Machine-Learning-Assisted Signal Detection in Ambient Backscatter Communication Networks

Usman Saleh Toro, Basem M. ElHalawany, Aslan B. Wong, Lu Wang, and Kaishun Wu

Abstract

Ambient backscatter communication (AmBC) has emerged as a promising paradigm for enabling sustainable low-power operation of Internet of Things devices. This is due to its ability to enable sensing and communication through backscattering ambient wireless signals (e.g., WiFi and TV signals). But a great impediment to AmBC-enabled networks is the difficulty in decoding the backscatter signals because the ambient signals are usually modulated and meant for other legacy receivers rather than AmBC devices. Drawing from the ability of machine learning (ML) to enhance the performance of wireless communication systems, some ML-aided techniques have been developed to assist signal detection in AmBC. Hence, this article aims to provide a comprehensive overview of the subject by describing the operation of the AmBC network, highlighting the major challenges to signal detection in AmBC, discussing and comparing the performance of some existing ML-assisted solutions to AmBC signal detection, and highlighting some future research that could be carried out on the subject.

Introduction

The Internet of Things (IoT) will drastically revolutionize human-to-human (H2H), human-to-device (H2D), and machine-to-machine (M2M) interactions in the near future. This will lead to myriad intelligent pervasive applications in various sectors of human life including agriculture, transportation, commerce, and healthcare [1]. The key to enabling such applications is addressing the limited energy problem of IoT devices. Recently, ambient backscatter communication (AmBC) has emerged as a strong contender for enabling low-power and sustainable operation of IoT devices.

Backscatter communication (BackCom) involves the transmission of sensed data at a backscatter device (BD) or tag by modulating it into an incident signal from a source (or reader) and reflecting the modulated incident signal to a receiver. This allows the BD to sense data and transmit signals without actively generating a carrier signal, thereby providing a very low-powered means of sensing and communication and also enabling the development of battery-free sensors. To enable battery-free operation, the BD harvests energy from the incident signal and stores it in capacitors for powering the BD's operation. To enhance the sustainable operation of the BDs, energy harvesting (EH) techniques [2] have been developed to supplement that harvested from the incident ambient signal. In addition to the benefits of traditional BackCom, AmBC, shown in Fig. 1, leverages ambient wireless signals (e.g., WiFi, GSM, TV, and FM radio) as an incident signal at the BD for modulating sensed data. This eliminates the need to deploy a dedicated source for carrier generation and further decreases the cost of deploying sensors in the IoT ecosystem [2].

Despite the benefits that come along with deploying AmBC in wireless networks, decoding the backscatter signal at the receiver is challenging due to various reasons. They include interference at the receiver from direct path signal [3], challenges in backscatter channel estimation [3], low strength of backscatter signal at the receiver [4], absence of a distributed multiple access control (MAC) protocol [4], and complex operation dynamics of AmBC network components. Techniques to address these challenges have been developed, but further work to minimize the challenges is still required. Hence, considering the ability of machine learning (ML) techniques to leverage trained models for improving wireless communication systems [5], several works have developed ML-based solutions to address the problem of signal detection in the AmBC network [6–13] despite being in early stages of deployment. To provide a comprehensive view of the subject, this article aims to bring a survey of the existing ML-based solutions and also provides a discussion of future research on the subject.

The article is structured as follows. First, we give an introduction to ML-assisted signal detection in AmBC. The operation of AmBC is described. Then we discuss the bottlenecks to signal detection in the AmBC network. Some existing ML-assisted signal detection solutions are discussed. Further, a comparison of the performance of existing techniques in assisting signal detection in AmBC is presented. We describe some future research that could further enhance ML-assisted signal detection. Lastly, we conclude the article.

Overview on AmBC Network Operation

This section explains the operation principle of an AmBC network.

The AmBC network consists of an ambient source, a BD, and a receiver, as shown in Fig. 1a. At the top level, AmBC operates just like a heliograph. The ambient source transmits signals that are meant for other legacy devices such as

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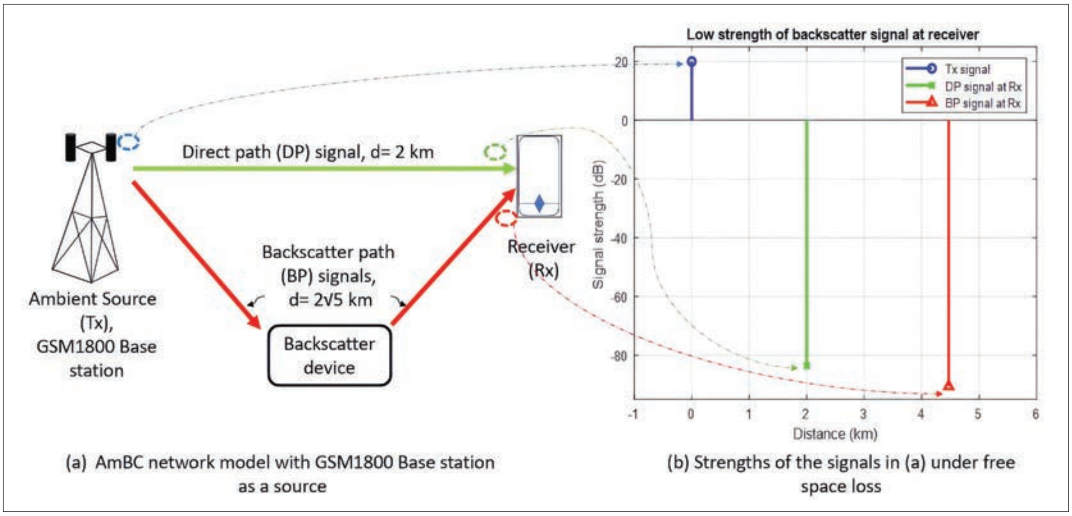

FIGURE 1. AmBC system model showing signal strengths at various positions with free space loss.

mobile phones, TV, and FM radio. When the ambient signals are incidental to the BD, they provide two main functions: to serve as an energy source and serve as a carrier signal for modulating sensing data. As an energy source, the ambient signals will be converted into electrical energy and stored in capacitors or small batteries. For modulating sensing data, a technique called load modulation is leveraged to enable sensing data at the BD to be reflected toward a receiver. Load modulation involves switching the impedance of the BD between various states based on the value of data to be transmitted by the BD. Since the weak incident signals at the BD are on the same channel as the received signals at legacy devices, the BD could apply some techniques that can move the backscatter signal to a different channel to avoid co-channel interference. Further, the BD could amplify the signal strength of the reflected signal to lessen the impact of fading on its path to the receiver. At the receiver, the backscatter signal is decoded to extract the sensing data. Since the receiver could be a device with high computational resources such as mobile phones and computers, they allow signal processing and ML techniques to be adopted by the receiver for enhanced signal detection.

Bottlenecks to Signal Detection in AmBC Networks

This section identifies and describes some of the most critical challenges to signal detection in AmBC networks. The challenges are arranged based on the OSI layer of the network they affect. These challenges are shown in Fig. 3:

- Direct path signal interference (physical layer): As shown in Fig. 1a, the stronger direct path signal and the weaker backscatter signals are picked up by the same receiver. Since there are transmission channels from the ambient source to the BD and receiver, co-channel interference will occur at the receiver of AmBC systems that do not have techniques to combat this type of interference. Although some BDs can shift the backscatter signal to another channel, techniques to nullify or avoid the stronger direct path signals are required for efficient signal detection.

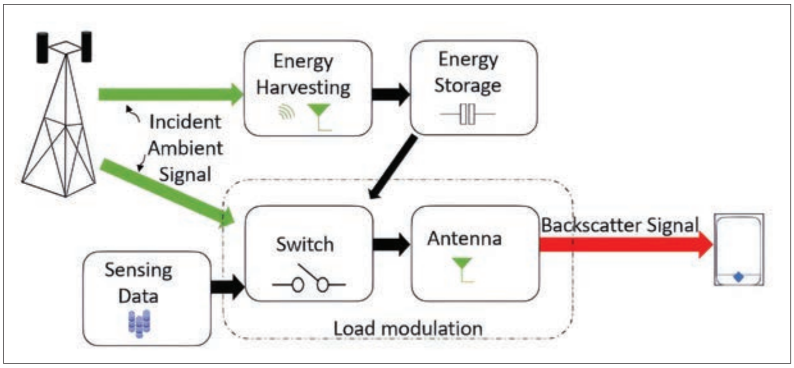

FIGURE 2. Operation of AmBC.

- Low strength of backscatter signal (physical layer): Naturally, wireless signals will fade over distance. In conventional communication systems, signal strength will degrade with the inverse of squared distance. However, since AmBC consists of the incident signal and backscatter signal paths, the doubly faded backscatter signal at the receiver becomes very weak (sometimes beyond the noise floor) at the receiver. This leads to difficulty in signal detection at the receiver.
- Backscatter channel estimation (physical layer): Channel estimation at the receiver is a vital process in wireless communication for ensuring accurate decoding of the received signal. For that, the receiver needs to have access to the channel via which data is transmitted. In the AmBC system shown in Fig. 1a, the receiver does not have access to the channel between the ambient source and BD. This results in challenges in estimating the backscatter channel and hence signal detection.
- Absence of MAC protocol (MAC layer): Since the ambient sources in AmBC are meant for other legacy devices, they do not provide MAC for BDs. Further, the AmBC network could consist of multiple BDs that leverage the same ambient source for sensing and communication. In such scenarios, the tags could transmit data to the receiver in a multihop or single-hop manner. In sin-

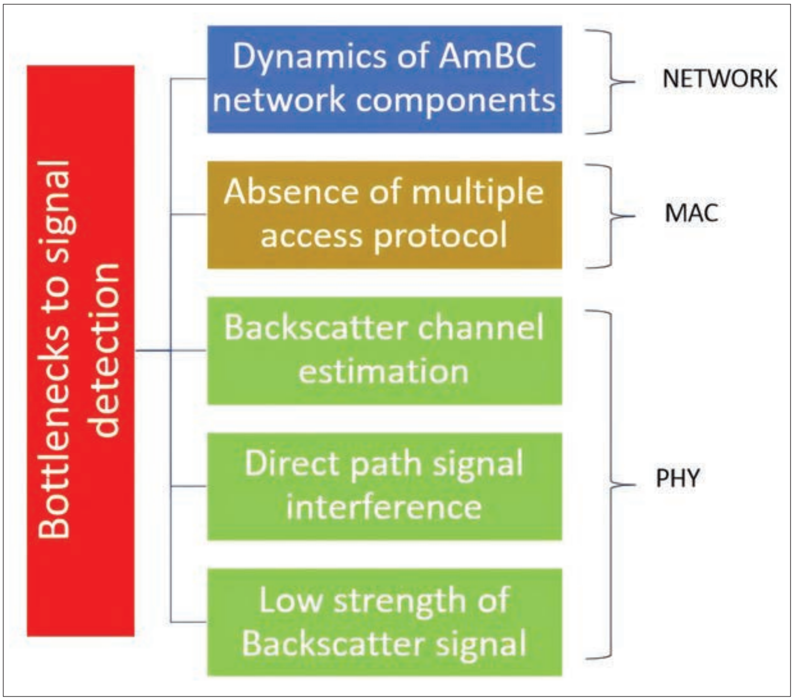

FIGURE 3. Bottlenecks to signal detection in AmBC networks.

gle-hop transmission, the BDs could transmit at the same time slots, leading to collisions at the receiver. In multihop transmission, the order of packet transmission between tags could be distorted, preventing correct data from reaching the receiver.

- Dynamics of AmBC network components (network layer): The benefits of eliminating a dedicated source in AmBC come at the expense of having to consider the operation of the ambient source when designing signal detection techniques. This is more complicated when the signal source is a smart interferer whose operation is difficult to predict. Hence, an efficient signal detection technique in AmBC requires cognizance of the dynamic operations of both ambient sources and BDs.

Existing Solutions

In this section, we shed light on several attempts to address the bottlenecks of signal detection in an AmBC network using various ML-based techniques. The solutions are discussed based on the category of underlying ML algorithms adopted. Also, a comparison of the solutions is shown in Table 1.

Unsupervised Learning

In order to develop a technique for detecting reflected ambient signals without the need for channel estimation, the authors of [6] leveraged the clustering phenomenon. The clustering phenomenon in the AmBC system network allows reflected signals from tags (or BD) to naturally fall into clusters at the receiver. The clusters are formed based on the type of information contained in the reflected signal. Hence, the authors developed an AmBC network that adopts amplitude modulation at the tag. The amplitude modulation adopted allows the tag to assign two distinct energy levels to the reflected signal, which will eventually form two clusters at the receiver. Then unsupervised learning (UL) algorithms based on expectation maximization (EM) were used to classify and detect the transmitted data from the tag. In order to optimize the detection thresholds, learned parameters from the developed algorithms were used to obtain a minimum bit error rate (BER).

Similarly, the author of [7] leveraged UL to aid signal detection in AmBC. Rather than exploiting the clustering phenomenon of AmBC, joint coherent signal estimation and detection at the receiver were leveraged. The AmBC network was modeled with an orthogonal frequency-division multiplexing (OFDM)-enabled source, a BD, and a receiver. Since coherent backscatter signal detection requires the channel state information (CSI) of the backscatter device, a matched filter was used at the backscatter device to estimate the carrier CSI from the source. The estimated carrier CSI is then used at the receiver to efficiently estimate the backscatter signal. Due to the computational complexity of decoding at the receiver, an EM-based algorithm with complexity linear to the length of OFDM was developed to aid the detection of backscatter signals.

UL learns patterns from unlabeled data and thus is suitable for signal detection in AmBC without channel estimation. However, if the wireless environment becomes complicated, there is little room for improvement. To achieve high signal detection accuracy, traditional signal processing techniques, such as de-noising and signal estimation, are required to better estimate and detect the ambient signals. With advanced signal processing techniques, the detection efficiency and accuracy can be much improved.

Supervised Learning

Considering tag signal detection as a classification task, the authors of [8] deployed supervised learning (SL) algorithms (support vector machines and random forest) for backscatter tag signal detection. Simple conventional signal detectors in AmBC use energy detection to identify transmitted tag symbols (0 and 1) that signify backscatter and non-backscatter states. However, the energy detection techniques suffer due to the low signal-to-noise ratio (SNR) of backscatter path signals. Hence, the authors used the received signals and tag symbols as training data and labels, respectively. The tag first transmits some labeled symbols for training at the receiver. Then the trained model is used to detect tag data by classifying the received data into two groups corresponding to 0 and 1. The proposed SL-based detection showed better performance (low BER) in low SNR conditions over conventional energy-detection-based tag signal detection.

Leveraging the clustering phenomenon from a different perspective, the authors of [9] developed an SL-like technique to aid the detection of backscatter signals without the need for channel estimation. In the adopted model, a multi-antenna receiver was deployed to decode backscatter signals from a modulated RF source through a tag. Since decoding clustered received data is tasking, the authors proposed a label-assisted clustering technique. In the proposed technique, the tag assigns known labels before each data transmission. Hence, the received data will fall into clusters based on the known labels. An EM algorithm with less complexity due to modulation constraints from the tag and RF source was used to learn parameters that are then used to decode the transmitted

Reference	ML category	Phenomenon employed to aid signal detection	Main bottleneck(s) addressed
[6]	UL	Clustering of received signals	Backscatter channel estimation
[7]	UL	Joint coherent signal detection and channel estimation	Backscatter channel estimation
[8]	SL	Varying energy levels of received data	Direct-path signal interference, low strength of backscatter signal
[9]	SL	Label-assisted clustering of received signal	Backscatter channel estimation
[10]	RL	Varying transmit power levels in an SDN-based AmBC network	Direct-path signal interference, low strength of backscatter signal
[11]	RL	Autonomous environment learning	Dynamics of AmBC network components
[12]	DL	Feature extraction and transfer learning	Backscatter channel estimation
[13]	DL	Feature extraction and residual learning	Backscatter channel estimation

TABLE 1. Comparison of existing solutions.

signal. This technique achieved similar results to an optimal detector with perfect CSI.

SL algorithms are commonly used for classification, regression, and recognition tasks. Thus, it is effective to address signal interferences and estimate wireless channels. But it requires data training in advance, and the model training is highly dependent on the wireless environment. SL itself does not have much room for improvement when applied to another environment. With the help of transfer learning (TL), training knowledge can be stored and applied to a different wireless environment for interference cancellation and channel estimation.

Reinforcement Learning

An AmBC network contains multiple (AmBC and legacy) devices coexist in a heterogeneous way, making the interaction between those devices difficult due to interference. In order to address this problem, the authors of [10] proposed a software-defined networking (SDN)-based AmBC network. However, the SDN-based AmBC network needs to learn from the operating environment in order to manage interference. Hence, a reinforcement learning (RL) technique was developed to achieve optimal rewards. The RL technique enabled efficient interference management by controlling the transmit power levels of heterogeneous devices. Results of the SDN-based AmBC showed improved performance among legacy devices and ensured the required quality of service (QoS) for AmBC devices.

In order to explore the ability to combine RL and game theory for avoiding interference, the authors of [11] developed a technique for detecting backscatter signals in the presence of a smart interferer. In order to achieve that, the interaction between an interferer and the AmBC system was modeled as a game. Since the AmBC device's operation time is divided into energy harvesting time (EHT) and backscatter time (BT), those time durations were considered when developing the utility functions. For each sub-game, RL was used to obtain the optimal policy for the game due to the non-availability of the interferer operation times. The developed technique showed better signal detection when compared to techniques that consider random and fixed BTs.

RL has the ability to interact with the environment; thus, it is suitable to fight against dynamics of network components and detect AmBC signals in the presence of interference. However, if the network is complex and large-scale, the state and action spaces are usually large in AmBC networks, and RL may not be able to find the optimal policy in a reasonable time and thus deteriorate the performance. Possible solutions may involve a type of deep learning (DL), known as deep reinforcement learning (DRL), to deal with such scenarios.

Deep Learning

As a novel technique with strong ability to extract features from data, the authors of [12] developed a deep transfer learning (DTL) framework. DTL involves adopting a deep neural network (DNN) to extract the features of the received signal at the tag without the need for CSI. But in order to capture the time-varying conditions of the AmBC channel and avoid the need for large training data required to achieve low BER, the authors adopted offline learning, transfer learning, and online tag data detection. Hence, the tag parameters learned during the offline tag detection are transferred for use in detecting the parameters of other related tags in real time. Simulation results of the proposed framework showed near-optimal performance when compared to perfect CSI conditions.

On the other hand, the authors of [13] leveraged deep residual learning to estimate CSI and enhance signal detection in AmBC. Since channel estimation in AmBC is challenging, the authors modeled it as a denoising problem. In the model, a CNN was used to directly recover the channel coefficients (in time and frequency domains) from the received pilot signals at the receiver. Simulated results of the proposed model showed similar results to systems with an optimal minimum mean square error (MMSE) estimator.

As DL has a strong ability to extract features, it is feasible to apply DL for channel estimation in a complex AmBC environment. DL has the potential to achieve high estimation accuracy. The only problem is that it requires a very large amount of data, and it is extremely expensive to train due to complex data models. Therefore, reducing the computational expense is indispensable for AmBC networks.

Case Study: Conventional vs. ML-Assisted Detection

In this section, we compare the performance of a conventional signal detection technique with some ML-assisted signal detection techniques of AmBC models. The conventional signal detection technique considered is the rule-based signal processing of an FM radio demodulator, while the considered ML-assisted techniques are UL [6], SL [9], and DL

Reference	Detection technique	Model properties	Result (BER)
Simulated	Signal processing	Ambient RF source, modulation: FM, carrier frequency: 90 MHz, SNR:10 dB	0.6536
[6]	UL	Ambient RF source, modulation: QPSK, SNR:10 dB	0.04
[9]	SL	Ambient RF source, modulation:16-QAM, SNR:10 dB	0.007
[12]	DL	Ambient RF source, modulation: QPSK, SNR:10 dB	0.0008

TABLE 2. Performance comparison of signal detection techniques.

[12]. To efficiently characterize the performance, we consider the type of ambient source, the modulation at the ambient source, and the SNR at the receiver as the AmBC model parameters.

The conventional model considered in this section is an AmBC system that exploits ambient FM radio signals as the source of excitation. The system is modeled and developed using the communication toolbox of Simulink. The FM message signal is modeled as a sequence of randomly generated bits, while a carrier signal of 90 MHz is generated at the transmitter. The modulated FM signal is transmitted over a fading channel to the BD and then to the receiver. At the receiver, we set the SNR to 10 dB in order to observe the demodulated results.

The BER is used as the performance metric in the experiment. For the conventional system, the original transmitted bits (message signal) were compared to the decoded bits at the FM demodulator to obtain the BER of the system. For the ML-assisted techniques [6, 9, 12], we obtained the results (BER) of those systems where the AmBC systems designed adopted signal detection schemes at the receiver with an SNR of 10 dB and fading ambient signals.

The FM radio-based AmBC simulation parameters, and the results of existing solutions are shown in Table 2. The results show that the conventional detection method of the FM radio-based AmBC has the highest BER compared to other ML-assisted techniques. This is because the demodulator adopts rule-based (signal processing) techniques to detect the transmitted signal. However, the BER can be improved when advanced signal processing techniques are adopted. We also observe that the BER values show significant improvement with the adoption of ML techniques at the receiver. Furthermore, the DL method shows the best performance over the other ML techniques due to its strong feature extraction ability when properly modeled according to the application scenario. Hence, we conclude that ML-assisted signal detection improves the performance of AmBC networks.

Future Work

This section discusses some open research issues related to signal detection in the AmBC network and possible suggestions on how to address those issues.

- Accuracy vs. energy trade-off: While improving the accuracy of ML techniques for backscatter signal detection is desired, the limited power budget of AmBC devices is still a bottleneck to BDs. This becomes more evident when a wearable device is used as a receiver for backscatter signal detection. In such a scenario, leveraging an ML-assisted technique for signal detection requires training a model deployed on the wearable device with some size of a dataset. The higher the amount of training data, the more accurate the model will perform while increasing the power consumption of the already power-stretched wearable device. Hence, considering both ends of the situation, future ML-assisted techniques need to deploy low training data in order to achieve appreciable detection accuracy without overstretching the power demands of AmBC receivers.
- Intelligent non-coherent techniques: Non-coherent signal detection techniques have shown promising results when applied in detecting AmBC signals despite their non-dependence on channel estimation. Despite that, there is still a need to develop ML-assisted techniques that can capture the complexities of the AmBC network, from the properties of the channels (incident path and backscatter path) of AmBC, the dynamics of an incident signal from an ambient source, the interaction between components (ambient source, backscatter device, and interferer) of the AmBC network to the operation of the backscatter tags itself. Incorporating these parameters in designing non-coherent signal detection techniques will further enhance its appeal for adoption in AmBC networks. Pioneering work by the authors of [14] showed the promise of incorporating channel properties (time-selective fading) in improving signal detection.
- Intelligent re-configurable architecture of the receiver: The existing ML-assisted techniques involve the development and training of models that inherently affect the software architecture of the AmBC receiver. In other words, the hardware architecture of the AmBC receiver does not incorporate some elements of intelligent reconfigurability. Developing hardware architectures at the receiver that can optimize the signal detection process at the receiver due to available energy, modulation adopted by the backscatter tag, and CSI will certainly enhance the overall detection process at the receiver. For instance, AmBC systems have shown the promise of enhanced signal detection when multiple tag antennas are adopted [15]. With many ambient sources, such as WiFi access points and cellular base stations, adopting OFDM, the benefits of channel diversity can be fully leveraged in AmBC signal detection by adopting multiple antennas at the source, tag, and receiver of an AmBC network to achieve higher throughput and lower BER.

Conclusion

Addressing the signal detection problem of AmBC will go a long way in enhancing its appeal for enabling sustainable communication networks. The comprehensive discussion presented in this article addresses the contributors to difficulty in signal detection and explicitly describes how existing solutions leveraged ML to assist signal detection. Lastly, the future research issues discussed provide possible succinct ways of improving ML-assisted signal detection. The results in our case study show that DL techniques have shown great improvements in solving the signal detection problem. However, to characterize how well the different sub-categories of DL models solves the problem in different AmBC models needs further investigation, which can be pursued in future work.

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