International Conference KNOWLEDGE-BASED ORGANIZATION
Vol. XXIX No 3 2023

MACHINE-LEARNING-BASED CLASSIFICATION OF FREQUENCY HOPPING IN RADIO NETWORKS FOR COMMUNICATION RECONNAISSANCE

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Abstract: *This article presents a customized approach for training a supervised learning neural network with the adaptive moment estimation algorithm, to classify the number of frequency hopping networks in an operational area. The algorithm was constructed based on data experimentally collected from a real-time spectrum analyzer for military very high frequency hopping networks. The impact of some training parameters on classification efficiency is briefly discussed while the obtained accuracy was above 97% for both test and validation data in all training variations. With this promising result, the proposed algorithm has the potential to be utilized in developing operational systems capable of real-time signal reconnaissance for military frequency hopping radio networks.*

Keywords: machine learning, frequency hopping, communication reconnaissance

1. Introduction

Frequency hopping (FH) is a technique used in communication systems that involves the rapid switching of transmission frequencies. Due to its ability to resist interference and jamming, FH represents a valuable tool for ensuring effective communication in a variety of challenging environments including military operations [1], [2].

Communication reconnaissance is a critical component in military operations that involves the gathering of information on the adversary's communication systems and infrastructure, including radio frequencies, network protocols, and encryption methods. The information collected through communication reconnaissance is used to gain a tactical advantage on the battlefield and to protect troops and equipment from potential threats.

Due to the rapid switch of carrier frequency, communication reconnaissance becomes a challenging task in complex electromagnetic (EM) environments where multiple FH networks are deployed.

The knowledge of the number of FH networks deployed in an operational area is of interest for communication reconnaissance specialists and represents the starting point for developing FH tracking and sorting algorithms. Advanced, spectrum measurement systems with real-time capabilities are needed to monitor the EM spectrum when FH networks are enabled. The analysis of the captured spectrum must also be performed in real-time. Moreover, due to fast changing conditions, the task requires automatization. The rapidly growing field of machine learning (ML) algorithms opens new perspectives for signal and spectrum classification. Current applications of ML for signal classification include speech recognition [3], image classification [4],

DOI: 10.2478/kbo-2023-0079

and anomaly detection in sensor data [5].

Several papers report the use of ML algorithms to determine the frequency-hopping patterns of cognitive radio networks [6], [10]. The published approaches focus on the determination of the next hopping frequency for adaptive jamming purposes. As reported in [10], to achieve good accuracy, the number of training samples must be increased affecting the total simulation time. In a real operational environment this affects the real-time capability of the system and makes such jammers difficult to implement. Therefore, real-time frequency hopping and tracking algorithms must be used for implementation of adaptive jamming systems. These types of algorithms are based on fast measurement systems and analyze the signal time of arrival and power levels. Knowledge of the number of FH networks to track and sort is a prerequisite for developing such systems.

This paper completes the already published results with a particularized approach driven by experimentally measured data and customized for very high frequency (VHF) FH networks used in military domain. To obtain the spectrum measurement data, we exploit the features of a high-end real-time spectrum analyzer (SA). We have used a supervised learning neural network trained with the adaptive moment estimation (ADAM) algorithm to classify the number of FH networks in the retrieved spectrogram images.

2. Materials and Methods

This section presents the setup used for data collection and pre-processing and the deep learning network design.

2.1. Data Collection and Pre-processing

The training, validation and test data were collected for up to 3 FH networks enabled by Harris 7800 V HH [11] radio transceivers. Each radio network was programmed with a different hop set ID and 4 operational scenarios were constructed: 1) 1 FH network present, 2) 2 FH network present, 3) 3 FH networks present and 4) no FH networks present.

The measurements were collected over the air by means of a system composed of a VHF antenna, a real-time SA and a computer used for measurement automatization. A python script was used for remote-control of the SA and spectrogram retrieval. Spectrograms were saved from the SA to a local hard drive as RGB images of 250 kB each (.jpg extension). The experimental setup used for data acquisition is presented in Figure 1.

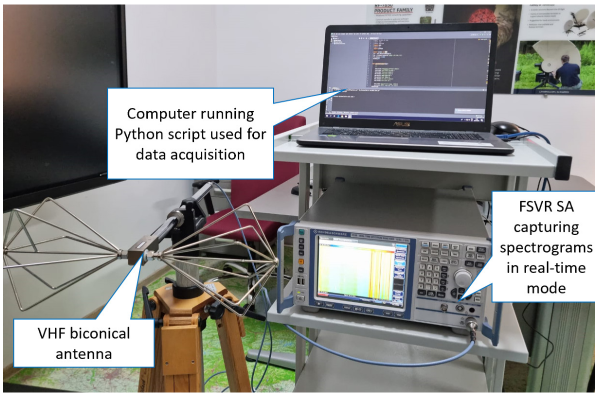
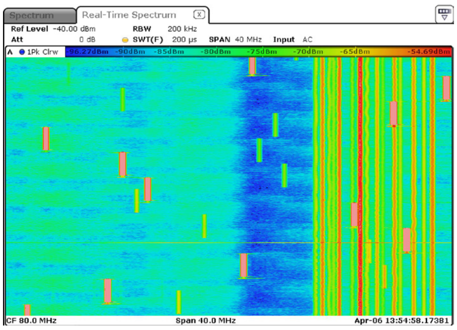


Figure 1: Setup for data acquisition

The R&S FSVR spectrum analyzer (SA) with an attached Schwarzbeck biconical antenna was used to measure the spectrogram in real-time mode. In real-time operation, the instrument seamlessly measures and displays the spectrum in the time domain with a span of up to 40 MHz, capturing every event for analysis, regardless of its short duration.

The main settings of the SA used were central frequency=80 MHz, frequency span=40 MHz (maximum available in real-time mode) and frame duration (SWT)=0,2 ms. The SA resolution bandwidth (RBW) was 200 kHz, to maintain real-time operation in a span of 40 MHz.

A spectrogram corresponding to scenario 2 is presented in Figure 2. The two hopping sequences are visible in the spectrogram with red and green segments corresponding to different signal to noise (SNR) conditions. In the upper part of the spectrum (>85 MHz) one can observe the presence of continuous emission corresponding to local FM radio stations. Other emissions are also present in the monitored spectrum, increasing the noise floor in the first half of the spectrogram. For each experimental scenario data collection was performed for SNR values ranging between 5 and 45 dB.



Ref Level -40.00 dBm
Att 0 dB
RBW 200 kHz
SWT(F) 200 µs
SPAN 40 MHz
Input AC
CF 80.0 MHz
Span 40.0 MHz
Apr-06 13:54:58.17381

Figure 2: Spectrogram of 2 FH networks

The 3 channel RGB images were cropped to a 955x1584 size corresponding to the spectrogram part solely and imported in a MATLAB datastore. Table I presents the total number of acquired spectrogram images for each scenario.

Table I Total number of spectrogram images

Label	Count
1 FH network	993
2 FH networks	590
3 FH networks	546
4 FH networks	1000

Figure 3: Histogram representing the number of training images

The images in the datastore were split in 85% training data, 7.5% validation data and 7.5% test data. A histogram presenting the number of training images is presented in Figure 3.

2.2. Deep Learning Network Design

There are several types of ML algorithms that can be used for signal classification, including supervised learning, unsupervised learning, and semi-supervised learning. Supervised learning algorithms require labelled data for training, while unsupervised learning algorithms can learn patterns in data without any labels. Semi-supervised learning algorithms use a combination of labelled and unlabeled data.

In this paper we have used MATAB to design and train a supervised neural network. The neural network is composed of several convolution layers, batch normalization layers, rectified linear unit layers (RELU) and maximum pooling layers an image input layer, a fully connected layer, a SoftMax layer and a classification output layer. The general architecture of the network is presented in Figure 4.

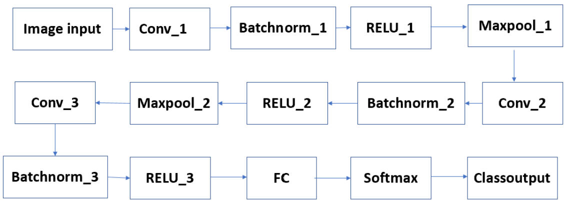


Figure 4: Network architecture

The ADAM optimizer was chosen to train the network. The ADAM solver is a popular optimization algorithm used in ML, specifically for training deep neural networks. It is a variant of stochastic gradient descent (SGD) that computes adaptive learning rates for each parameter, and it is designed to combine the advantages of both AdaGrad and RMSProp optimizers.

ADAM works by maintaining a running estimate of the first and second moments of the gradients, which are used to update the parameters. The first moment is the average of the gradients, while the second moment is the average of the squares of the gradients. These estimates are used to compute the adaptive learning rates, which are then used to update the parameters.

The ADAM algorithm also includes bias correction to improve the accuracy of the estimates, and it has been shown to converge faster and more reliably than traditional SGD or other optimization algorithms, especially in the presence of noisy gradients or sparse data.

Table II Training options

Training option	Value
Solver	ADAM
Initial Learn Rate	0.01
Learn Rate Schedule	piecewise
Learn Rate Drop Factor	0.2
Learn Rate Drop Period	1
Max Epochs	2
Shuffle	Every epoch
Mini Batch Size	16
Validation Frequency	5
Validation patience	3
Output Network	Best validation loss

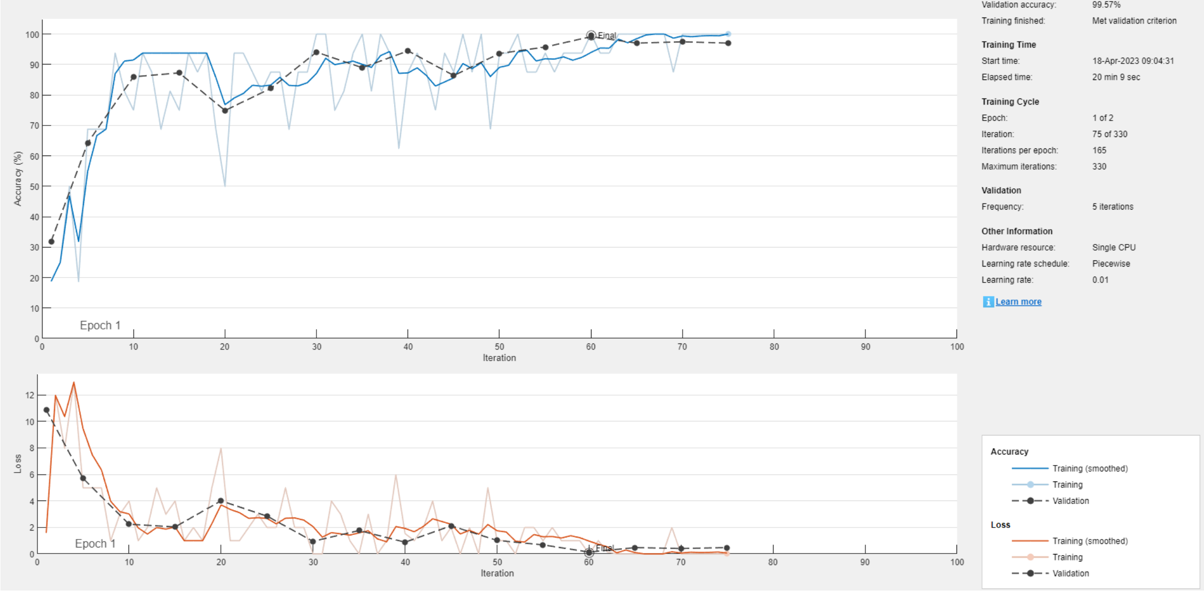
The initial training options are presented in Table II. The other available training options were set to the MATLAB default values.

The minibatch size and validation frequency were varied to optimize the classification accuracy.

The network was trained on a 64-bit Windows 10 machine with the following hardware resources: i7-8700 CPU 3.2 GHz, 16 GB installed RAM and 4GB Radeon Pro WX GPU.

3. Results and Discussion

In Figure 5 we present the training progress obtained for the first version of the designed network. From analyzing Figure 5 we observe that the network stopped training to prevent overfitting in the first epoch when the validation criteria were met. The achieved validation accuracy was of 99,5%. The confusion matrix was constructed based on a sample of 120 spectrograms (30 for each classification output) from the test dataset. The corresponding confusion matrix is presented in Figure 6.


Validation accuracy: 99.57%
Training finished: Met validation criterion

Training Time
Start time: 18-Apr-2023 09:04:31
Elapsed time: 20 min 9 sec

Training Cycle
Epoch: 1 of 2
Iteration: 75 of 330
Iterations per epoch: 165
Maximum iterations: 330

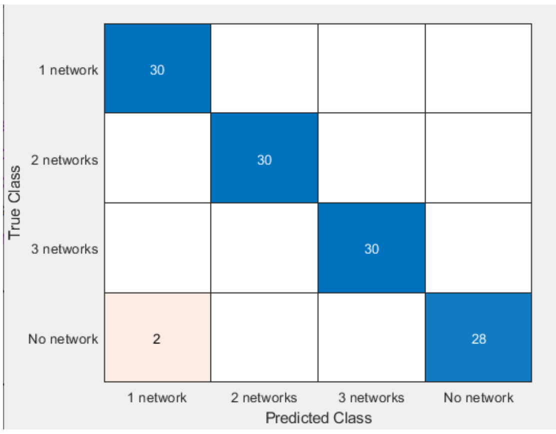
Validation
Frequency: 5 iterations

Other Information
Hardware resource: Single CPU
Learning rate schedule: Piecewise
Learning rate: 0.01

Figure 5: Network training progress- V1

In the confusion matrix we can observe that the network correctly classifies most of the spectrograms achieving a test accuracy of 98,33%. We can observe that the network is confusing between no FH network and 1 FH network and in the following paragraphs we will present some attempts to improve the network classification ability.

In the next step, we considered that the network confusion is due to the unbalanced number of acquired spectrogram images (see Figure 3) and we have resized the training data to contain exactly 450 files for each group.



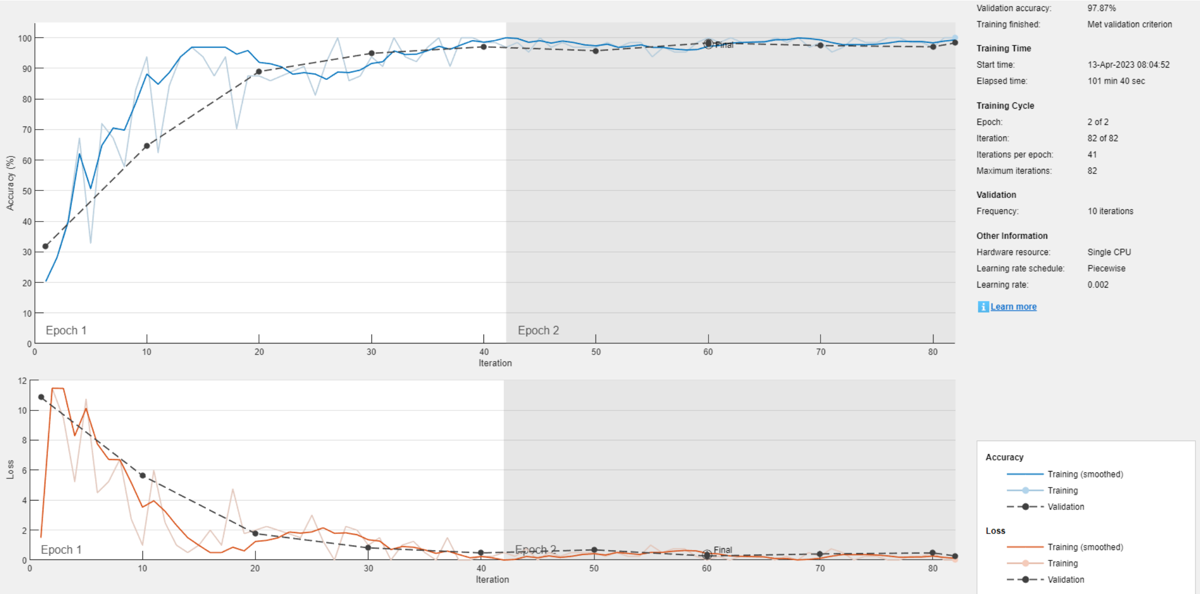
True Class \ Predicted Class	1 network	2 networks	3 networks	No network
1 network	30			
2 networks		30		
3 networks			30	
No network	2			28

Figure 6: Confusion matrix-V1

A second training was performed with the training parameters presented in Table II, except for the minibatch size which was increased to 64. According to the same validation criteria, the second training stopped in the second epoch at the 45th iteration achieving a validation accuracy of 99,17%. The test accuracy for the second trained network was of 97,5%.

Following we have modified the validation criteria (validation frequency and validation patience was increased to 10 and 5 respectively) and performed a new training to investigate the impact on the achieved accuracy. The training progress for the third network is presented in Figure 7. From analyzing Figure 7 we can observe that the training was performed for both epochs and all iterations achieving a validation accuracy of 97,87%.

We appreciate that the small differences between the achieved accuracies in the three versions of training are given by data randomization rather than training options. The difference in the spectrogram SNR condition was not recorded and we appreciate that it could be the source of the accuracy variations. Further research is needed to validate this assumption.



Validation accuracy: 97.87%
Training finished: Met validation criterion

Training Time
Start time: 13-Apr-2023 08:04:52
Elapsed time: 101 min 40 sec

Training Cycle
Epoch: 2 of 2
Iteration: 82 of 82
Iterations per epoch: 41
Maximum iterations: 82

Validation
Frequency: 10 iterations

Other Information
Hardware resource: Single CPU
Learning rate schedule: Piecewise
Learning rate: 0.002

Figure 7: Network training progress- V3

4. Conclusions

In this paper we have designed a ML algorithm to classify spectrogram images and obtain the number of FH networks in an operational area. The novelty of the approach lies in experimental collection of data for training, validation and testing and particularization for military VHF FH networks.

Both data collection and network training phases are detailed. The obtained classification accuracy was in all situations above 97% for both test and validation data. Some accuracy variations were observed for different training parameters but as the overall accuracy was very high in all network training variants, we appreciate that it could be due to other specific experimental parameters that were not recorded (e.g. SNR).

The results are promising and bring important improvements in the field of signal reconnaissance. Our findings suggest the possibility of using the proposed algorithm to implement operational systems capable of performing real-time signal reconnaissance of military frequency hopping radio networks. The experimental data used to drive the algorithm development and testing phases is an extremely important feature for this future development phase.

References List

[1] Harris F., Chen X. & Venosa E. "Efficient implementation of multicarrier frequency hopping receiver via polyphase channelizer". MILCOM 2015 - 2015 IEEE Military Communications Conference, Tampa, FL, USA, 2015, pp. 826-830, doi: 10.1109/MILCOM.2015.7357547.

[2] Lee K.-G., & Oh S.-J. (2019). Detection of Fast Frequency-Hopping Signals Using Dirty Template in the Frequency Domain. In IEEE Wireless Communications Letters (Vol. 8, Issue 1, pp. 281–284). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/lwc.2018.2870275.

[3] Padmanabhan J., & Johnson Premkumar, M. J. (2015). Machine Learning in Automatic Speech Recognition: A Survey. In IETE Technical Review (Vol. 32, Issue 4, pp. 240–251). Informa UK Limited. https://doi.org/10.1080/02564602.2015.1010611.

[4] Jadhav S.R., Das R., Thepade S.D. & De S. "Applications of Hybrid Machine Learning for Improved Content Based Image Classification". 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, 2018, pp. 1-6, doi: 10.1109/ICCUBEA.2018.8697580.

[5] Dwivedi R.K., Rai A.K. & Kumar R. "A Study on Machine Learning Based Anomaly Detection Approaches in Wireless Sensor Network". 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 2020, pp. 194-199, doi: 10.1109/Confluence47617.2020.9058311.

[6] Kartchner D.R. & Jayaweera S.K. "A Frequency-Hopping Game Between a Smart Jammer and a Cognitive Radio". 2019 IEEE International Conference on Internet of Things and Intelligence System (IoTaIS), Bali, Indonesia, 2019, pp. 12-17, doi: 10.1109/IoTaIS47347.2019.8980452.

[7] Valieva I., Shashidhar B., Bjorkman M., Akerberg J., Ekstrom M., & Voitenko I. (2022). Machine Learning-Based Frequency Bands Classification for Efficient Frequency Hopping Spread Spectrum Applications. In MILCOM 2022 - 2022 IEEE Military Communications Conference (MILCOM). MILCOM 2022 - 2022 IEEE Military Communications Conference (MILCOM). IEEE. https://doi.org/10.1109/milcom55135.2022.10017912.

[8] Lee J., Park C., & Roh H. (2021). Revisiting Bluetooth Adaptive Frequency Hopping Prediction with a Ubertooth. In 2021 International Conference on Information Networking (ICOIN). 2021 International Conference on Information Networking (ICOIN). IEEE. https://doi.org/10.1109/icoin50884.2021.9333996.

[9] Li Z., Liu R., Lin X. & Shi H. "Detection of Frequency-Hopping Signals Based on Deep Neural Networks". 2018 IEEE 3rd International Conference on Communication and Information Systems (ICCIS), Singapore, 2018, pp. 49-52, doi: 10.1109/ICOMIS.2018.8645029.

[10] Zhu S., Wang Y., Zheng J., & Wang S. (2021). RBF Neural Network-Based Frequency Band Prediction for Future Frequency Hopping Communications. In W. Wang (Ed.), Wireless Communications and Mobile Computing (Vol. 2021, pp. 1–13). Hindawi Limited. https://doi.org/10.1155/2021/5570685.

[11] https://www.l3harris.com/sites/default/files/2020-11/cs-tcom-rf-7800v-hh-handheld-vhf-tactical-combat-net-radio-datasheet.pdf, accesed 20.04.2023.