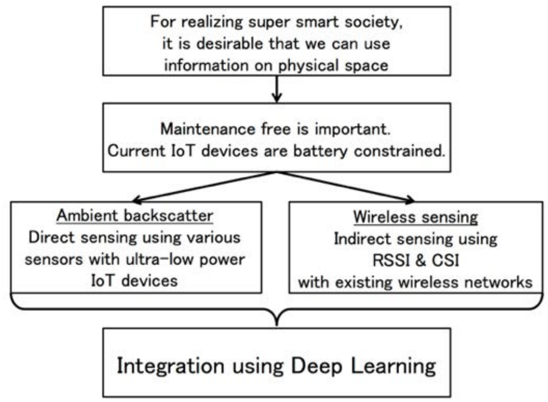


Fig. 3. Context Recognition on Zero-Energy IoT Device Networks

C. *Context Recognition Technology in the Near Future*

If people move, radio waves such as WiFi will fluctuate. By grasping the fluctuation directly by backscatter communication, it is possible to create new technology to grasp the behavior of humans with higher accuracy than the conventional techniques. Stimuli-responsive hydrogels exhibiting physical changes in response to environmental conditions have attracted growing attention for the past few decades [56]. Recent 3D printers can easily produce such materials exhibiting physical changes. A battery-less IoT devices for temperature estimation can be constructed by constructing a structure that changes the shape and size according to the temperature change and generates a different radio wave fluctuation depending on the shape change.

Furthermore, by creating zero-energy IoT devices that detect illuminance or by creating zero-energy IoT devices that detect vibration and acceleration using springs, various context recognition techniques can be created [36][57]. In addition to battery-less IoT devices, we can also use environmental power generation technology to gather and use a small amount of environmental energy such as light, vibration, heat and so on in capacitors, and use it for the development of ultra-low power IoT devices for context recognition of humans and objects.

Using such new technology, we can create several techniques for context recognition. For example, Ref. [58] presents RF-ECG based on commercial-off-the-shelf (COTS) RFID, a wireless approach to sense the human heartbeat through an RFID tag array attached on the chest area in the clothes. Ref. [7][35] present techniques for detecting fall down of people. Such techniques can be used for (i) monitoring elderly people's sleep and context changes at the elderly facilities. Ref. [59] proposes GRfid, a device-free gesture recognition system by exploiting phase information of RFID signals with COTS devices. RF-Kinect in Fig. 2(a) a training-free system which tracks the body movement in 3D space [60]. Such techniques can be used for (ii) grasping activities of athletes. Ref. [61] proposes a method to determine the movement direction of tagged object through a Radio Frequency Identification (RFID)-based system. Ref. [7] also proposes a method for detecting the movement of humans using film typed human sensors. Such techniques might be able to be used for (iii) grasping the movement trajectory of people and detecting intrusion of wild animals. By attaching RFID tags to kindergarten children's clothes and installing multiple WiFi base stations sending out WiFi signals that can only reach certain specific areas on play equipment, classrooms, corridors in the kindergarten, each WiFi base station can collect children's tag IDs who play together. Then, we can estimate the friendship of kindergarten's children as a graph called *sociogram*. Some children might interact with various friends and others might be isolated. Such relationships can be represented by (iv) building a *sociogram* for a target children group. There are several types of ultra-low power accelerometers using environmental power. Combining such devices and backscatter communication devices, we might be able to construct a monitoring system for (v) grasping wind speeds and ground fluctuation of sloping lands. (vi) Autonomous air conditioning management of commercial facilities might be also possible.

Although the technology for ambient backscatter and wireless sensing is expected to become promising means to construct future smart societies, we need much study for practical purposes.

IV. OUR CURRENT ON-GOING WORK

In this section, we explain our current on-going work concerning backscatter communication, channel state information and context recognition.

A. *Integration of Wireless LAN and Ambient Backscatter*

We are working on how to integrate ambient backscatter technology into existing wireless networks. Fig. 4 shows the overview of the wireless network that we are aiming for. Our target is wireless networks where IEEE 802.11 nodes and ambient backscatter nodes coexist in the same frequency band. An access point equips the ability of in-band full-duplexing, and communicates with PCs and smartphones using IEEE 802.11 signals. IoT devices communicate with the access point with backscattering the IEEE 802.11 signals. The access point transmits and receives data simultaneously using the same frequency channel, which is performed by utilizing a self-interference cancellation technique. Therefore, the in-band full-duplexing transmission in wireless communications potentially doubles the spectral efficiency relative to the conventional half-duplex operation.

For the integration of IEEE 802.11 and ambient backscatter, we believe that it is important to provide an environment in which the research community easily tests communication protocols and applications. To this end, we are developing an open-source ambient backscatter testbed which realizes ZigBee backscatter in the 2.4 GHz band using commercial-off-the-shelf (COTS) products.

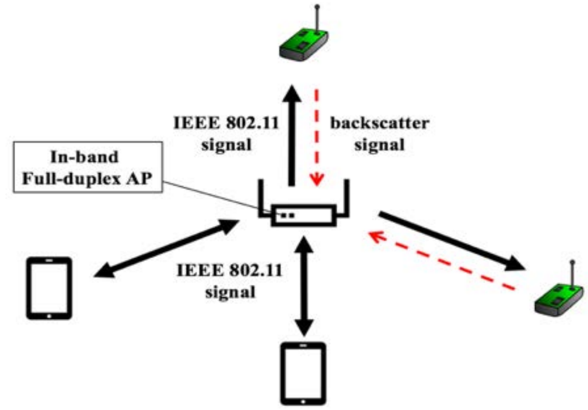


Fig. 4. Integration of Wireless LAN and Ambient Backscatter

There are three reasons for implementing backscatter devices using ZigBee (IEEE 802.15.4). The first reason is a good balance between communication distance and communication speed. Since IEEE 802.15.4 realizes 250 kbps communication speed using direct sequence spread spectrum, communication distance is long due to spread gain. The low-power 250 kbps communication is suitable for many sensor-based applications. For example, the communication speed is too slow when LoRa is used, and the communication distance is short and power consumption is large when using Wi-Fi for ambient backscatter. The second reason is that there are many IEEE 802.15.4 development environments which are commercially available. The transceivers of IEEE 802.15.4 are sold at less than $100, and many development and analysis tools are provided. On the other hand, the history of LoRa has less history than IEEE 802.15.4, resulting in few transceiver choices. Wi-Fi has many products that cannot access the physical layer and the MAC layer, and it is not suitable for research and development. The third reason is 2.4 GHz band. As mentioned above, we are trying to integrate wireless LAN and backscatter communication. Thanks to the long history of 2.4 GHz communication, we can easily get 2.4 GHz COTS products and build the experimental environment.

We are developing an experimental environment for protocol study. Fig. 5 shows the experimental apparatus for

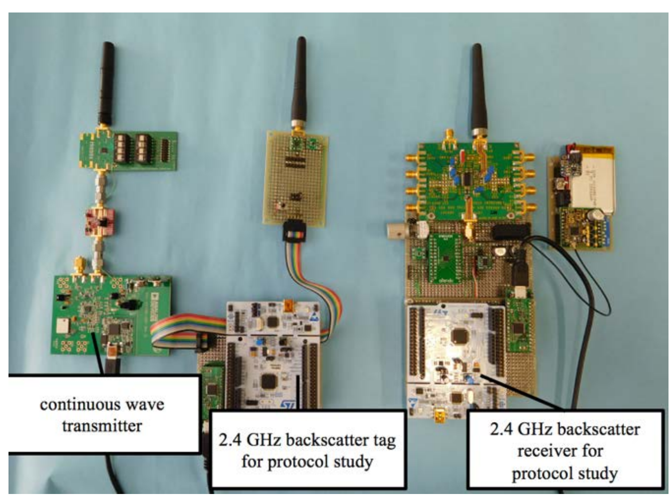


Fig. 5. Experimental Apparatus for 2.4 GHz Backscatter

protocol study on 2.4 GHz backscatter. The experimental apparatus is constructed to enable researchers to easily modify the protocols of the physical layer and MAC layer, and consists of a continuous wave transmitter, 2.4 GHz backscatter node, and backscatter receiver. The continuous wave transmitter consists of a frequency synthesizer and power amplifier. The 2.4 GHz backscatter node consists of an STM32 Nucleo board [62] and an RF switch. The backscatter receiver consists of an STM32 Nucleo board, a switch capacity filter, an orthogonal transducer, and a local oscillator. The total cost of these components is less than $1,000. The software on STM32 Nucleo board can be implemented using free online IDE called as mbed compiler [63].

We are also developing a ZigBee backscatter node for application researcher: small size (2cm × 4.25cm) and only support IEEE 802.15.4. Fig. 6 shows the ZigBee backscatter node. The ZigBee backscatter node consists of STM32 CPU, an RF switch, a chip antenna, and a button battery. The size of the node is constrained by the button battery and the chip antenna. We use CR2032 as a button battery which diameter is 2cm. The chip antenna has restrictions that the area of the ground must be sufficient and a metal plate must not be near the chip antenna. The chip antenna has restrictions that the area of the ground must be sufficient and there is no characteristic if there is a metal plate in the vicinity. The transmitter side of ZigBee backscatter is as same as the continuous wave transmitter in above mentioned experimental apparatus for protocol study. We can use commercial IEEE 802.15.4 modules as the receiver side.

In order to integrate wireless LAN and ambient backscatter communication, it is not just a matter of the hardware testbed. Since the existing IEEE 802.11 MAC protocol cannot be used for the integrated networks, it is necessary to design a new communication protocol. For example, when backscatter communication is generated every time wireless LAN communication is performed, and the communication capacity is consumed. As a result, the communication performance of the wireless LAN is deteriorated. Additionally, since the communication speed of backscatter communication is much slower than that of wireless LAN, the packet error rate of backscatter communication increases when there is not enough wireless LAN traffic.

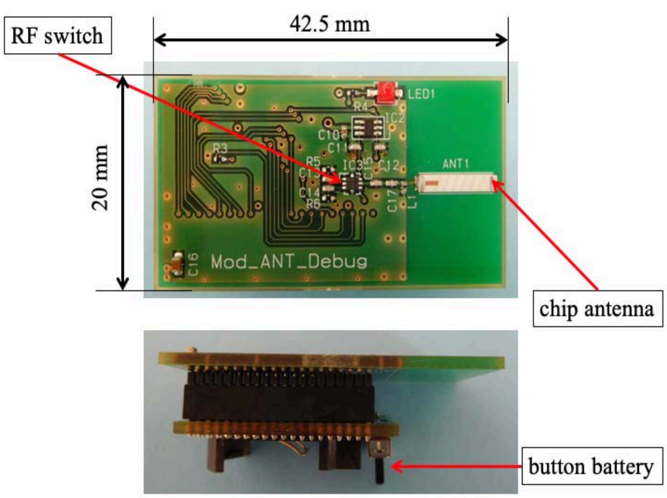


Fig. 6. ZigBee Backscatter Node for Application Study

In [64], the authors have proposed a MAC protocol of wireless LAN supporting ambient backscatter. The proposed MAC protocol utilizes IoT specific features: many applications have their own constant communication cycles which vary depending on target applications. Only by registering the data acquisition cycle of each IoT device to the access point, the proposed MAC protocol enables the wireless LAN communication and backscatter communication to coexist with low overhead. Scheduling is performed according to the communication cycle and band occupation time to reduce the band-utilization efficiency and communication error rate. The scheduling includes which IoT device's backscatter communication is permitted, and whether the access point sends a dummy packet for backscattering.

B. *Wireless Sensing*

One of our wireless sensing works is congestion estimation in train cars based on Bluetooth RSSI among smartphones [65] (Fig. 7). It is natural that human body causes signal attenuation. However, in train cars, RF is also affected by other complex factors such as train car body itself, distribution of people, distance between the phone pair, and so on. This makes the car-level congestion estimation non-trivial. We have overcome this challenge by aggregating measurements from multiple users estimated to be in the same train car. We note that the user positions are also estimated by relying on RSSI combined with reference nodes whose positions are given. Since doors between train cars significantly attenuate the signal, our method estimates car-level positions regardless of congestion levels based on RSSI measured among users. Then, we estimate car-level congestion by majority voting weighted by the reliability of estimated positions. Our method is based on the likelihood functions for both of the congestion and position estimation. These functions are built according to our preliminary experiments. In [65], we have conducted real experiments and achieved car-level positioning with the accuracy of 83%. Also, we have confirmed that our method achieves the estimation of three-level congestion (low/medium/high) with the F-measure of 0.82.

(a) Uncrowded (b) Crowded

Fig. 7. Snapshots of Different Congestion Levels

We are also working on wireless sensing utilizing already deployed wireless networks. In [66], we have proposed a congestion estimation using synchronized RSSIs measured by IEEE 802.15.4. First, we have proposed a mechanism to measure two kinds of RSSIs: the inter-node RSSI and surrounding RSSI. The inter-node RSSI is the strength of a radio signal when a sensor node receives the signal that another sensor node transmits. The surrounding RSSI is the strength of radio waves when a sensor node receives signals that other sensor nodes do not transmit. Both of these RSSIs are strictly synchronized using “Choco” which is a wireless sensor network platform utilizing simultaneous transmission [66]. The proposed method enables us to estimate the congestion just by adding RSSI acquirement features to IEEE 802.15.4 wireless sensor networks already-deployed for a different purpose. The examples of different purpose include structural health monitoring and smart meters. Next, we have also proposed congestion estimation algorithms that estimate the number of people from the inter-node RSSI and the number of devices from the surrounding RSSI. An experiment conducted in our laboratory has confirmed that the algorithm succeeds to estimate the number of people with approximately 79% accuracy, with errors up to two people.

In [8], we have proposed an IEEE 802.11ac explicit feedback-based channel state information (CSI) learning system. The proposed CSI learning system automatically collects IEEE 802.11ac CSI feedback frames among a Wi-Fi access point and devices with Wi-Fi capture interface. A CSI feedback frame includes compressed angles information, and our system extracts 624 features from the frame. In the learning phase, the user inputs label information to the learning system, and the learning system automatically relates the captured CSI with the input label information. In the estimation phase, our learning system infers a label using captured CSI frames at that time. We have evaluated our learning system for device-free user location estimation with six patterns: different combinations of the behavior of a user and the antenna orientation of an access point. The evaluation results show that our CSI learning system achieves approximately 96% accuracy for seven positions when the behavior of the user is walking and the orientations of the antennas have divergence.

C. Deep Learning on IoT device networks

Distributed machine learning is nowadays becoming more popular. Most of the existing frameworks that support distributed machine learning adopt a data parallelization concept where multiple learning instances are launched and the trained parameters in DNN are aggregated and shared for more lightweight, faster training [50]. For example, in Distributed Machine Learning Toolkit (DMTK) framework operated by Microsoft supports inter-process communication libraries (MPI and ZMQ) for exchanging data block among processes. Distributed TensorFlow [51] by Google adopts a parameter-server and workers model. ChainerMN, which is an add-on package, also supports MPI such as OpenMP for the same purpose. However, the data parallelization model is basically a technique for a set of parallel, networked servers with rich computational and networking resources, which is not applicable to our case.

The fundamental problem which we aim in this paper is how to manage and utilize data in in-situ environment [52]. We will have a number of small or tiny edge (or end-user) devices in future, each of which has very limited capability of computation and communication. But delivering the data stream from those edge devices to a remote server is not reasonable. We need to arrange a communication channel, including expensive cellular communication, for each sensing location. For example, for remote monitoring and tracking of daily life of elderly, who live alone in mountainous area (this is a big issue in Japanese society), 3G is still an important way of communication due to the limitation of LTE/4G service in such areas. Consuming the most of the limited channel capacity by delivering raw sensor data, most of which is useless after training or classification, is not a feasible solution.

For more ambient, energy-aware processing, we have proposed a framework called *MicroDeep* [7]. The key concept of MicroDeep lies in embedding deep learning (both training/testing functions) onto wireless sensor networks, which are composed of tiny IoT processors with sensors. Since those sensors will be embedded in our environment in future, leveraging their processing power and communication devices will benefit energy-efficient sensing and feedback. Particularly, additional investment for deep learning is not necessary as tiny sensor nodes cooperate with each other to conduct the training task.

The idea is to appropriately distribute the neurons of CNN (Convolutional Neural Network) to wireless nodes, each of which has limited processing capability but can have some power when they are united. We use a distributed version of CNNs which are designed for this purpose. Normally, the wireless sensors nodes are installed in 2D (or 3D) space and they are close to each other to form a mesh-like network. We regard each block of sensing data from those sensor nodes at the same time as an image data, and apply CNN to each data block. For this purpose, we assign each sensor node onto XY-coordinates as shown in Fig. 8. The forward propagation of data that includes convolution, pooling and fully-connect layers (units) is carried out based on the assigned coordinates, where a unit executed on a sensor node takes the sensing data owned by the neighboring/surrounding sensor nodes as inputs.

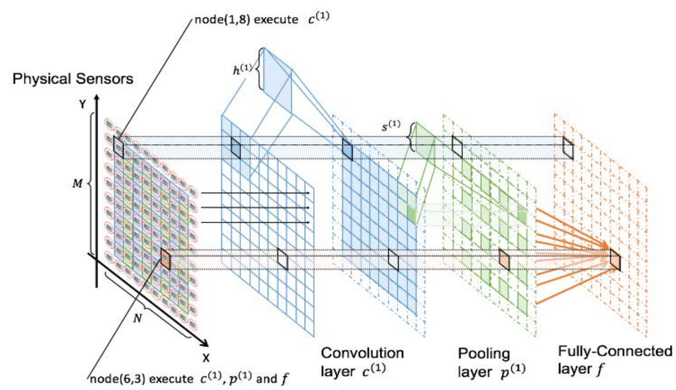


Fig. 8. Assignment of CNN to XY-Coordinates

The backpropagation process is carried out in a distributed fashion, which is originally designed as a centralized process. Weights of units are updated independently by each sensor node to avoid communication overhead, sacrificing some accuracy.

We conducted two experiments using real data. One is performed using the temperature data measured in an over-1,400m^2 lounge space using 50 temperature sensors. The lounge space is divided into 25 x 17 cells, and the temperature measured within a cell is associated with its coordinates. Each sensor measured the temperature every 30 minutes, and we finally collected 2,961 temperature samples from August 26th to

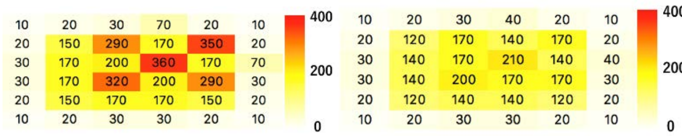
October 27th in 2016. We trained CNN to detect discomfort in the space, and as a result of our MicroDeep, the accuracy was about 95\% while 97% by the standard CNN with the optimized hyperparameters. The maximal communication cost compared with this standard version is just 13%, which means MicroDeep can reduce the peak traffic concentrated onto a single node.

Fig. 9. Prototyped IR-sensor Array for Motion Detection

Another experiment is for narrow space, where a sensor array is built using thin-, energy-efficient film-type infra-red sensors with microprocessors. Fig. 9 shows a prototyped IR-sensor array. This is used for activity recognition, particularly, fall detection of elders. Every sensor transfers its measured data by 2.4GHz wireless communication. We have collected 55 gait samples from five (young) subjects who imitated falling down behavior of elders. We regard each sample as a stream of 66 images where the frame rate is five frames per second. Although the walking speed is not uniform among different persons, we empirically determined two seconds (= 10 frames) window to cover a single passage. We gave 6,610 3D arrays as inputs to CNN. We used CNN consisting of one convolutional layer, one pooling layer and two fully-connected layers.

We have compared the following two cases: (a) best accuracy by using standard CNN with optimal parameter setting and (b) heuristic assignment to maximize the correspondence of CNN links and WSN links equalizing the number of units assigned to each sensor node. Fig. 10 shows the communication costs of the sensor nodes for both cases. We have carried out ten trials of learning and validation with a randomly split pair of training and validation dataset. For each trial, the weight parameters have been randomly initialized. We have evaluated the best accuracy by using standard CNN with optimal parameter setting where the accuracy is 91.875% and the maximal communication cost becomes 360 as shown in Fig. 10(a). On the other hand, for the case of heuristic assignment to maximize the correspondence of CNN links and WSN links, we have found 89.7275% accuracy and the maximal communication cost becomes 210 as shown in Fig. 10(b). Hence, the performance of our prototype is 2% lower than that of the optimized CNN while we can achieve 40% mitigation of the maximal communication cost. For designing energy harvesting IoT sensor systems, it is very important to equalize the number of units assigned to each sensor node and to minimize the maximal communication costs of the sensor nodes so that all the sensor nodes can be alive and work well using a small amount of energy. We believe our approach is one of the promising approaches for constructing tiny IoT device networks and providing effective deep learning mechanisms on such tiny IoT device networks.

Although the current version of *Micro Deep* uses general 2.4 GHz Wi-Fi, we can reduce the electric power of wireless communication by using ambient backscatter communication. This is our on-going future work.



(a) with Optimal Parameter Set (b) with Feasible Parameter Set

Fig. 10. Communication Cost of Sensor Node (Motion)

V. RESEARCH CHALLENGE

As mentioned above, understanding humans and its environment is a key enabler for providing smart and intelligent applications and services in future smart society. In order to deploy such services in our ambient environment, it is essential to fully utilize battery-less and maintenance-free IoT devices and their corresponding technologies. A significant challenge is how to make use of inferior, less-powerful zero-energy IoT devices to achieve processing of interest, i.e., accurate recognition of humans and objects, while a single device does not work. We need to make such distributed tiny IoT devices orchestrate for both sensing and communications.

From the communication point of view, it is important to be able to successfully use general wireless communication such as WiFi and ZigBee and ambient backscatter communication in parallel as shown in Fig. 1. In general, there are cases where many zero-energy IoT devices need to be placed in a target area. In such a case, it is important to avoid the collision of communication IoT devices. If we use multiple channels in parallel, we need to consider practical channel assignments among those IoT devices according to data size, transmission frequency, and channel quality as well as application requirements. In a given IoT device network, it is cumbersome for the system designer to individually specify the setting of transmission/reception timing, channel assignment and recovery procedure at the time of transmission/reception errors. It is important to devise mechanisms to automatically generate necessary information collection algorithms from (a) 3D map and obstacle information of a given IoT device network, (b) the necessary information collection cycle and (c) the recovery methods when errors occur.

From the sensing point of view, as shown in Section III.B, distributed processing on zero-energy IoT device networks will achieve highly promising sensing in ambient environments. In Section IV.C, we show that the development of machine learning mechanisms on tiny IoT device networks with low communication costs is an important research issue. Also, the nature of radio wave propagation differs considerably depending on the location and the presence of obstacles. The efficiency of machine learning strongly depends on the initial values and/or teaching data. The radio wave propagation evaluation tools and network simulators can be used together to generate appropriate initial values depending on given location environments. A part of tiny IoT devices may be broken. The development of resilient distributed machine learning mechanisms in the environments containing such broken IoT devices is also important.

VI. Conclusion

In this paper, we focus on ambient backscatter communication technology capable of communication using radio waves in the environments and survey the latest technology of backscatter communication, wireless sensing and context recognition of humans and objects. In general, since each zero-energy IoT device does not have enough recognition capability by itself, we need to construct an edge computing-based network with a large number of zero-energy IoT devices in order to acquire diverse sensing information. Here, we present issues to be considered in distributed processing on zero-energy IoT device networks and their solutions. we also explain our current on-going work concerning backscatter communication, channel state information and context recognition. We show that AI technology such as Convolutional Neural Networks (CNNs) on wireless sensor networks (WSNs) can integrate ambient backscatter based direct sensing with ultra-low power IoT devices and wireless sensing based indirect sensing with existing wireless networks in order to create energy harvested context recognition technology of humans and objects. We hope zero-energy IoT device networks using backscatter communication become more popular and they will be used for constructing our smart societies in the near future.

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