Classification of Radio Signals and HF Transmission Modes with Deep Learning

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Abstract—**This paper investigates deep neural networks for radio signal classification. Instead of performing modulation recognition and combining it with further analysis methods, the classifier operates directly on the IQ data of the signals and outputs the transmission mode. A data set of radio signals of 18 different modes, that commonly occur in the HF radio band, is presented and used as a showcase example. The data set considers HF channel properties and is used to train four different deep neural network architectures. The results of the best networks show an excellent accuracy of up to 98%.**

I. INTRODUCTION

Classification of radio signals is an essential task in signal intelligence and surveillance applications and is recently adopted in applications like cognitive radio and dynamic spectrum access to continuously monitor the spectrum and its occupancy by various different radio signals, modes and services.

Traditional approaches to radio signal classification rely on signal features based on probabilistic methods, statistics or cyclostationarity. These features need to be carefully designed by expert developers and thus depend on their experience and knowledge on the problem structure [1].

Recently advanced machine learning techniques, like deep neural networks, gained huge interest and showed extremely good performance for classification tasks in various applications. Instead of formulating hand-crafted features by a designer, a training algorithm uses large amounts of labelled example data to learn and extract good features from the data that are discriminative for the classification task. While this data-driven approach first proved to be very successful for object classification in image processing [2], it quickly advanced to numerous further applications, such as different challenges in radio communications [3].

For the task of signal classification, the neural network trains on large amounts of raw data of radio signals (e.g. IQ data samples), such that it is enabled to distinguish the different signal classes. Especially for the task of modulation classification, neural networks have shown to exhibit very good performance [4], [5].

Although recent work is based on IQ data samples as input, the output classes are restricted to modulation types (e.g. FSK, PSK, AM). To determine the actual transmission mode or service (Wi-fi, mobile telephony (GSM, LTE), digital radio (DAB), radioteletype (RTTY), AM broadcasting, etc.) further processing is required, like the additional measurement of baud rate, pulse shape or bit pattern structures. These additional features are not learnt by the neural network trained on modulation types and therefore this second step follows the classical way of designing expert features by hand.

This paper investigates how neural networks can be used to classify signals by their transmission mode directly, instead of classifying only modulation types. The approach purely follows the data driven paradigm by mapping input IQ data to the output modes directly. As an example application this paper considers radio signals typically present in the HF band (3-30 MHz), because this wireless band contains many different modes that coexist closely spaced in the frequency spectrum. In total, 18 different HF transmission modes are considered for classification. Four different types of neural networks are trained on a synthetically generated data set, considering a noisy HF channel environment under imperfect receiver conditions.

The investigation shows, that neural networks are very powerful in classifying signals into their transmission modes even if they exhibit very similar properties. An accuracy of 98% for moderate SNRs can be obtained with reasonable training effort.

The remainder of the paper is structured as follows: Section II describes the training data in more detail, Section III introduces the models and the training process, followed by the results in Section IV.

II. DATA SET

A. Modes and Data Format

The training data consists of the 18 different transmission modes shown in Table I, of which many are commonly found in the HF bands. This includes AM broadcasting, single-sideband (SSB) audio, radioteletype (RTTY, Navtex) [6], morse code [7], facsimile and further modes for digital data transmission like PSK31 [8], Olivia [9] and others. The selected 18 modes cover very different modulation techniques, including analog (AM, facsimilie and SSB) and various digital modulation types (PSK, FSK, M-FSK, OOK, multicarrier). However, there are also very similar modes, such as RTTY45 and RTTY50, that differ only by their baud rate of 45 and 50 Bd and are expected to be especially hard to classify. Other similar modes are PSK31 and PSK63, as well as SSB in upper (USB) and lower (LSB) sideband.

The training data is generated synthetically by simulation. The raw data used to generate the training signals is plain text for the digital modes and speech and music (various genres) for the analog modes. Fax data is generated by modulating different black & white images, such as e.g. transmitted by

Mode Name	Modulation	Baud Rate
Morse Code	OOK	variable
PSK31	PSK	31
PSK63	PSK	63
QPSK31	QPSK	31
RTTY 45/170	FSK, 170 Hz shift	45
RTTY 50/170	FSK, 170 Hz shift	50
RTTY 100/850	FSK, 850 Hz shift	850
Olivia 8/250	8-MFSK	31
Olivia 16/500	16-MFSK	31
Olivia 16/1000	16-MFSK	62
Olivia 32/1000	32-MFSK	31
DominoEx	18-MFSK	11
MT63 / 1000	multi-carrier	10
Navtex / Sitor-B	FSK, 170 Hz shift	100
Single-Sideband (upper)	USB	-
Single-Sideband (lower)	LSB	-
AM broadcast	AM	-
HF/radiofax	radiofax	-

Table I
TRANSMISSION MODES

weather services. Then standard software modulates the raw signals in order to obtain baseband signals, which are then artificially distorted by a HF channel model, described in detail below.

Transmission in the HF band is mostly characterized by comparably small bandwidths (often less than 3 kHz) and therefore low data rates. The data set contains vectors of complex IQ data of length 2048 with a sample rate of 6 kHz. Thus a data vector corresponds to a time of approximately 0.3 s. In total, the data set consists of 120,000 training vectors and another 30,000 vectors for validation.

B. HF Channel Properties

Since signals that are transmitted via the HF band exhibit special distortions, these effects needs to be reflected by the training data. The HF band ranges from 3 to 30 MHz and is characterized by sky wave propagation, i.e. radio waves do not travel by line-of-sight, but are reflected by the earth's ionosphere, which enables intercontinental communication with little technical effort. In fact, different ionospheric layers, that may be located in different heights, contribute to the propagation of radio waves. This complex propagation behaviour presents a multi path propagation environment resulting in fading effects. Moreover, these ionospheric layers are not stationary, but are in continuous movement, which introduces varying doppler shifts.

For modelling radio wave propagation in the HF band, the Watterson model is commonly applied [10], that covers fading and doppler shift introduced by multipath propagation effects. The ITU has defined several channel models based on the Watterson model, called CCIR 520 [11]. CCIR 520 includes different scenarios for complex wave propagation, that differ in the amount of distortion introduced, i.e. frequency spread, frequency offset and differential time delay. The scenarios employed in the training data sets are *good conditions*, *moderate conditions*, *bad conditions*, *flutter fading* and *doppler fading*, plus data vectors without any fading and doppler distortion.

In addition, all data vectors are distorted by Gaussian noise (AWGN) of different strength, such that the SNR of the data is evenly distributed from -10 to +25 dB. To account for non-coherent reception and receiver frequency mismatch also random phase and frequency offsets are applied. In summary, the training data set incorporates the following types of distortion to provide robust training results that perform well in real-world scenarios:

- CCIR 520 channel models
- AWGN noise (from -10 to +25 dB)
- random frequency offset (+- 250 Hz)
- random phase offset

III. MODELS AND TRAINING

This paper investigates four neural networks or models for signal classification, that range from ordinary convolutional neural nets (CNN) [12] to advanced models, like residual nets [13]. The structure of the models is depicted in Fig. 1.

- **Classical CNN**: It consists of six convolutional layers each followed by max pooling. At the output two large dense layers are located.
- **All Convolutional Net**: It is only composed of convolutional layers with stride 2 (instead of max pooling layers) and it has a global average pooling layer at its output [14].
- **Deep CNN**: It uses 16 convolutional layers, with max pooling after every second convolutional layer and a single small dense layer at the output, roughly following the concept of the VGG net [15].
- **Residual Net**: It uses a large number of layers enhanced by residual connections. While residual nets as described in [13] (including the bottleneck architecture) did not provide convincing results, an arrangement of eight 5-layer residual stacks of [4] proved to be more appropriate for the task of signal classification and is applied here (Fig. 2).

The nets are chosen to have a similar number of parameters around 1.4M. They adopt ReLU activation functions and softmax for the output layers. The nets use dropout layers for regularization and batch normalization. Following the ideas of [15] the convolutional layers mostly use a filter size of 3.

Training is done with adam optimization [16] enhanced by a learning rate scheduler, that reduces the learning rate as soon as the training process plateaus. The batch size is 128 and the number of training epochs is 30 to keep the training time moderate while achieving very good training accuracy.

IV. RESULTS

Table II shows a comparison of the results for the four models that have been trained with the previously described data set. The validation data set to measure accuracy also contains signal data evenly distributed over the whole SNR range from -10 to 25 dB. Therefore the provided accuracy values in Table II are an average over all SNR values.

Best performance show the deep CNN (17 layers) with 93.7% and the residual net (41 layers) with 94.1%. Although the residual net has much more layers, it provides only a minor improvement in accuracy. Larger improvement in accuracy by
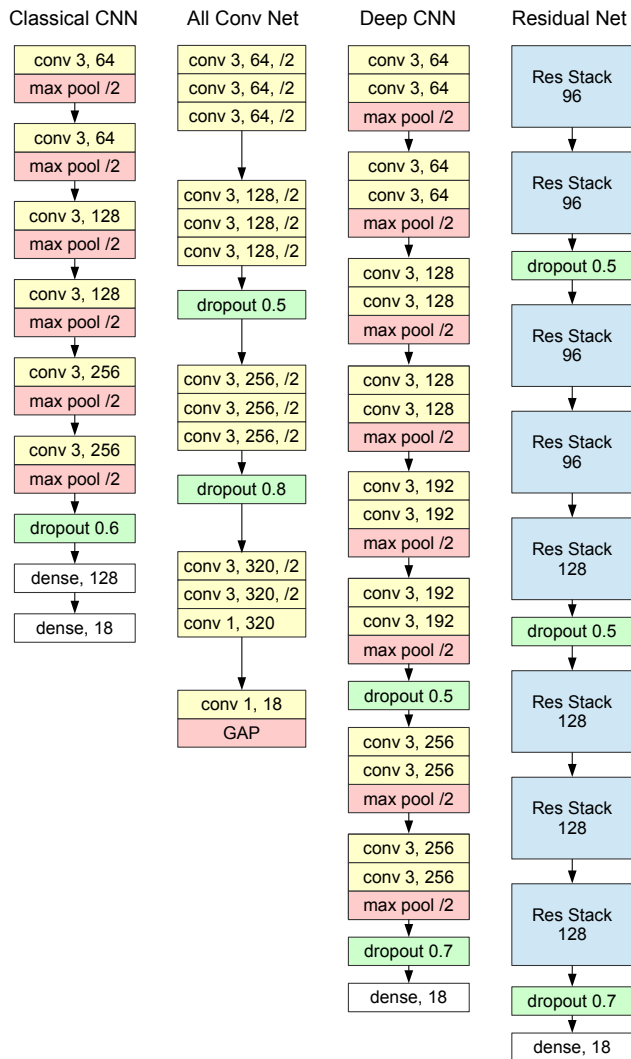
Figure 1. Different neural network architectures

Figure 2. The residual stack as used in the residual net. The parameter N provides the number of filters for the stack.

Figure 3. Comparison of the results of the different models

the much deeper residual net may be obtained when using much more training time than the 30 epochs used for economic training in this paper.

Model	Layers	#Parameters	Accuracy	Training Time
Classical CNN	8	1.4 M	85.8%	1.2 h
All conv net	13	1.3 M	90.3%	0.7 h
Deep CNN	17	1.4 M	93.7%	1.9 h
Residual net	41	1.4 M	94.1%	5.3 h

Table II
OVERVIEW OF THE DIFFERENT MODELS AND THEIR PERFORMANCE

Fig. 3 shows the accuracy of the different models over SNR. Even for small SNR values of -5 dB, the accuracy for the best models is above 90%. When SNR is above 5 dB the accuracy increases to an excellent value of approximately 98%.

Fig. 4 shows the confusion matrix for the residual net, that provides the best results. Since the overall performance of the net is very good, confusions are very rare. Minor confusions occur between QPSK and BPSK modes. Also
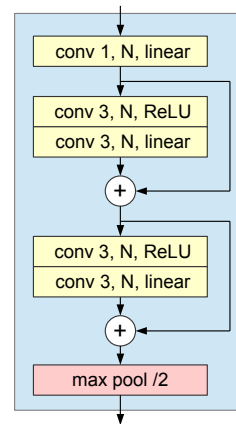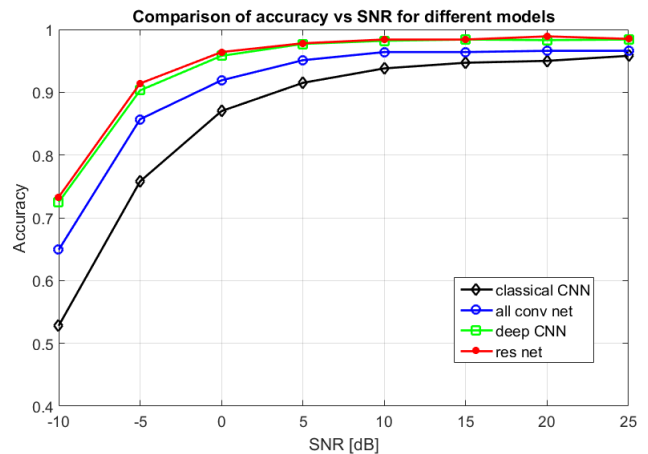
RTTY45 and RTTY50 tend to rarely be confused, because the only difference between these modes is the slightly deviating baud rate of 45 and 50. Although LSB und USB are quite similar modes, they are classified with very high reliability.

V. CONCLUSION

This paper presented four different neural networks for the classification of radio signals. Instead of focusing on modulation recognition, the models learn to classify different transmission modes directly. This saves additional post-processing required to determine the modes from modulation and other signal parameters. An exemplary data set with 18 different transmission modes that occur the HF band has been utilized, with an excellent accuracy of up to 98%.

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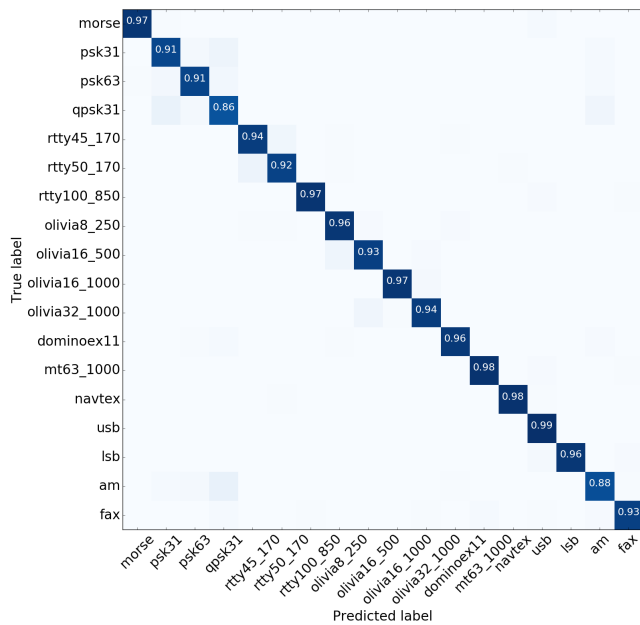
Figure 4. Confusion matrix for the residual net (all SNR values)

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