RF Sensing in the Internet of Things: A General Deep Learning Framework

Xuyu Wang, Xiangyu Wang, and Shiwen Mao

The authors propose a general deep learning framework for RF sensing in the IoT. They present the proposed framework, and then review various RF sensing techniques, deep learning techniques, and canonical RF sensing applications. They apply the proposed framework to fingerprinting, activity recognition, and vital sign monitoring using WiFi CSI and present experimental results.

Abstract

In this article, we propose a general deep learning framework for RF sensing in the IoT. We first present the proposed framework, and then review various RF sensing techniques, deep learning techniques, and canonical RF sensing applications. We apply the proposed framework to fingerprinting, activity recognition, and vital sign monitoring using WiFi CSI and present experimental results. We conclude this article with a discussion of research challenges and open problems.

Introduction

With the fast advances in mobile devices and communication technologies, various machines and devices are capable of interacting with each other within a network, that is, the Internet of Things (IoT) [1]. Many emerging applications benefit from the development of the IoT. In general, IoT-based applications consist of three layers: the sensing layer, the gateway layer, and the cloud layer. As shown in Fig. 1, the left block represents the *sensing layer*, where sensed data is captured by various sensors, such as accelerometers and gyroscopes. Recently, researchers have also utilized RF signals to capture events in the IoT environment (i.e., *RF sensing*). While RF signals are transmitted, reflected, blocked, and scattered by objects like walls, furniture, vehicles, and human bodies, it is possible to extract useful information, such as position, movement direction, speed, and vital signs of a human subject, from received RF signals. Unlike traditional hardware sensors, RF sensing provides users with low-cost and unobtrusive services. Furthermore, due to the broadcast nature of RF signals, RF sensing can be used not only to monitor multiple subjects, but also to capture changes in the environment over a large area.

The *gateway layer* in Fig. 1 (the middle block) transfers sensed signals to the *cloud layer* (the right block). Usually, captured signals are analyzed in the cloud layer with various signal processing techniques or machine learning algorithms. Recently, there has been considerable interest in applying deep learning techniques such as deep autoencoder, convolutional neural network (CNN), and long short-term memory (LSTM) to RF sensing [2–4]. Traditional machine learning algorithms, such as support vector machine (SVM) and *K*-nearest neighbor (KNN), are effective for relatively small datasets and easy classification tasks. They do not scale well with increased numbers of samples. Moreover, SVM and KNN require careful data preprocessing and parameters selection to avoid over-fitting and under-fitting. For example, principal component analysis (PCA) is always required for feature extraction with traditional machine learning. Deep learning can handle large datasets and complex classification tasks to obtain higher classification accuracy. Moreover, deep learning models can predict well, although they are highly over-parametrized. Finally, deep learning algorithms also have great potential to process high dimensional data that could not be effectively handled by shallow machine learning algorithms.

In this article, we present a general deep learning framework for RF sensing in the IoT, along with several experimental case studies, and a discussion of challenges and open problems. The general architecture is presented in the following section, where various RF sensing techniques, including WiFi, RF identification (RFID), acoustics, ultra-wideband (UWB), and three representative deep learning algorithms, including deep autoencoder, CNN, and LSTM, are examined in detail. Next, we review three canonical RF sensing applications, including indoor localization, activity recognition, and health sensing, and present three experimental case studies by applying the proposed framework. We then discuss challenges and research directions for RF sensing with deep learning, including utilizing multiple data sources, exploiting new spectra for RF sensing, moving deep learning from the cloud to the edge and/or mobile devices, security and privacy issues, and deep learning theory. The final section concludes this article.

General Deep Learning Framework for RF Sensing

The General Framework

We present a general framework to leverage deep learning techniques for RF sensing applications. As shown in Fig. 2, various types of RF signals can be utilized as inputs to deep learning algorithms, such as WiFi, RFID, UWB, and acoustics. Data pre-processing is an essential step before employing deep learning algorithms. Compared to traditional shallow machine learning techniques, such as SVM and KNN, feature extraction is not necessary in our framework, because deep learning has an excellent ability to represent data and

Digital Object Identifier: 10.1109/MCOM.2018.1701277

The authors are with Auburn University.

extract features from data. In fact, the pre-processing step needs to first obtain calibrated data from RF signals, where randomness errors, such as the packet boundary detection (PBD) error, sampling frequency offset (SFO), and central frequency offset (CFO), are removed. For example, calibrated phase or phase difference between two antennas for RF signals should be implemented in the pre-processing step. Then, for different deep network architectures, different inputs are obtained in the pre-processing step. For example, when CNN is used, images are constructed from the calibrated phases or amplitudes When LSTM is employed, signals can be divided into short time series. When an autoencoder is used, signals can be directly utilized for the proposed deep learning framework.

The proposed framework consists of two stages: an offline training stage and an online prediction stage. In the offline stage, training data is used to train the deep leaning model. For different types of applications, the deep network models exhibit different potentials. For example, CNN achieves outstanding performance in image classification and pattern recognition, since it emulates the natural visual perception mechanism. LSTM is effective at processing variable-length input sequences, which makes it highly suited for time related applications. In the online stage, test data is fed into the well trained deep network to provide prediction results. In this stage, strategies such as Bayesian methods have been used to optimize the output of the deep network [2]. The output of the deep network can be directly used as prediction results, such as in some recognition and detection applications. When the surrounding environment changes, the proposed framework can employ transfer learning to update weights with small measurement datasets.

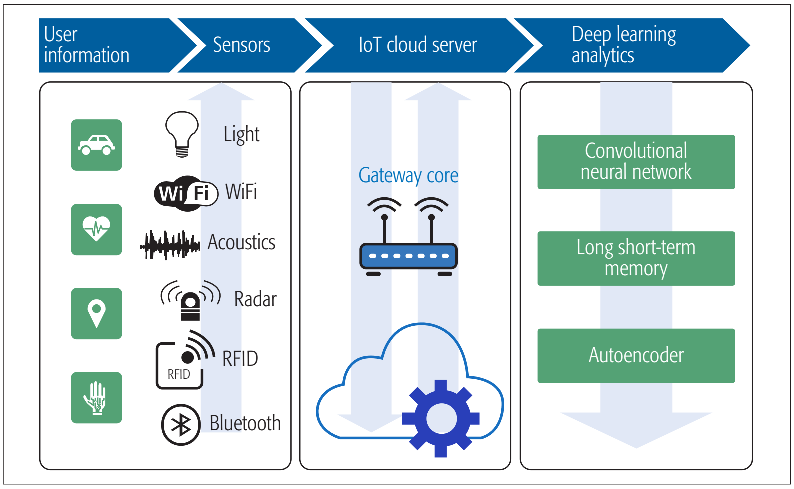

Figure 1. The layered architecture for RF sensing in the IoT.

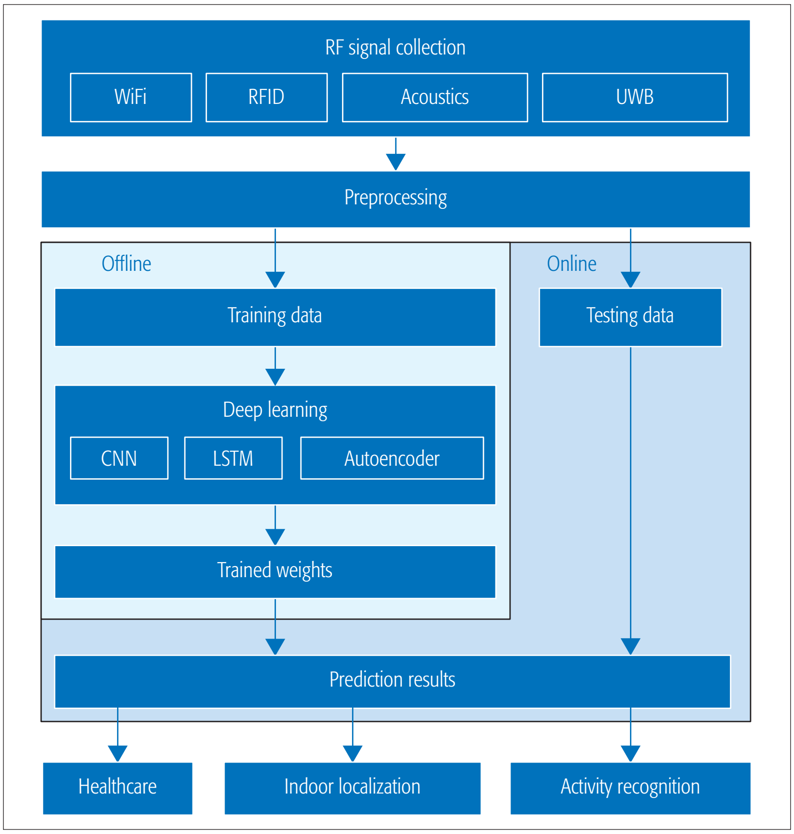

Figure 2. A general deep learning framework for RF sensing.

RF Sensing Techniques

Various wireless signals have been used for RF sensing, such as WiFi, RFID, UWB, and acoustic signals. Their main features are summarized in Table 1.

WiFi has become the dominant data access technology for mobile users in the 2.4 GHz and 5.8 GHz bands (while IEEE 802.11ad uses the 60 GHz band). WiFi access is ubiquitous in many indoor and outdoor environments, which makes WiFi an ideal candidate for RF sensing to capture changes in the environment. Compared to traditional sensors, WiFi is capable of monitoring a large and crowded area, but WiFi signals are susceptible to interference.

There are two types of RFID systems: active and passive. An active RFID system depends on the internal power supply to reflect a response to the reader. Although longer ranges can be achieved, active RFID systems usually have a higher cost and larger form factor. Passive RFID tags draw much attention because of their smaller size and lower cost, and no need for power sources. RFID is limited by its extremely simple design. For instance, when a reader attempts to read multiple tags close to each other, there may be collision among the response signals or large delay if a medium access control scheme is in place.

UWB is a carrierless communication technology that achieves high date rates by utilizing ultra-short pulses with a duration of less than 1 ns. Due to the ultra-short pulses, the power consumption of UWB is much lower than traditional communication systems. Ultra-short pulses also mitigate the multipath effect and enable high-precision time of flight (TOF) estimation, which is beneficial to many RF sensing applications. UWB signals can penetrate materials, and many through-wall imaging systems are proposed to exploit this feature. Furthermore, because of its unique wide spectrum, UWB signals are robust to interference from other wireless sources.

Although at much lower frequencies, we include acoustic signals for the sake of completeness. Considering the lower propagation speed and narrow bandwidth of an acoustic signal, high-speed resolution can be provided to capture the

Signal	Protocol	Frequency	Bandwidth	Max. data rate (theoretical)	Approximate indoor rage	Pros	Cons
WiFi [5]	802.11 a/b/g/n/ac	11–2.4 GHz 11a–3.7/5 GHz 11b–2.4GHz 11g–2.4 GHz 11n–20/40 MHz 11ac–5 GHz	11–22 MHz 11a–20 MHz 11b–20 MHz 11g–20 MHz 11n–20/40 MHz 11ac–20/40/80/160 MHz	11–2 Mb/s 11a–54 Mb/s 11b–11 Mb/s 11g–54 Mb/s 11n–450 Mb/s 11ac–1.73 Gb/s	11–20 m 11a–35 m 11b–35 m 11g–35 m 11n–70 m 11ac–35 m	1. Low cost 2. Ubiquitousness 3. Large coverage	1. Susceptible to environmental influence
RFID [6]	ISO11784/85 ISO15693 ISO14443 EPCglobal	LF: 125–134 kHz HF: 13.553–13.567 MHz UHF: 868 MHz, 915 MHz	LF: 10 kHz HF: 15 kHZ UHF: 500 kHz (North America)	26.7 kb/s up to 640 kb/s	LF: 0.2 m–1 m HF: 0.1 m–0.7m UHF: 3 m–10 m	1. Directional performance 2. Privacy	1. Signal collision and data loss 2. Security concerns
UWB	802.15.7	3.1–10.6 GHz	>500 MHz	480 Mb/s up to 1.6 Gb/s	10 m	1. Large bandwidth 2. Low power requirement 3. Low probability of intercept and detection 4. NLOS and LOS could be easily distinguished 5. Large coverage	1. Hardware dependency
Acoustics	N/A	20 to 20 kHz	N/A	N/A	Several meters	1. Ubiquitousness 2. High speed resolution 3. High resolution in detecting phase shift	1. Susceptible to environment 2. Small coverage 3. Bad user experience

Table 1. Features of RF sensing techniques.

	Applications	Operation	Training methods	Comparison with traditional ML
Autoencoder [7]	Data compression, signal denoising	Restricted Bolzmann machine	Pretraining, unrolling, fine-tuning	1. Nonlinear transform
CNN [8]	Image recognition, video analysis, natural language processing	Convolutional layer, pooling layer, fully connected layer	Standard backpropagation	1. Requires relatively large datasets 2. Performs well with complex problems such as image classification 3. No need to extract features
LSTM [9]	Time-series prediction, speech recognition, activity recognition	Input gate, output gate, forget gate	Backpropagation through time	1. Handle long-range dependency 2. Better capability to represent data

Table 2. Features of three popular deep learning techniques.

small movements of an object. Acoustic signals have been exploited for activity recognition and speed detection based on machine learning and Doppler shift. However, compared to WiFi and RFID, acoustic signals can easily be affected by other sound sources. Acoustic signals transmitted from smartphones also do not have strong penetration ability. Thus, applications with smartphone acoustic signals can only be deployed within small distances.

Deep Learning Techniques

Deep learning is a branch of machine learning that achieves multiple levels of representation of data with a general-purpose learning procedure. Recently, there has been considerable interest in applying deep learning to wireless systems, largely motivated by the huge success of deep learning in several areas, such as natural language processing, pattern recognition, image classification, and gaming. In Table 2, we compare the features of three widely used deep learning models, including autoencoder, CNN, and LSTM.

Autoencoder Neural Network: An autoencoder neural network is an unsupervised learning algorithm [7].The architecture of the autoencoder, shown in Fig. 3 (top), is composed of three parts: an input layer, one or more hidden layers, and an output layer. To reconstruct its own input, the output layer has an identical number of nodes as the input layer. The number of nodes in the hidden layers is always smaller than the number of nodes in the input layer, so a compressed representation can be extracted from the input data.

There are three stages in the training process, including pretraining, unrolling, and fine-tuning. In the pretraining stage, each neighboring set of two layers is modeled as a restricted Boltzmann machine (RBM). Then the deep network is unrolled to obtain the reconstructed input with forward propagation. Next, the backpropagation technique is used to fine-tune the results. Like PCA, the purpose of the autoencoder is to find low-dimensional representations of the input data. Naturally, the autoencoder is widely used in data compression and signal denoising. The first work that utilizes an autoencoder in RF sensing is DeepFi [2]. With the proposed framework in Fig. 2, we can also use the deep autoencoder for activity recognition and health sensing.

Convolutional Neural Network: CNN is inspired by emulating the natural visual perception mechanism of living creatures, and consequently, CNN has achieved great success in computer vision. The first CNN architecture was LeNet-5 [8]. In Fig. 3, the convolution and subsampling operations of LeNet-5 are first applied to the input data in the convolutional layer and subsampling layer, respectively. After two groups of such computation, the output of the higher layer is processed by a fully connected neural network, where the final classification results are improved.

In 2015, a residual learning framework, called ResNet, was proposed by Microsoft Research [10]. The 152-layer residual network achieves an error rate of 3.57 percent on the ImageNet test set, and won first place in the ILSVRC 2015 classification competition. To solve the vanishing gradient problem caused by greatly increased depth, the residual module creates a shortcut path between the input and output, which implies an identity mapping.

The great performance of CNNs also attracts RF sensing researchers' attention. For example, ResLoc [4], an indoor localization system with commodity 5 GHz WiFi, uses bimodal channel state information (CSI) tensor data to train a deep residual sharing learning. ResLoc has achieved superior performance and outperformed several existing deep-learning-based methods [4].

Long Short-Term Memory: The LSTM model, shown in Fig. 3, is proposed to handle data with long-term dependencies [9]. Unlike the traditional RNN, an LSTM unit utilizes three gates to control the data flow. An *input gate* decides if a new value could flow into the memory; a *forget gate* controls if a value should remain in memory; and an *output gate* determines if the value in memory could be used to compute the output of the unit. These gates ensure the effectiveness of gradient-based optimization methods in training the LSTM. LSTM has been used widely in machine translation, speech recognition, and time-series prediction, with emerging applications in RF sensing.

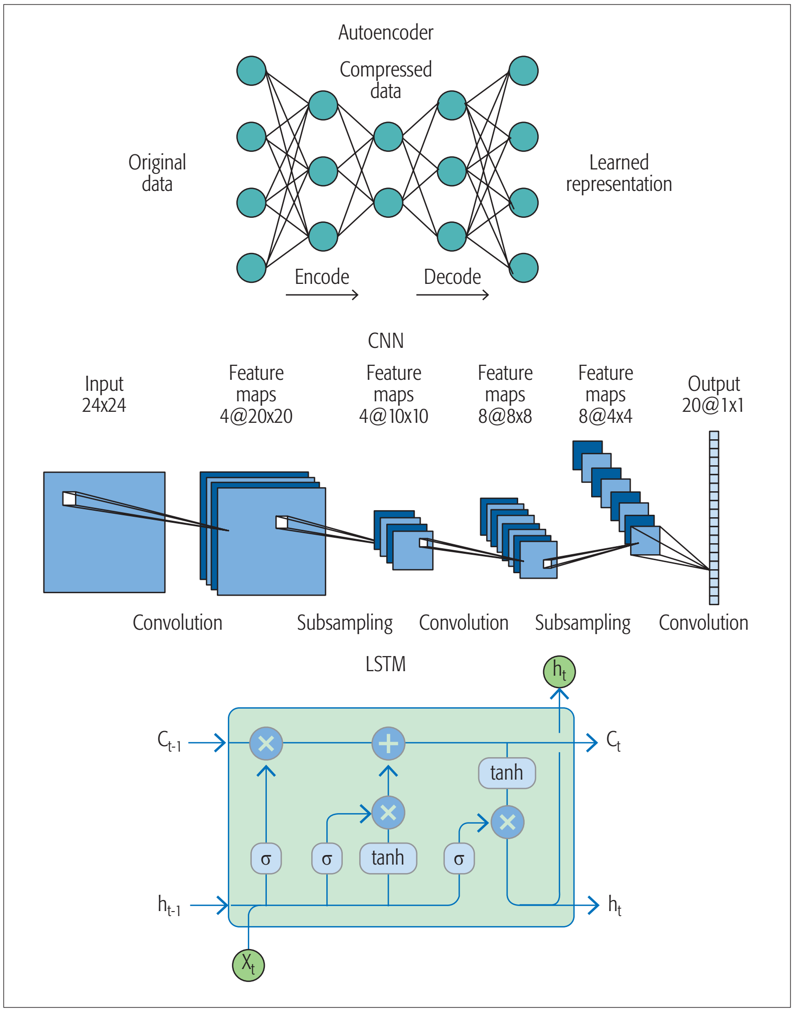

Figure 3. Three popular deep learning networks: CNN (top), autoencoder (middle), LSTM (bottom).

Applications and Experiment Results

RF Sensing Applications

Indoor Localization: Recently, deep learning has been employed for indoor fingerprinting, which is a model-free approach. The representation work is DeepFi [2], which exploits CSI amplitude data for fingerprinting. To build a fingerprint database, WiFi CSI values are collected at each test position and used to train a deep autoencoder. In the online phase, a probabilistic method based on the radial basis function is employed for location estimation. The difference between traditional fingerprinting methods and DeepFi is that the trained weights of the deep autoencoder network are utilized as fingerprints. This is a much more effective way to extract the features of the CSI values from every test location. DeepFi is a special case of the proposed deep learning framework, which can be used for indoor localization with different deep network architectures and different RF signals [4].

Activity Recognition: Activity recognition is the key component of many useful RF sensing applications, such as fall detection and security surveillance. The idea is to classify activities based on extracted features from RF signals. Different feature extraction and classification models have been explored, such as PCA, anomaly detection, DWT, and hidden Markov model (HMM).

Several recent works have utilized deep learning techniques for classification. For example, a deep learning architecture that uses only RFID data for detection of process phases and activities during a trauma is proposed in [11]. 3D matrices are generated by processed RFID signals using a network of three convolutional layers and three fully connected layers. The CNN is used to classify the activities into different categories. This system achieves an average accuracy of 80.40 percent for recognition of 11 types of activities and an average accuracy of 72.03 percent for detection of five phases.

Healthcare Sensing: Long-term monitoring of vital signs, such as respiration and heartbeat, in indoor environments has become a hot research area. Many existing RF-based vital sign monitoring systems rely on specially designed hardware, such as a Doppler radar or ultra wideband (UWB) radar. Some other systems employ WiFi signals. For example, PhaseBeat [3] monitors respiration and heart rates with commodity WiFi utilizing CSI phase difference data, where discrete wave-

By applying deep learning techniques to new signals from 5G spectra, RF sensing could be greatly enhanced with a stronger data representation ability, not only for personal IoT applications such as indoor localization, activity recognition, and healthcare, but also for other IoT applications.

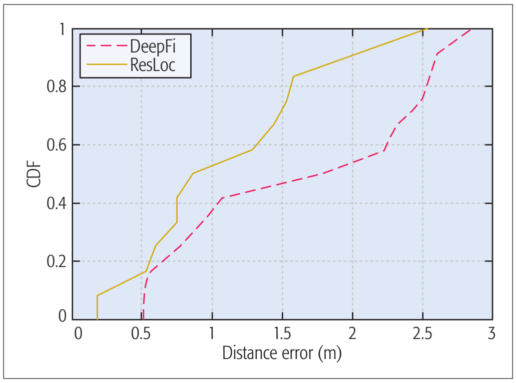

Figure 4. Performances of localization with deep autoencoder and CNN networks.

let transform is leveraged to decompose the processed phase difference data into respiration and heart signals, and peak detection and Root-MUSIC are used to estimate the respiration rate for a single person and multiple subjects, respectively. Fast Fourier transform (FFT) is used for estimating the heart rate. The median error of PhaseBeat for respiration rate and heart rate are 0.25 beat per minute and 1 beat per minute, respectively [3].

Experiments and Results

In the following experiments, a desktop computer is used as a WiFi access point and a Dell laptop is used as a mobile device. Both computers are equipped with an Intel 5300 network interface card (NIC), and both run the Ubuntu Desktop 14.04 LTS system. To accelerate the training process, Keras with tensorflow backend on a PC with Intel® Core™ i7-6700K CPU and a Nvidia GTX1070 GPU are used for training.

First, we experiment with ResLoc [4], a deep-residual-learning-based indoor localization system, and DeepFi [2], a deep-autoencoder-based indoor fingerprinting system, in a computer laboratory with size 6 m × 9 m, where CSI data collected from 30 locations are separated equally into the training dataset and testing dataset. The input to ResLoc is bimodal CSI data that includes CSI amplitude and phase difference, while the input to DeepFi only contains CSI amplitude. The cumulative distribution function (CDF) of localization errors are plotted in Fig. 4. The median errors are about 0.86 m and 1.785 m for ResLoc and DeepFi, respectively. The maximum errors for ResLoc and DeepFi are 2.55 m and 2.87 m, respectively. The results show that deep residual learning and autoencoder can both achieve accurate indoor localization.

We also leverage the proposed framework for activity recognition using LSTM. We collect a CSI dataset that contains CSI amplitude data and phase difference data. The dataset includes five types of activities, denoted as "fall, run, sit down, stand up, and walk." The LSTM network has two hidden layers, with 125 hidden units in each layer. The detection accuracy for the five activities are 95.1, 92.3, 91.8, 89.9, and 73.5 percent, respectively. The overall accuracy and average recall are 90.37 and 88.52 percent for all activities, respectively. Only the accuracy of "walk" and "stand" are below 90 percent, due to the high similarity between these two activities.

Finally, we apply the proposed framework to health sensing for an apnea detection application. Apnea means temporary suspension of breathing during which the volume of the lungs does not change. LSTM is chosen as the deep learning model to process CSI data for apnea detection. We use CSI amplitude and phase difference that capture the respiration and apnea signals. We find the overall accuracy for LSTM with CSI amplitude is 90.16 percent, and that for LSTM with CSI phase difference is 98.36 percent. The results show that our deep-learning-based RF sensing framework can effectively detect apnea.

Challenges and Future Directions

Fusion of Multiple Data Sources

As shown in our experimental studies, bimodal or even multimodal data can improve RF sensing performance. For example, WiFi and light sensors are both available on smartphones and can be integrated for indoor localization, where WiFi and light signals are complementary to each other. Using bimodal data of WiFi received signal strength (RSS) and light intensity can increase data diversity, which results in higher location accuracy.

The key to exploiting multimodal data is how to effectively fuse various data. One solution to train multimodal data is to adopt a multi-channel deep network architecture, one for each data source [4, 12]. Signals from different channels can be fused at intermediate layers [4] and/or at the output layer [12]. Other deep networks such as deep reinforcement learning and generative adversarial networks can also be incorporated for fusion of multiple data sources to improve sensing accuracy or reduce cost with small training data. For effective data fusion, the input data from different sources should be normalized, and data samples from different sources should be aligned.

Exploring New Spectrum for RF Sensing

With the fast growth of 5G technologies, signals from new spectra, such as the low-bands (below 1 GHz), mid-bands (1 GHz to 6 GHz), and high-bands (above 24 GHz, e.g., the millimeter-wave, mmWave, band), could be leveraged for RF sensing. Specifically, the low-bands spectrum can be utilized for massive IoT and mobile broadband; the mid-band spectrum provides wider bandwidths and can be employed for mission-critical applications and enhanced mobile broadband (eMBB); the high-band spectrum provides a huge amount of bandwidth and can be used for high-throughput communications. In the literature, mmWave massive multiple-input multiple-output (MIMO) has been applied for fingerprinting with a deep learning approach. Moreover, narrowband (NB) IoT technologies, such as LoRaWAN and SIGFOX with low power and long range, can also be leveraged for detecting multiple objects.

Channel estimation based on deep learning could become an interesting research topic. Some key parameters, such as amplitude, angle of arrival (AOA), and time of arrival (TOA), from the multipaths can be predicted from training data with deep learning. By applying deep learning techniques to new signals from 5G spectra, RF sensing could be greatly enhanced with a stronger data representation ability, not only for personal IoT applications such as indoor localization, activity recognition, and healthcare, but also for other IoT applications such as smart city, manufacturing, supply chain management, precision agriculture, and animal tracking.

From Cloud to Edge and Mobile Devices

Deep learning models are usually computation-intensive and require large storage space. For image and speech recognition applications, usually the programs are executed at a server or in the cloud. For RF sensing applications, it would be more appealing to execute the deep learning models at the edge or mobile devices to avoid large delay for better user experience [13].

The challenge is how to execute deep learning models at the relatively more resource-constrained edge or mobile devices. To this end, compressed deep network can be utilized for RF sensing on edge devices, and parallel and distributed deep learning are suitable for execution on edge and mobile devices. Finally, graphic processing unit and field-programmable-gate-array-accelerated hardware can be used at the edge or mobile devices to greatly accelerate the computation for RF sensing applications.

Security and Privacy Preservation

By leveraging features of multi-path RF signals, deep learning can be used to classify eavesdropping, denial of service attack, bad data injection, and intrusion detection in smart homes. Specifically, deep LSTM networks can be used for real-time intrusion detection. RF sensing can be incorporated for user authentication with different RF signals such as WiFi, RFID, acoustics, and UWB, where implicit authentication can be used.

Deep learning security has become a hot research topic recently [14]. The main challenge is how to recognize adversarial data and clean data. An attacker can easily inject noise or jamming signals to RF sensing signals. Such adversarial data should be recognized in the beginning stage. Another challenge is how to preserve user privacy. While RF signals mostly propagate in all directions, it is important to prevent an illegitimate user from detecting a user's location or monitoring a patient's vital signs.

Deep learning security has become a hot research topic recently [14]. The main challenge is how to recognize adversarial data and clean data. An attacker can easily inject noise or jamming signals to RF sensing signals. Such adversarial data should be recognized in the beginning stage. Another challenge is how to preserve user privacy.

Deep Learning Theory

To explain why deep learning can achieve promising performance, opening the black box of deep learning has become a hot research topic recently. Researchers are tackling three main issues:

- The expressive power that defines deep networks' ability from depth, width, and layer type to approximate functions
- The generalization capability that explains why the deep learning models can predict well although they are highly over-parametrized
- Optimization of the empirical loss that considers why stochastic gradient descent (SGD) on the non-convex empirical loss is effective [15]

Conclusions

In this article, we discuss RF sensing techniques for the IoT with a general deep learning framework. After presenting the general architecture and the proposed framework, we provide an overview of existing RF sensing techniques and deep learning algorithms. We then review several canonical RF sensing applications and present three experimental studies that adopt the proposed framework. We conclude this article with a discussion of challenges and open problems.

Acknowledgment

This work is supported in part by the NSF under Grant CNS-1702957.

References

[1] G. Muhammad *et al.*, "Smart Health Solution Integrating IoT and Cloud: A Case Study of Voice Pathology Monitoring," *IEEE Commun. Mag.*, vol. 55, no. 1, 2017, pp. 69–73.

[2] X. Wang *et al.*, "CSI-Based Fingerprinting for Indoor Localization: A Deep Learning Approach," *IEEE Trans. Vehic. Tech.*, vol. 66, no. 1, Jan. 2017, pp. 763–76.

[3] X. Wang, C. Yang, and S. Mao, "PhaseBeat: Exploiting CSI Phase Data for Vital Sign Monitoring with Commodity WiFi Devices," *Proc. IEEE ICDCS '17*, Atlanta, GA, June 2017, pp. 1230–39.

[4] X. Wang, X. Wang, and S. Mao, "ResLoc: Deep Residual Sharing Learning for Indoor Localization with CSI Tensors," *Proc. IEEE PIMRC '17*, Montreal, Canada, Oct. 2017, pp. 1–7.

[5] M. Gong, B. Hart, and S. Mao, "Advanced Wireless LAN Technologies: IEEE 802.11ac and Beyond," *ACM Mobile Comp. Commun. Rev.*, vol. 18, no. 4, Oct. 2014, pp. 48–52.

[6] D. M. Dobkin, *The RF in RFID: UHF RFID in Practice*, 2nd ed. Newnes, 2012.

[7] G. E. Hinton and R. R. Salakhutdinov, "Reducing the Dimensionality of Data with Neural Networks," *Science*, vol. 313, no. 5786, July 2006, pp. 504–07.

[8] Y. LeCun *et al.*, "Gradient-Based Learning Applied to Document Recognition," *Proc. IEEE*, vol. 86, no. 11, Nov. 1998, pp. 2278–2324.

[9] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Comp.*, vol. 9, no. 8, Nov. 1997, pp. 1735–80.

[10] K. He *et al.*, "Deep Residual Learning for Image Recognition," *Proc. IEEE CVPR '16*, Las Vegas, NV, June 2016, pp. 770–78.

[11] X. Li *et al.*, "Deep Learning for RFID-Based Activity Recognition," *ACM SenSys '16*, Stanford, CA, Nov. 2016, pp. 164–75.

[12] X. Wang, L. Gao, and S. Mao, "BiLoc: Bi-Modality Deep Learning for Indoor Localization with 5GHz Commodity Wi-Fi," *IEEE Access*, vol. 5, no. 1, Mar. 2017, pp. 4209–20.

[13] N. D. Lane *et al.*, "Squeezing Deep Learning into Mobile and Embedded Devices," *IEEE Pervasive Comp.*, vol. 16, no. 3, July 2017, pp. 82–88.

[14] N. Papernot *et al.*, "The Limitations of Deep Learning in Adversarial Settings," *Proc. 2016 IEEE Euro. Symp. Security and Privacy*, Saarbrucken, Germany, Mar. 2016, pp. 372–87.

[15] H. Mhaskar, Q. Liao, and T. A. Poggio, "When and Why Are Deep Networks Better than Shallow Ones?" *Proc. 31st AAAI Conf. Artificial Intelligence*, San Francisco, CA, Feb. 2017, pp. 2343–49.

Biographies

Xuyu Wang [S'13] received his M.S. in signal and information processing in 2012 and B.S. in electronic information engineering in 2009, both from Xidian University, Xi'an, China. Since 2013, he has been pursuing a Ph.D. degree in electrical and computer engineering (ECE) at Auburn University, Alabama. His research interests include indoor localization, deep learning, software defined radio, and big data.

Xiangyu Wang received his B.S. degree in electrical engineering from Taiyuan Institute of Technology, China, in 2014, and his M.S. degree in ECE from Auburn University in 2017. He is currently a Ph.D. student in the Department of ECE at Auburn University. His research interests focus on machine learning, indoor localization, and IoT.

Shiwen Mao [S'99, M'04, SM'09] received his Ph.D. in ECE from Polytechnic University, Brooklyn, New York. He is the Samuel Ginn Distinguished Professor and director of the Wireless Engineering Research and Education Center, Auburn University. His research interests include 5G and IoT. He is a Distinguished Lecturer of the IEEE Vehicular Technology Society. He is on the Editorial Boards of *IEEE Transactions on Multimedia*, the *IEEE Internet of Things Journal*, and *IEEE Multimedia*, among others.