Novel Method in Robust Radio Communication Emission Classification

Jovan Bajčetić and Davorin Mikluc

Abstract - This paper presents a new concept of deep learning technique usage for frequency spectrum image classification. The presented research gives the overview of the image database creation, acquired data processing and emission type recognition model developing. Image database is created using real time generated, differently modulated robust radio emissions using 25 kHz wide radio channels within 15 to 55 MHz frequency band. Those radio emissions are then represented using 300-time sample power distribution over given frequency band. Every each of those representations is defined with 500 data points. Using around 100 of spectrogram and polar images of the acquired data, we developed a deep learning model capable to perform multiclass classification for detected robust radio emission.
Keywords – Image classification, Deep learning, Radio emission, Robust radio communication.

I. Introduction

Deep learning (DL) procedures has enhanced image processing technology to the extent to be the inevitable technology of the 4th industrial revolution [1], [2]. It is the main driver of the autonomous driving technologies and is becoming more and more affordable for commercial use [3]. In data science, neural networks are in the core of DL techniques and can be considered as computing systems based on biological neural networks. Basic idea of artificial neural network is to simulate a large amount of densely packed, interconnected nerve cells within the computer, so that it can provide learning of terms, pattern recognizing or decisions making. Using this feature, today is achievable what was not possible before, thanks to the immensely improved computing capabilities of GPU based systems.

Tactical radio communications provide users with reliable narrow band communication links. In a harsh electronic warfare environment, it is essential to be undetectable, efficient in terms of information exchange while mobile, operating in the mash organized radio networks. Robust radio communication systems working in VHF (Very High Frequency – 30-300 MHz) and HF (High Frequency – 3-30 MHz) frequency bands yield for the possibility of real-time radio emission classification. Since modern tactical radio communications use various kinds of media access technologies that enable Low Probability of Interception (LPI) and power consumption [4], we initiated the research in order to develop the software that could automatically identify the received radio signal modulation technique and media access technology. That could furtherly allow intelligent spectrum utilisation in order to enable coexistence of multiple networks within the same area.

One of the conceivable DL use cases is to provide efficient, real-time radio emission classification out of the crumbled radio spectrum. That motivation drove us to conduct the research in order to generate the tool for such challengeable task.

The research was conducted in the following order:

1. Reference image database creation;
2. Image classification model defining;
3. Four class multiclass model training;
4. Model testing.

Jovan Bajčetić and Davorin Mikluc, University of Defence in Belgrade, Military Academy, Pavla Jurišića Šturma 33, Belgrade, E-mail: bajce05@gmail.com, miklucd@yahoo.com.

II. Radio spectrum emission classification

A. Reference image database creation

DL techniques require a huge amount of data in order to be properly trained. The research preparation was directed towards a suitable image database creation of different modulation emission recordings. The first step in software development was image acquiring into the database which was used as a source of data for DL processing. Images were the representations of radio emission spectrum within defined frequency band and the actual image creation was done using the Matlab software environment that provides connection to a wide variety of data acquisition hardware solutions.

The receiving signal spectrum acquiring was performed using Tektronix RSA306B USB Real Time Spectrum Analyzer which provides real time spectrum analysis, streaming capture, signal analysis and +20 dBm to -160 dBm measurement range for signals within 9 kHz to 6.2 GHz frequency band. The transmitter of this communication system was the genuine radio transceiver that generate defined modulated radio signal. Emission was produced using Thales HF and VHF transceivers as suitable transmitters since they offer possibility of different modulation modes which are between 15 MHz and 30 MHz and 30 MHz and 88 MHz, respectively. Those frequency bands are intensively used in the HF and VHF tactical military communication systems.

Modulations that were used in this research were Amplitude Modulation (AM), Frequency Modulation (FM), Frequency Shift Keying (FSK) and Fast Frequency Hopping (FFH). The communication system used was formed as presented in Fig. 1. Signal distortion due to interference and

noise was avoided using a proper attenuator in order to overcome the receiver overloading.

Fig. 1. Experiment setup – data acquisition

The spectrogram made from the sampled received signal was generated by VHF device between 30 MHz and 55 MHz for FFH, FSK and FM modulation techniques. For that frequency band, measurements were done for 100 different modulated carriers with 250 kHz step between them (100 recordings). For each frequency, the 15 MHz wide frequency band was sampled in 300 points. Each recording was stored using Matlab, in the structure that contains 3 matrixes. Those matrixes store time results in 500 samples of each recording for 15 MHz wide frequency band during the time of approximately of 2,5 seconds. The first matrix stores time of the recording, the second matrix is consisted of acquired IQ data for m=300, and the third matrix is consisted of produced signal spectrum generated with FFT (Fast Fourier Transformation).

AM modulation measurements were done with HF device as the trasmitter on 100 modulation frequencies between 15 and 30 MHz with 150 kHz step. Results were structured and stored in the same way as with VHF device. The analyzed spectrum bandwidth was 40 MHz broad with sampling points 80 kHz distant from each other. The acquired time moment spectrums ($SIG_{0...m}$) can be represented with I and Q values for each frequency/time sample:

$$\begin{aligned} SIG_0 &= I_{0,1} + Q_{0,1}i + I_{0,2} + Q_{0,2}i + \ldots + I_{0,500} + Q_{0,500}i \\ SIG_1 &= I_{1,1} + Q_{1,1}i + I_{1,2} + Q_{1,2}i + \ldots + I_{1,500} + Q_{1,500}i \\ &\ldots \\ SIG_m &= I_{m,1} + Q_{m,1}i + I_{m,2} + Q_{m,2}i + \ldots + I_{m,500} + Q_{m,500}i \end{aligned} \tag{1}$$

The sum of spectrum data *SIG* that can be used for spectrogram presentation is defined in 500 frequency points (*n*) and 300 time recordings (*m*) with the acquired I and Q values:

$$SIG = \sum_{m=1}^{300} \sum_{n=1}^{500} I_{\mathrm{m},n} + Q_{m,n} i \tag{2}$$

Finally, $RFSIG_m$ is the representation of the emitted radio signal for each recorded moment of the radio emission:

$$RFSIG_m = \sum_{n=1}^{500} I_{m,n} \cos(2\pi f_n t) + Q_{m,n} \sin(2\pi f_n t) \tag{3}$$

The samples of produced spectrograms for each modulation technique are presented in Fig. 2.

B. Image classification model defining

Considering the database of the produced recordings coming from the experiment, the next stage was to produce adequate images which would be optimal for the multiclass image classification using DL implemented in a chosen neural networks API (Application Programming Interface). DL model used in the experiment is realized using nowadays one of the most popular APIs – Keras written in Python and capable of running on top of TensorFlow [5].

Keras is a very popular DL API with several advantages. First of all, it allows easy and fast prototyping because of user friendly code, modularity and extensibility (we used 3 classes multiclass classification model which we extended to 4 classes), Second, it supports both convolutional and recurrent networks, as well as combination of those two (we used convolutional). Finally, it can be run on both CPU and GPU (we used CPU). Four-class classification was implemented using model with the parameters shown in Table 1.

TABLE I
THE MOST IMPORTANT MODEL PARAMETERS

Type of DL model	Convolution
Number of layers	2
Number of classes	4
Number of training epochs	20
Number of the training set images	100
Number of validation images	6

Images were uniformly dispersed in four classes for the training process – 100 images representing spectrograms of the acquired data. In order to find more optimal image representation of the spectrogram for more efficient modulation recognition, we made two different types of the spectrogram depiction. The first one is classical 2D spectrogram representation of power distribution over time and frequency, and the second one is polar plotted representation of the same data.

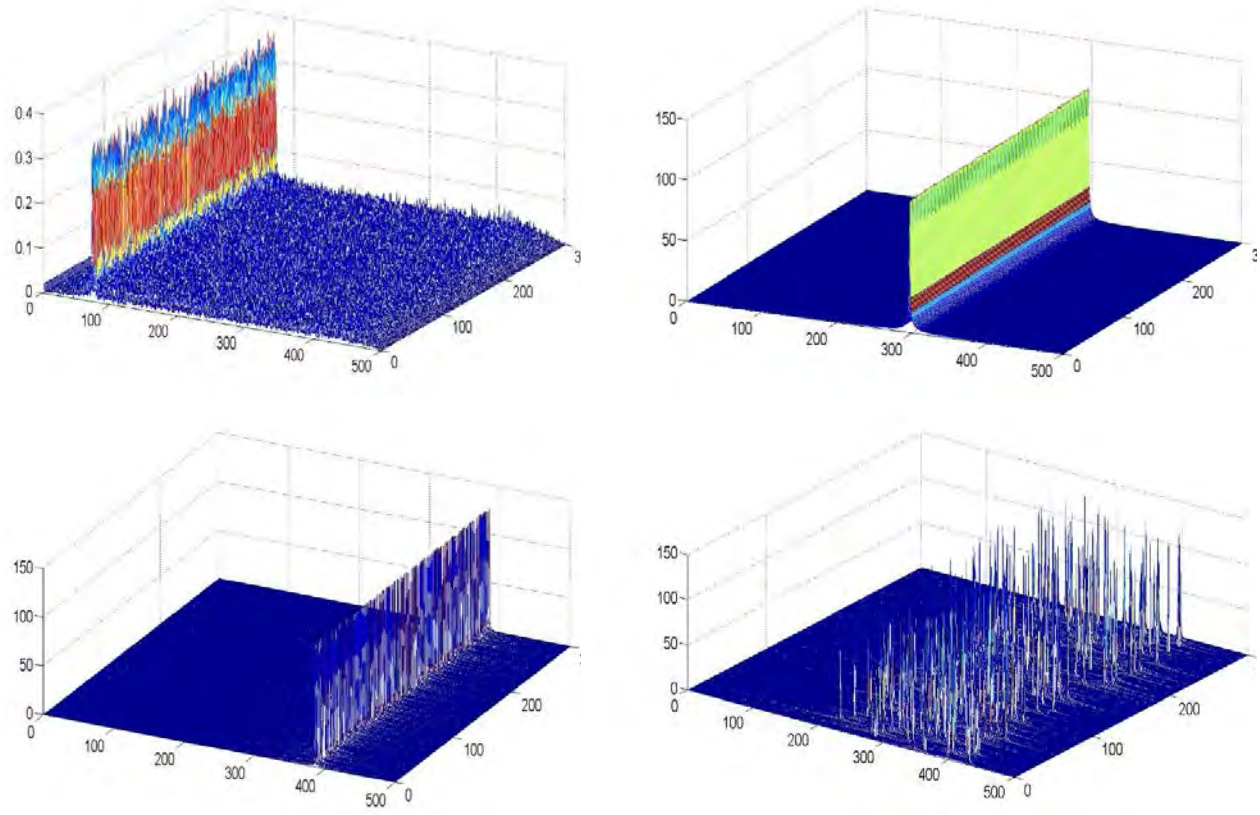

Fig. 2. Spectrogram images – AM (up left), FM (up right), FSK (down left), FH (down right)

C. Four class multiclass model training

One of the main problems in DL mechanism for image classification is model overfitting which occurs when there is not enough number of learn pattern examples (training samples) for feeding the model. It leads to the case that the model makes false predictions due to irrelevant features. To overcome this, it is advisable to make large training database, to use adequate number of layers and their size, to use "dropout" function and to ″augment″ samples, i.e. to transform images randomly in order to make our model never see twice the same image.

Those improvements were implemented in our model using *keras.preprocessing.image.ImageDataGenerators* class along with random image transformations and normalization operations. Each image was 1200 x 900 pixels in dimension, with the resolution of 96 dpi and 24-bit depth, compressed with JPG standard.

DL model was a simple stack of two convolutional layers with a ReLU activation and followed by max-polling layers. In top of it, we stick two fully connected layers and finish the model with a single unit and a softmax activation and categorical_crossentropy loss, since it is convenient for multiclass image classification. Dropout function was implemented with 0.5 factor in the last layer.

The randomizations that were used are rescaling, shear_range and zoom_range. The first one makes image scaling with 1/255 factor to enable model to perform faster with scaled image values between 0 and 1. The second one apply random shear transformations (displace each point in fixed direction by the amount proportional to its signed distance from the line that is parallel to that direction), while the last one makes random zooming inside images.

Training generator was constructed with 240x240 pixels image size, 32 batch size, 20 epochs and 1000 samples per epoch. In Fig. 3 are presented examples of images for each of four classes used in two different scenarios for DL image-based modulation recognition.

D. Model testing

Model performance is defined using training and validation accuracy which are the measures how well-developed model is. When training a machine learning model, one of the main things that should be avoided, as already being said is the overfitting. Practically, that term is related to the situation when a model fits the training data well, but it isn't able to generalize and make accurate predictions for data it hasn't seen before. In order to find out if a model is overfitting, a technique called cross-validation is used.

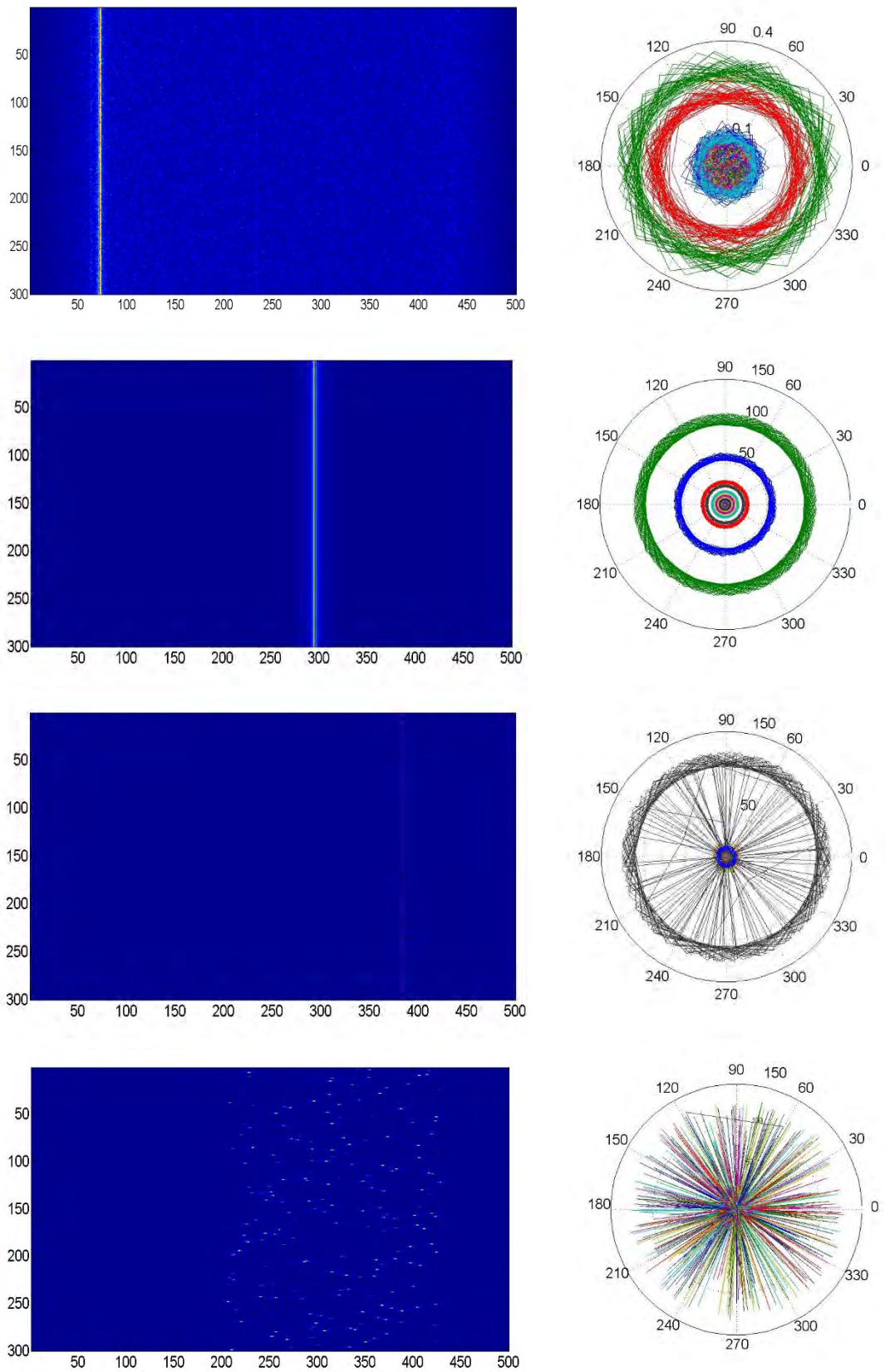

Fig. 3. Examples of images used in DL model (spectrogram-left, polar-right)

It requires the data to be split into two parts - the training set and the validation set. The training set which is in our case comprised of about 100 images in each class is used to train the model, while the validation set consisted of 6 images in our case is only used to evaluate the model's performance.

Metrics on the training set expressed as training loss and accuracy enable one to see how the model is progressing in terms of its training, and the metrics shown as validation loss and accuracy on the validation set that gives a measure of the quality of the model – how well it's able to make new predictions based on data it hasn't seen before.

III. Conclusion

Considering results given in Fig. 4, there are some conclusions that could be made on the developed model performing:

1. Training accuracy which is a measure of the training effectiveness is better on the same number of images in the training set for the polar representation of the spectrogram. It comes to the training accuracy of 90% in just 8 epochs, while for the same value of classical spectrogram image data set it is required to make at least 14 epochs;
2. Validation accuracy (the measurement of how the model performs when introduced to the data that hasn't been introduced to before) is quite better for the polar trained model, as well, since it comes to the high value of more than 85% very quickly (after only 2 epochs);
3. The same situation is considering validation loss as the summation of the errors made for each example in validation sets. Referring to the Fig. 4, it can be concluded that again polar based image classification model is much better since it classifies new images with fewer errors after just two epochs which is quite improvement related to classical spectrogram model.

Our future work is going to be directed towards the real-world application designing for radio emission pattern recognition. This indicates development of optimized DL models for near-real-time multiclass emission classification which is going to be a quite demanding challenge. In order to perform such a task, it is an obligate to use GPU (Graphics Processing Unit) as a platform for deep learning model training and validation because of the much faster processing capabilities.

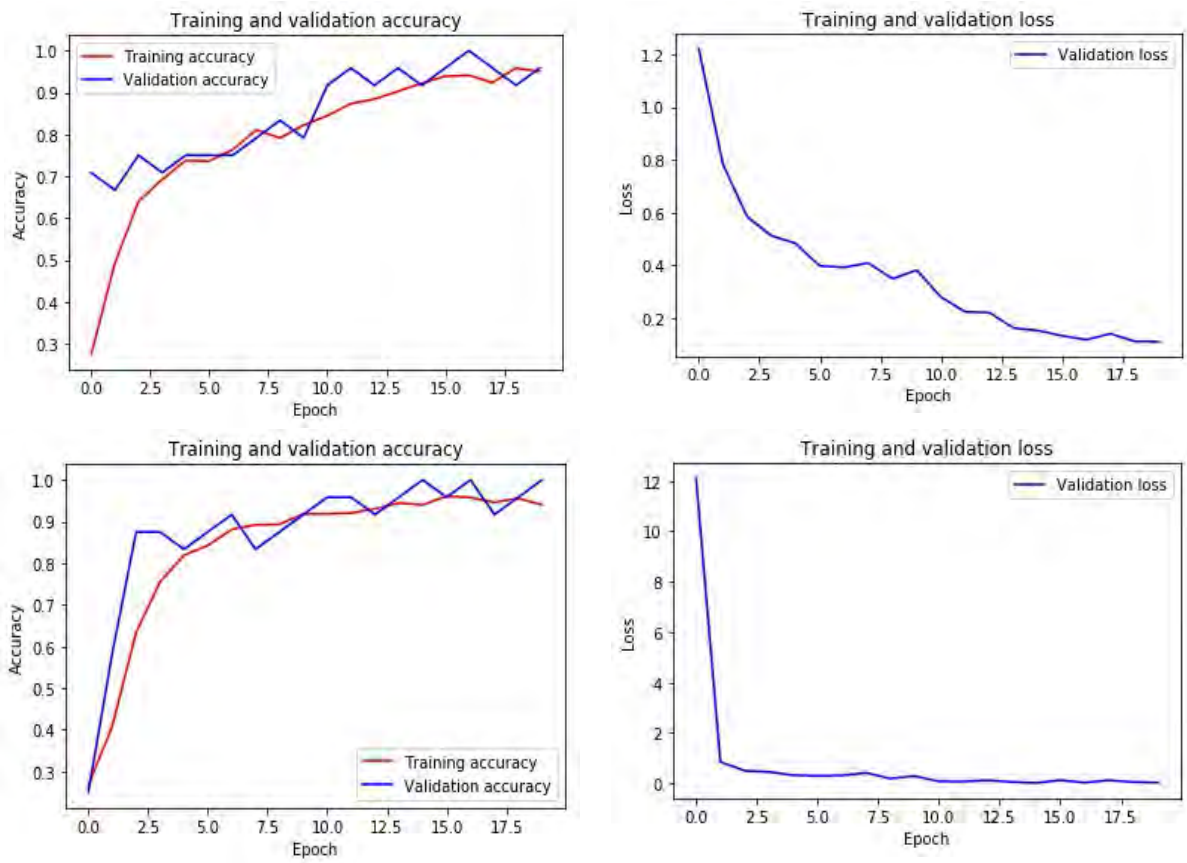

Fig. 4. Model performance – spectrogram (up), polar (down)

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