2021

Machine Learning (ML) for Signal Detection

Kragh, Frank E.; Miller, Donna L.

Monterey, California: Naval Postgraduate School

http://hdl.handle.net/10945/69842

NPS NRP Executive Summary

Title: Machine Learning (ML) for Signal Detection

Period of Performance: 09/23/2021 – 12/25/2021

Report Date: 12/25/2021 | Project Number: NPS-21-N260-A

Naval Postgraduate School, Graduate School of Engineering and Applied Sciences (GSEAS)

NAVAL RESEARCH PROGRAM

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

MACHINE LEARNING (ML) FOR SIGNAL DETECTION

EXECUTIVE SUMMARY

Principal Investigator (PI): Dr. Frank Kragh, Graduate School of Engineering & Applied Science (GSEAS), Electrical and Computer Engineering (ECE)

Additional Researcher(s): Ms. Donna Miller, Graduate School of Engineering & Applied Science (GSEAS), Electrical and Computer Engineering (ECE)

Student Participation: Lieutenant Commander Bart Ellison, US Navy, Electrical and Computer Engineering (ECE)

Prepared for:

Topic Sponsor Lead Organization:	N2/N6 - Information Warfare
Topic Sponsor Organization:	Naval Special Warfare Command – United States Navy
Topic Sponsor Name(s):	CPO, Nicholas Pealstrom, USN
Topic Sponsor Contact Information:	nicholas.pealstrom@socom.mil, 619-537-3952

This research is supported by funding from the
Naval Postgraduate School, Naval Research Program (PE 0605853N/2098).
Approved for public release. Distribution is unlimited.

Project Summary
Often, United States reconnaissance systems collect a very large amount of data that must be sorted into the data useful to the mission (signals of interest [SOI]) and the rest of the data. Often, the SOIs represent a small portion of the large data set. It is important to effective warfighting to find these SOIs quickly and with high probability of success. Usually, not enough manpower or manhours are available to do this task manually. Automatic techniques are required. In this research, we use a type of neural network to enable a machine to learn how to discriminate between SOIs and other signals. This machine learning method successfully performed the discrimination using our synthetically generated radio signal data set. We conclude that this method is valuable to the sorting task, and therefore to warfighting, and should be examined further to determine if it is as successful on fully realistic radio signals.

Keywords: *Signals Intelligence, SIGINT, Communications Intelligence, COMINT, neural networks, machine learning, ML, generative adversarial networks, radio communications*

Background
The radio signals of an adversary, often called SOIs, provide an opportunity for gathering information known as Communications Intelligence (COMINT). American forces use various methods and systems to collect radio signals, resulting in large collection sets of digitally recorded radio signals, often including all radio signals in a wide frequency band transmitted over a large geographic area. It is important to quickly and efficiently identify adversarial SOIs from the often much larger collection of signals. The raw communications data collected for analysis is typically a huge amount of data, generally too large for human analysts to search through the communications signals to find the adversarial SOIs for further study. Furthermore, collected signals are often stored as raw down-converted, but not demodulated, in-phase and quadrature discrete-time samples, sometimes called pre-demodulated. The growth of wireless technologies over the past several decades has greatly expanded the density of signals present within the radio frequency spectrum, compounding this sorting problem. This has intensified the need for automatic computer-based techniques for quickly sorting through large collections of pre-demodulated communications signals. Automatic search methods can help put the SOIs that the warfighters need in their hands more quickly, enhancing their effectiveness.

Generative adversarial networks (GANs) are a specific configuration of two neural networks, called the generator and the discriminator, first discussed in the literature in 2014 (Goodfellow et al., 2014). Most of the use of GANs has been associated with images, with very few applications involving radio signals. Our research group continues to expand the applications of GANs to radio signals. In other work, we have shown that GANs can be used with great effect in analyzing channel-induced distortions on a signal (Germain & Kragh, 2020; 2021a; 2021b). Herein, we use GANs to analyze the message information in radio signals, which we believe is a first. This shows promise for being able to ascertain the message information in radio signals without traditional demodulation. While that remains a yet-to-be-achieved goal and distinct from our goals in this research, that would allow the determination of the message without knowing the modulation scheme, which would have great application to Signals Intelligence, adaptive radio technologies, and other communications engineering endeavors.

The data used in this research were four sets of computer-generated, quadrature phase shift keying signals. Two sets were not SOIs, some labeled and some unlabeled. The other two sets were SOIs, some labeled and some unlabeled. The GAN was trained data using some data from each set with the GAN aware of the labels, when present. The GAN learns the statistical distinctions between with SOIs and the others, and the discriminator calculates a probability that each signal is an SOI. When the GAN learns sufficiently well that the discriminator calculates probabilities near one for each SOI and near zero for each non-SOI, for even those unlabeled, the GAN is sufficiently trained. Thenceforth, the discriminator can be used to classify unknown signals as likely or not likely to be an SOI.

Findings and Conclusions

The semi-supervised generative adversarial network (SGAN) was able to classify signals within a dataset consisting of a single modulation type using only pre-demodulated data. The SGAN performed exceptionally well at classifying these signals. The research showed minimal difference in the performance of the SGAN when using 25%, 50%, or 75% of the dataset for training, which is good. Other forms of neural networks require more training. The most significant factor in SGAN classifier performance was the length of the snippets. Using the snippets of length, 256 discrete-time samples outperformed training using either the snippets of length 128 or 512 discrete-time samples. Regardless of the training dataset size and snippet length, the SGANs performed almost identically at each signal-power-to-noise-power ratio (SNR). All of the SGAN classifiers were at or above 99% accurate at SNRs of 0 decibel and greater. This performance was exceptionally high and we view it as a success. A more varied dataset, incorporating variations expected at a typical receiver, including multipath channel distortions and initial unknown phase, could affect the accuracy. Training time for the single modulation SGANs varied greatly as the dataset size and length of the snippets increased. SGAN 3, the most successful configuration, using the 256 discrete-time sample length, required about 4.5 minutes to train using 25% of the dataset. Overall, the SGAN was able to classify signals within a single modulation scheme as SOI or non-SOI with great accuracy with modest training time.

Our research shows promise, and we believe we are the first to apply GANs to signal sorting within a single modulation scheme. We recommend more work be done to ensure the original goals are met. Specifically, it is important to confirm these results are repeatable with a dataset that includes typical multipath channel distortions and other realistic effects which are expected in typical signal collections. Our new understanding of these automated SGAN-based processes will allow accurate automatic identification of SOIs in a timely manner, identifying more SOIs and saving time as compared to manual identification of SOIs, achieving the original goals.

Recommendations for Further Research

This research has shown that the semi-supervised generative adversarial network (SGAN) has the ability to identify signals of interest (SOIs) within a large set of signals. The SGAN architecture showed great promise as a way to train a neural network to identify an SOI.

One potential area of future research would be to explore a different architecture such as an Auxiliary Classifier-GAN or an improvement on the existing SGAN by adding more neural layers, perhaps yielding even faster training. A second area for future research would be to experiment with an early stop-training feature when the accuracy has stopped improving, thereby decreasing training times. Third, the amount of training data required could be explored. At our smallest size, we used 25% of the dataset to train the SGAN. The performance of the classifiers indicates that the amount of the dataset used to train could be even lower, likely resulting in faster training. Fourth, the signal dataset could be enhanced to make the classification more realistic, and perhaps, challenging. The dataset used only white Gaussian noise as an impairment. More impairments such as center frequency offset, random initial phase, sample rate jitter, and multipath fading could be added to the dataset. Over-the-air signals could be collected to create a more realistic dataset. Another dataset using a more complicated modulation scheme could also be created to test the limits of the SGAN's ability to classify signals. While all of these four recommendations would explore important issues, the last one seems to us the most important to improve the likelihood that a deployable solution could be developed and used successfully.

References

Germain, K. S., & Kragh, F. (2020, December). Physical-layer authentication using channel state information and machine learning. *2020 14th International Conference on Signal Processing and Communication Systems (ICSPCS)*, 1-8. 10.1109/ICSPCS50536.2020.9310070

Germain, K. S., & Kragh, F. (2021a). Channel prediction and transmitter authentication with adversarially-trained recurrent neural networks. *IEEE Open Journal of the Communications Society*, *2*, 964-974. 10.1109/OJCOMS.2021.3072569

Germain, K. S., & Kragh, F. (2021b, April). Mobile physical-layer authentication using channel state information and conditional recurrent neural networks. *2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring)*, 1-6. 10.1109/VTC2021-Spring51267.2021.9448652

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Aaron Courville, & Bengio, Y. (2014). Generative adversarial nets. *Advances in Neural Information Processing Systems*, *27*.

Acronyms

COMINT	Communications Intelligence
GAN	generative adversarial network
ML	machine learning
SGAN	semi-supervised generative adversarial network
SIGINT	Signals Intelligence
SNR	signal-power-to-noise-power ratio
SOI	signal of interest