ISSN: 2581-3404 (Online)
International Journal of Innovative Research in Technology and Management, Vol-4, Issue-6, 2020.

Anomaly Detection in Wireless Communication: Survey and Discussions

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ABSTRACT

Wireless technology enables many services and applications and will play a key role for enabling the smart and autonomous systems of the future. Wireless networks also provide mission critical infrastructure for public safety, national security, and military communications. This popularity of wireless technology can be attributed to its ease of access and high availability; however, these very same features contribute too many of its vulnerabilities Attacks such as jamming, spoofing, and eavesdropping. With the rapid development of the information age, the hidden dangers of radio order and spectrum security are becoming more and more serious. In this paper we present the survey for the anomaly based detection in wireless networks.

Keywords:- Cognitive Radio, Wireless Communication, Unsupervised techniques, Supervised Techniques.

INRODUCTION

Radio spectrum is one of our most precious and widely used natural resources. With the advent of new wireless communication technologies, spectrum usage has become very complex resulting in airwave congestion and other interference issues [4]. Diverse spectrum regulations across countries have also contributed to this chaotic spectrum usage when non-standardized wireless devices cross country borders.

In addition, easily available illegal wireless jammers or low-cost Software Defined Radio (SDR) devices which are capable of generating custom wireless signals are making the problem worse. Unintentional and intentional jamming of localization services such as Global Navigation Satellite System (GNSS), which is used for a wide range of applications such as automated vehicle navigation, airplane landing procedures and maritime vessel tracking, is increasing with the availability of easy jamming devices. Furthermore, illegal repeaters, which are used to boost mobile coverage, can adversely affect the cell planning of mobile operators resulting in poor coverage and dropouts. On the other hand, densified small cells are becoming fundamental for the new high throughput and low latency networks. Automated analysis and detection of anomalous behaviors in the spectrum is becoming crucial to promote the growth of new generation wireless systems. The wide range of wireless spectrum anomalies makes it infeasible to collect and label all types of anomalies and formulate anomaly detection as a supervised learning problem.

The proliferation of wireless devices due to the emerging technologies has elevated spectrum scarcity problem. There has been a risk that spectrum might be congested and more users cannot be facilitated. However, measurements have shown that a large portion of the spectrum experiences low utilization. To cope with such a problem, Cognitive Radio (CR) is envisioned as a potential candidate that enhances spectrum efficiency and abstains network from spectrum underutilization issue. CR has been defined to exhibit three integral attributes which are observations, reconfiguration, and cognition. In the observation process, CR gathers information about the radio environment. In the reconfiguration step, radio parameters are adjusted or changed. Whereas, cognition is related to understanding the radio environment, taking decisions on gathered information and learning the implications of such decisions on radio performance. Learning and reasoning are fundamental aspects of cognition that may be achieved if the CR network subsumes a certain degree of Self-Awareness (SA) which can be developed by implementing Artificial Intelligence (AI) techniques [9].

As carriers of communication information, spectrum signals carry many important information, it's of great significance to mine valuable hidden information or intelligence from spectrum signals, especially in military communication, anti-terrorism, communication security and other related fields. However, the analysis of massive spectrum monitoring data is mainly presented at the level of the spectrum situation display. For further research and analysis, such as communication relationship mining, the investigation and identification of information containing potential threats in the massive signal transmission are not deep enough. There are almost no researches on how to dig deep into the hidden information of massive spectrum signals and the behavioral relationship between communication targets [14].

Anomaly detection is an active area of research encompassing a significant number of techniques developed in diverse fields such as statistics, process control, signal processing and machine learning. The goal is to be able to identify data deviating from or not being in agreement with what is considered normal, expected or likely in terms of the data probability distribution, or the shape and amplitude of a signal in time series. Another commonly used term for anomaly is outlier and both are sometimes used interchangeably. Also, the term novelty detection to anomaly detection when the goal is to identify data differing in some degree from the data previously observed, even though the underlying detection methods are often the same. The distinction between novel data and anomalies is that the former is usually considered as normal data after being detected [7].

The motivation of this survey is to review the state-of-the-art in data-driven anomaly detection methods and their application to the aviation domain: special attention is given to the techniques applicable to large-scale high-dimensional time-series data, i.e., flight trajectories and sensor-generated data for prognostics and health management (PHM) purposes, widely applied in the predictive and condition-based aircraft fleet maintenance. Recent advances in neural networks and deep learning as well as on anomaly detection using temporal logic based learning justify an up-to-date review of the taxonomy of classical anomaly detection techniques covered in the review sections.

II RELATED WORK

[1] Here author present, spectrum anomaly detector with interpretable features (SAIFE), an adversarial autoencoder (AAE)-based anomaly detector for wireless spectrum anomaly detection using power spectral density (PSD) data. This model achieves an average anomaly detection accuracy above 80% at a constant false alarm rate of 1% along with anomaly localization in an unsupervised setting. In addition, we investigate the model's capabilities to learn interpretable features, such as signal bandwidth, class, and center frequency in a semi-supervised fashion. Along with anomaly detection the model exhibits promising results for lossy PSD data compression up to 120× and semi-supervised signal classification accuracy close to 100% on three datasets just using 20% labeled samples. Finally, the model is tested on data from one of the distributed electrosense sensors over a long term

of 500 h showing its anomaly detection capabilities.

[2] Author designed a spectrum monitoring system for wireless environment cognizance that incrementally learns about the wireless environment in which it is deployed. They have presented not just new classification methods but a full system design that is adaptive and robust against changes in deployed environment and/or computing resources. They addressed several practical challenges including supporting flexible addition/removal of new signal classes without retraining existing models, detecting shifted signals, and clustering without knowing the number of the unknown signals present a priori. A thorough evaluation of our approach demonstrated its adaptability and high accuracy with signal data from several over-the-air scenarios.

[3] In this context, Cognitive Radio (CR) is capable of managing the mmWave spectrum sharing efficiently. However, Cognitive mmWave Radios are vulnerable to malicious users due to the complex dynamic radio environment and the shared access medium. This indicates the necessity to implement techniques able to detect precisely any anomalous behaviour in the spectrum to build secure and efficient radios. In this work, we propose a comparison framework between deep generative models: Conditional Generative Adversarial Network (C-GAN), Auxiliary Classifier Generative Adversarial Network (AC-GAN), and Variational Auto Encoder (VAE) used to detect anomalies inside the dynamic radio spectrum. For the sake of the evaluation, a real mmWave dataset is used, and results show that all of the models achieve high probability in detecting spectrum anomalies. Especially, AC-GAN that outperforms C-GAN and VAE in terms of accuracy and probability of detection.

[4] Manual and fine-grained spectrum analysis is becoming impossible because of the large number of measurement locations and complexity of the spectrum use landscape. Detecting unexpected behaviors in the wireless spectrum from the collected data is a crucial part of this automated monitoring, and the control of detected anomalies is a key functionality to enable interaction between the automated system and the end user. In this paper they look into the wireless spectrum anomaly detection problem for crowd sourced sensors. They first analyze in detail the nature of these anomalies and design effective algorithms to bring the higher dimensional input data to a common feature space across sensors. Anomalies can then be detected as outliers in this feature space. In addition, we investigate the importance of user feedback in the anomaly detection process to improve the performance of unsupervised anomaly detection. Furthermore, schemes for generalizing user feedback across sensors are also developed to close the anomaly detection loop.

[5] Wireless spectrum anomalies can take a wide range of forms from the presence of an unwanted signal in a licensed band to the absence of an expected signal, which makes manual labeling of anomalies difficult and suboptimal. They present, Spectrum Anomaly Detector with Interpretable Features (SAIFE), an Adversarial Auto-encoder (AAE) based anomaly detector for wireless spectrum anomaly detection using Power Spectral Density (PSD) data which achieves good anomaly detection and localization in an unsupervised setting. In addition, we investigate the model's capabilities to learn interpretable features such as signal bandwidth, class and center frequency in a semi-supervised fashion. Along with anomaly detection the model exhibits promising results for lossy PSD data compression up to 120X and semi-supervised signal classification accuracy close to 100% on three datasets just using 20% labeled samples. Finally the model is tested on data from one of the distributed Electrosense sensors over a long term of 500 hours showing its anomaly detection capabilities.

[6] This paper presents a novel Spectral and Time Auto-encoder Learning for Anomaly Detection (STALAD) framework. The design consists of four innovations: (1) identification of cycle series and spectral transformation (CSST) from ESD, (2)

unsupervised learning from CSST of ESD by exploiting Stacked Auto-Encoders, (3) hypothesis test for AD based on the difference between the learned normal data and the tested sample data, (4) dynamic procedure control enabling periodic and parallel learning and testing. Applications to ESD of an HDP-CVD tool demonstrate that STALAD learns normality without engineers' prior knowledge, is tolerant to some abnormal data in training input, performs correct AD, and is efficient and adaptive for fab applications. Complementary to the current practice of using control wafer monitoring for AD, STALAD may facilitate early detection of equipment anomaly and assessment of impacts to process quality.

[7] As intelligent sensing and sensor network systems have made progress and low-cost online structural health monitoring has become possible and widely implemented, large quantities of highly heterogeneous data can be acquired during the monitoring. This has resulted in exceeding the capacity of traditional data analytics techniques, especially in monitoring large-scale or critical civil structures. In particular, data storage has become a big challenge, hence, resulting in the emergence of data compression and reconstruction as a new area in structural health monitoring (SHM) of large infrastructure systems. SHM data generally include anomalies that can disturb structural analysis and assessment. The fundamental reasons for the abnormality of data are extremely complex. Therefore, reconstruction of the abnormal data is generally difficult and poses serious challenges to achieve high-accuracy after data has been compressed. Considering these significant challenges, in this paper, a novel deep learning enabled data compression and reconstruction framework is proposed that can be divided into two phases: (a) a one-dimensional Convolutional Neural Network (CNN) that extracts features directly from the input signals is designed to detect abnormal data with validated high accuracy; (b) a new SHM data compression and reconstruction method based on Auto-encoder structure is further developed, which can recover the data with high-accuracy under such a low compression ratio.

[8] In this review the recent advances in the area of neural networks, deep learning and temporal-logic based learning. In particular, we cover unsupervised techniques applicable to time series data because of their relevance to the aviation domain, where the lack of labeled data is the most usual case, and the nature of flight trajectories and sensor data is sequential, or temporal. The advantages and disadvantages of each method are presented in terms of computational efficiency and detection efficacy. The second part of the survey explores the application of anomaly detection techniques to aviation and their contributions to the improvement of the safety and performance of flight operations and aviation systems.

[9] In this work, author propose and implement Artificial Intelligence (AI)-based Abnormality Detection techniques at the physical (PHY)-layer in CR enabled by learning Generative Models. Specifically, two real-world practical applications related to different data dimensionality and sampling rates are presented. The first application implements the Conditional Generative Adversarial Network (CGAN) investigated on generalized state vectors extracted from spectrum representation samples to study the dynamic behavior of the wideband signal. While the second application is based on learning a Dynamic Bayesian Network (DBN) model from a generalized state vector which contains sub-bands information extracted from the radio spectrum. Results show that both of the proposed methods are capable of detecting abnormal signals in the spectrum and pave the road towards Self-Aware radio.

[11] The aim of this survey is two-fold, firstly they present a structured and comprehensive overview of research methods in deep learning-based anomaly detection. Furthermore, they review the adoption of these methods for anomaly across various application domains and assess their effectiveness. They have grouped state-of-the-art deep anomaly detection research techniques into different categories based on the underlying

assumptions and approach adopted. Within each category, they outline the basic anomaly detection technique, along with its variants and present key assumptions, to differentiate between normal and anomalous behavior. Besides, for each category, they also present the advantages and limitations and discuss the computational complexity of the techniques in real application domains. Finally, we outline open issues in research and challenges faced while adopting deep anomaly detection techniques for real-world problems.

[12] This paper presents a framework for anomaly detection in the presence of a sophisticated adversary and analyses its effectiveness numerically. The framework combines nonlinear data transformations in selective directions using a novel ranking index that we introduce together with unsupervised anomaly detection using OCSVMs and game theory. Their approach can be utilized to make a learning system secure by (i) reducing the impact of possible adversarial perturbations by contracting and moving the normal data cloud away from the origin in the projected space, and (ii) making it challenging for an adversary to guess the underlying details of the learner by making its search space unbounded by adding a layer of randomness.

[13] This paper proposes an anomaly detection methodology for wireless systems that is based on monitoring and analyzing radio frequency (RF) spectrum activities. Their detection technique leverages an existing solution for the video prediction problem, and uses it on image sequences generated from monitoring the wireless spectrum. The deep predictive coding network is trained with images corresponding to the normal behavior of the system, and whenever there is an anomaly, its detection is triggered by the deviation between the actual and predicted behavior. For our analysis, we use the images generated from the time-frequency spectrograms and spectral correlation functions of the received RF signal. They test their technique on a dataset which contains anomalies such as jamming, chirping of transmitters, spectrum hijacking, and node failure, and evaluate its performance using standard classifier metrics: detection ratio, and false alarm rate. Simulation results demonstrate that the proposed methodology effectively detects many unforeseen anomalous events in real time.

[14] The research work in this paper realizes the analysis and mining of spectrum monitoring data, and clusters the spectrum signals with communication relationship. It provides a new perspective and new method for further targeted cracking and analysis, obtaining hidden information of spectrum data, important information, and in-depth analysis of spectrum data. Combined with positioning technology and related information, other communication nodes can be tracked, and the communication range of nodes can be determined, which lays a foundation for further mining and speculating communication network structure and related behavior analysis from spectrum data.

III PROBLEM IDENTIFICATION

A majority of the algorithms in literature formulate wireless spectrum anomaly detection as an unsupervised learning problem where the models try to learn the normal spectrum data distributions and detect the uncommon patterns as anomalous. These models make the basic assumption that non-frequent behaviour is anomalous which is not always true. For example, transmissions in ISM bands exist that are very sparse but are not anomalies. Similarly, pirate transmitters or transmission duty cycle limit violations in a unlicensed band are anomalous even when they are very frequent. In addition, anomalies are often rare events, so labeled datasets for model training and validation are either unavailable or severely imbalanced in favor of normal instances. As a consequence, semi-supervised or unsupervised learning is more frequently used than supervised learning. Therefore, the goal of the present survey is to complete the previous contributions by proposing a review of anomaly detection techniques applied to wireless sensor spectrum and their techniques, including the recent advances on neural networks and deep learning as well as other algorithm.

IV CONCLUSION

In this work are currently analyzing the implications of different wireless network anomaly detection techniques, consider hyper-parameter searches, evaluate longer runs, larger datasets and additional types of anomalies and combinations of anomalies. More robustness in the detection can be achieved by machine learning techniques that process multiple transforms of the raw data or preprocessed data.

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