Adaptive Collaborative Autonomous Wireless Networks

by

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FOREWORD

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Aytac OZKAN

RÉSUMÉ

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Mots-clés: mot-clé1, mot-clé2

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ABSTRACT

Due to tremendous improvements of technology, the world is more connected than ever at the human history. Mobile devices, cell phones, smart home solutions, autonomous cars etc. These vehicles are usually using IEEE 802.15.4 communication protocols, the devices which uses this protocol has the limited number of communication channels and low transmit power, are especially susceptible for the jamming attacks. For example, some internet of things (IoT) devices (e.g., brain and heart inculcated IoT devices), jamming attacks can cause serous consequences for human health

Within this concern, to prevent this kind of intentional interference against the wireless networks, we are going to employ self learning algorithms such as deep reinforcement learning to develop resilient, intelligent, and self-supervised anti-jamming framework.

Since, The DeepMind has been introduced the Reinforcement Learning (RL) and Q-Learning algorithm H., A. & D. (2016), this tools become one of the major toolkit to develop mitigation and intelligent deceptions strategies to prevent against reactive jamming attacks. Despite it is a subset of machine learning Kasturi, Jain & Singh (2020),it is no need long training times and huge datasets, and this future is the key of its success at the field.

Keywords: reinforcement-Learning, transfer-learning,wireless-networks,anti-jamming,multi-agent, collaborative-learning

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ETS	École de Technologie Supérieure
ASC	Agence Spatiale Canadienne

LIST OF SYMBOLS AND UNITS OF MEASUREMENTS

a	Première lettre de l’alphabet
A	Première lettre de l’alphabet en majuscule

INTRODUCTION

The last decade has witnessed the rapid growth of Machine Learning (ML) applications in wireless networks thanks to its agility and efficacy, especially in dealing with uncertainty and dynamics in large-scale problems Sun, Peng, Zhou, Huang & Mao (2019) Bkassiny, Li & Jayaweera (2013) However, some recent studies have revealed that conventional ML solutions have shortcomings, especially when they are applied to solve emerging problems in wireless networks, due to special characteristics of wireless communications, such as high mobility, dynamic environments, diverse connections, and interferenceHowever, some recent studies have revealed that conventional ML solutions have shortcomings, especially when they are applied to solve emerging problems in wireless networks, due to special characteristics of wireless communications, such as high mobility, dynamic environments, diverse connections, and interference.

Moreover, the performances of ML techniques mainly rely on the availability of training data, but acquiring a sufficient amount of data might be costly and time-consuming. Even if the training data are sufficient, conventional ML techniques usually require a long training time, which makes them impractical for many latency-sensitive applications. Apart from the training time issues, many wire- less devices, e.g., IoT devices, are constrained by their limited computing capacity, and thus they are unable to run high-complexity ML tasks. Moreover, many ML techniques actually create more wireless traffic demands because data have to be sent to a central node for training and processing. Beside causing higher communication overhead, sending raw data may also threaten network users' privacy because sensitive information, e.g., healthcare, is sent via the wireless networks.

To address these challenges, Transfer Learning (TL) has recently emerged as a highly-effective solution. Unlike conventional ML techniques that are trained to solve a specific problem, TL leverages valuable knowledge from similar tasks and previous experiences to significantly enhance the learning performance of conventional ML techniques. As a result, TL possesses various advantages over traditional ML approaches which can be summarized as follows;

- Enhance quality and quantity of training data: One of the most challenging tasks for conventional ML approaches is finding sufficient and high-quality data for the training process. TL can easily overcome this problem by selecting and transferring knowledge from similar domains with a large amount of high-quality data. As a result, TL has been considered to be a highly-effective solution for ML-based wireless networks in the future.
- Speed-up learning processes: Instead of learning from scratch like conventional ML approaches, the training process in TL can be significantly sped up thanks to valuable knowledge shared from other similar domains and/or learned in the past. As a result, this can remarkably improve the learning rate, which is especially crucial for the development of ultra-low latency applications for future wireless networks.
- Reduce computing demands: Conventional ML approaches usually require a huge amount of computing resources for the training processes. However, with TL, most of the data were trained by other source domains before the trained models are transferred to the target domain, thereby significantly reducing computing demands for the training process at the target domain. This is particularly useful for wireless devices (e.g., smartphones and edge devices) as they usually have hardware constraints.
- Mitigate communication overhead: For TL approaches, instead of sending the raw data with large sizes, only knowledge, e.g., weights of trained models, needs to be sent. As a result, the communication overhead can be significantly reduced for the wireless networks.
- Protect data privacy: In TL, instead of learning from raw data from other domains, ones only need to learn from their trained models (expressed through weights), and thus data privacy can be protected. This feature of TL is very helpful for privacy-sensitive wireless applications such as healthcare and military communication networks.

CHAPTER 1

RESEARCH OBJECTIVES, MOTIVATION, RESEARCH QUESTIONS

1.1 Research Objectives

The main purpose of this research is develop efficient, reliable and relentless mitigation techniques against the jammer particularly reactive and powerful ones by employing machine learning (ML) and wireless communication technologies.

To achieve the objective defined above, we are going to use the Frequency Hopping Spectrum Sensing (FHSS) techniques. In the infinite time space, regarding the probability distribution of incoming signals, we are going to build the most accurate ML model to find out the optimal and the feasible prediction for communication channels.

Of course, the first paragraph is specified only the core part of communication node, but the particular contribution of this research is to develop multi-agent (multi-node) collaborative (transfer meta-learning) learning techniques to satisfy the constraints such as cost of learning (for each node), cost of transferring mitigation strategy. Predicate on these details, we would like to acquire an augmented Markov decision tuple for our ML model.

So we can divide our main objective into three sub sections and each of them address different research problem.

We assume in the wireless ad-hoc network, there are two communication node (CN) and one reactive jammer. Also CN1 and CN2 has data connection, which means they can transmit to the data to each other. In addition, the ad-hoc network is multi-channel. Constraints, respectively CN's power storage (limit), channel bandwidth, installed CPU or GPU power on the CN.

1.1.1 Objectives

- In the infinite time space, we are going to build a Machine Learning model which will take as input frequencies by sensing from the wireless network, and try to predict jammer next action

(channel estimation), literally means that try to find out the next communication channel will jam. And it will allow us to find out the Jamming activity pattern in the ad-hoc network, and by analyzing these patterns we are going to concrete mitigation strategies. So, related research will propose novel techniques to answer the question below,
How to catalyze the jamming activity pattern and initialize effective and relentless mitigation strategies for the communication nodes in wireless ad-hoc networks by using autonomous learning techniques ?

- In the first item, we have proposed a method which allows us to analyze the jammer behaviour pattern, and generate defence strategies for the CN based on this pattern. But in the wireless spectrum we have two different CNs and we can have more nodes, in this case we may transfer the produced policy (or strategy) from one node to another when suitable conditions satisfied. Also collaborative learning can increase to chances to mitigate against reactive and powerful jammer by saving time and energy of CNs. E.g, cost of learning, cost of transmission and accuracy of learning models have high importance roles in decision model of the framework. So, related research will address the question below, How the collaborative (transfer) learning can assist knowledge transmission between two different communication nodes in the wireless ad-hoc communication spectrum ?
- In second item we introduced collective (transfer learning) technique, but when a jamming attack hit the wireless network, there won't be any data transmission in this condition, each CNs have to run their own learning algorithm.

CHAPTER 2

LITERATURE REVIEW

CHAPTER 3

PROPOSED METHODOLOGIES

3.1 Preliminaries

3.1.1 Fundamentals of Transfer Learning

Transfer Learning, simply learned knowledge will be transferred from the source domain to the target domain to improve the learning process of the target task. Thus, in the following, we first present the definition of a "domain" and a "task". In our research problem, source domain is communication node (CN) that underwent by the jammer attacks, And the target domain likelihood the closest unattacked communication node in the wireless network.

Definition 3.1. *"Domain: A domain $\mathcal{D}$ is defined by two parts: (i) a feature space $\mathcal{X}$ and (ii) a marginal probability distribution $\mathcal{P}(X)$ in which $X = \{x_{1,\ldots,x_n}\} \in \mathcal{X}$ where n is the number of feature vectors in $\mathcal{X}$. As such $\mathcal{D} = \{\mathcal{X}, \mathcal{P}(X)\}$."*

Definition 3.2. *"Task: given domain $\mathcal{D}$, a task $\mathcal{T}$ is defined by two parts: (i) a label space $\mathcal{L}$ and (ii) a predictive function $f(.)$. The predictive function (or decision function) is learned from the feature vector and label space pairs $\{x_{i,\ l_i}\}$, with $x_i \in X$ and $l_i \in \mathcal{L}$. In other words, a task is defined by $\mathcal{T} = \{\mathcal{L},\ f(.)\}$."*

Definition 3.3. *"Transfer Learning: Given a source domain $\mathcal{D}_S$ with a corresponding source task $\mathcal{T}_S$ and a target domain $\mathcal{D}_T$ with a corresponding target task $\mathcal{T}_T$, the goal of TL is to learn the target predictive function $f_T(.)$ by leveraging the knowledge gained from $\mathcal{D}_S$ and $\mathcal{T}_S$ where $\mathcal{D}_S \neq \mathcal{D}_T$ or $\mathcal{T}_S \neq \mathcal{T}_T$."*

3.2 Problem Statement

We consider a wireless communication scenario where a sender such as a wireless device transmits data to the receiver at time slot k with a transmit power $P_s(k)$. while there are L

Notation	Description
$P_s(k)$	Transmit power of the sender
$P_J^l(k)$	Jamming power of the lth jammer
R	number of transmit power levels
I	number of jamming power levels
L	number of jammers
N	number of channels
$x^{(k)}$	channel chosen by the sender
$y_l^{(k)}$	channel choosen by the lth jammer
h_s	channel power gain of the sender
h_l	channel power gain of the lth jammer

Jammers who can launch jamming attacks by injecting meaningless interference signals denoted as $P_j^l(k) \in \left\{P_j^1(k), P_j^2(k), ..., P_j^L(k)\right\}$.

Each $P_j^l(k)$ has I different power levels.

In our model, each jammer is assumed to attack only one channel, At time slot k,the sender can choose one of N selectable frequency channels for transmitting denoted by $x^{(k)}$. Meanwhile, L jammers may select their frequency channels (denoted as $\left\{y_1^{(k)},\ y_2^{(k)}, \ldots, y_L^{(k)}\right\}$) for jamming.

h_s and h_l denote the channel power gains from the sender and the lth jammer to the receiver respectively.

In order to resist jamming attack, the sender needs to choose an unblocked channel $x^{(k)}$ and an appropriate transmit power. In general, variable transmit power model is shown to be superior to be the constant transmit power one under the constraint of the same average power. After the receiver gets the signal at time slot k, the $SINR(k)$ is calculated by (1) and returned to the sender through the feedback channel.

$$SINR(k) = \frac{P_s(k)h_s}{\beta + \sum_{l=1}^{L} P_J^l(k) h_l f\left(x^{(k)} = y_l^{(k)}\right)}, \tag{3.1}$$

where β is the receiver noise power, $P_J^l(k)$ denotes the jamming power chosen by the lth jammer and $f(\xi)$ is an indicator function that equals 1 if ξ is true and 0 otherwise. If the jammer is completely blocked by the jammers at time slot k, the sender needs to re-transmit the signal This will consume extra energy denoted as C_m.

It is reasonable that the channel is considered to be blocked if the jamming power takes the maximum value $P_J^L(k)$. In order to make a tradeoff between the energy saving and the communication performance, we define the utility $u_s^{(k)}$ of the sender by:

$$u_s^{(k)} = SINR(k) - C_m f\left(P_J^I(k) = P_j^L(k)\right) f\left(x^{(k)} = y_l^{(k)}\right) - \frac{C_s P_s(k)}{P_s^{max}} \tag{3.2}$$

where C_S and $P_S^{\max}$ denote the unit transmission cost and the maximum transmit power respectively.

Algorithm 3.1 Algorithm example

Input: Gallery with initial templates $\mathcal{G} = \{\mathbf{r}_1, ..., \mathbf{r}_J\}$, unlabeled adaptation set $\mathcal{D} = \{\mathbf{d}_1, ..., \mathbf{d}_L\}$
Output: Updated Gallery $\mathcal{G}' = \{\mathbf{r}_1, ..., \mathbf{r}_{J'}\}$, $J' \geq J$

Estimate updating threshold $\gamma^u \geq \gamma^d$ from $\mathcal{G}$;
$\mathcal{G} \leftarrow \mathcal{G}'$; `/* update gallery */`
for *all samples* $d_l \in \mathcal{D}$ *(*$l = 1, ..., L$*)* **do**
    for *all references* $r_j \in \mathcal{G}$ *(*$j = 1, ..., J$*)* **do**
        $s_j(\mathbf{d}_l) \leftarrow similarity\_measure(\mathbf{d}_l, \mathbf{r}_j)$;
    end for
end for
$S(\mathbf{d}_l) \leftarrow \max_{j \in [1,J]} \{s_j(\mathbf{d}_l)\}$;
if $S(\boldsymbol{d}_l) \geq \gamma_d$ **then**
    Output positive prediction;
    if $S(\boldsymbol{d}_l) \geq \gamma^u$ **then**
        $\mathcal{G}' \leftarrow \mathcal{G}' \cup \mathbf{d}_l$;
    end if
end if

CHAPTER 4

PRELIMINARY RESULTS

CONCLUSION AND RECOMMENDATIONS

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APPENDIX I

APPENDIX EXAMPLE

1. First section of the appendix

1.1 Figures in annexes

Figure-A I-1 Figure in an appendix

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1.1.1 Tables in annexes

Table-A I-1 Table in an appendix

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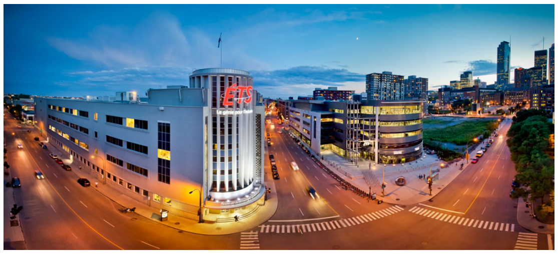

(a) first figure

(b) second figure

(c) third figure

(d) fourth figure

Figure-A I-2   Subfig example

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