Multi-Label Wireless Interference Identification with Convolutional Neural Networks

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Abstract—The steadily growing use of license-free frequency bands requires reliable coexistence management and therefore proper wireless interference identification (WII). In this work, we propose a WII approach based upon a deep convolutional neural network (CNN) which classifies multiple IEEE 802.15.1, IEEE 802.11 b/g and IEEE 802.15.4 interfering signals in the presence of a utilized signal. The generated multi-label dataset contains frequency- and time-limited sensing snapshots with the bandwidth of 10 MHz and duration of 12.8 µs, respectively. Each snapshot combines one utilized signal with up to multiple interfering signals.

The approach shows promising results for same-technology interference with a classification accuracy of approximately 100% for IEEE 802.15.1 and IEEE 802.15.4 signals. For IEEE 802.11 b/g signals the accuracy increases for cross-technology interference with at least 90%.

I. INTRODUCTION

Artificial neural networks and especially convolutional neural networks (CNNs) achieved excellent results for different benchmarks in recent years [1], [2], [3]. Neural networks achieve the best performance, e.g. for character recognition of the mixed National Institute of Standards and Technology (MNIST) database [4]. The results achieved by the CNNs from Ciresan et al. [1] are comparable to human performance. Therefore, a growing number of research fields apply CNNs as classification systems.

One of these research fields is wireless interference identification (WII) for coexistence management of license-free radio bands such as the 2.4 GHz industrial, scientific and medical (ISM) band. Such bands are shared between incompatible heterogeneous wireless communication systems (WCSs). In industrial environments, typically standardized wireless technologies (WTs) within the 2.4 GHz ISM band are wide-band high-rate IEEE 802.11b/g/n, narrow-band low-rate IEEE 802.15.4-based WirelessHART and ISA 100.11a, and IEEE 802.15.1-related PNO WSAN-FA and Bluetooth. Additionally, the radio band is shared with many proprietary WTs which target specific application requirements such as industrial WLAN (iWLAN) from Siemens AG which is derived from IEEE 802.11, FHSS-based Trusted Wireless from Phoenix Contact and IEEE 802.15.1-based WISA from ABB Group.

Heterogeneous temporal and spectral medium utilization of shared radio bands result in interferences. Any interference can cause packet loss and transmission latency for industrial WCSs. Both effects have to be mitigated for real-time medium requirements. The IEC 62657-2 norm [5] for industrial WCSs recommends an active coexistence management for reliable medium utilization. Therefore, it advises the utilization of (i) manual, (ii) automatic non-cooperative or (iii) automatic cooperative coexistence management. The first approach is the most inefficient one, due to time-consuming configuration effort. The automatic approaches (ii) and (iii) enable efficient self-reconfiguration without manual intervention and radio-specific expertise. Automatic cooperative coexistence management (iii) requires a control channel, i.e. a logical common communication connection between each coexisting WCS to enable deterministic medium access. For legacy WCSs without control channel, the non-cooperative approach (ii) is recommended. Non-cooperative coexistence management approaches are aware of existing WCSs based on independent WII and mitigation.

In our previous work [6], we proposed a WII approach upon deep CNNs. It classifies interference signals on a per sensing snapshot basis. In this paper, we extend the approach to target coexistence management for an utilized WCS which is
interfered by non-cooperative WCSs. Therefore, the proposed approach is capable of identification of multiple interfering signals in the presence of the utilized signal as illustrated in Fig. 1.

To face realistic WCS capabilities the approach is limited to a sensing bandwidth of 10 MHz and a sensing snapshot is limited to a duration of 12.8 µs, which results in 128 in-phase and quadrature (IQ) samples. The evaluation is performed with the standardized WTs IEEE 802.11b/g, IEEE 802.15.4 and IEEE 802.15.1, which are sharing the 2.4 GHz ISM band. In total 19 different variants of modulation types and symbol rates are utilized. Thereby, the WII approach has to differ between 15 allocated frequency channels of the WTs. Additionally, the sensing snapshots contain the dominant signal of the utilized WCS which aggravates WII even more. Hence, the interfering signal is acquired in the presence of the utilized signal. Hence, each sensing snapshot superimposes one utilized signal with multiple interfering signals.

The paper is structured as follows. In the next chapter II the related work is discussed. Then, in chapter III the generated dataset is explained. Chapter IV aims the CNN design. Chapter V shows the performance of the proposed approach. Finally, chapter VI concludes the paper and suggests future work.

II. RELATED WORK

Classification systems can be divided into (i) rule-based, (ii) kernel-based and (iii) representation learning ones as illustrated in Fig. 3. Rule-based systems are mostly engineered implementations of heuristic functions to result in approximate solutions based on problem domain knowledge. In contrast, kernel classification systems self-optimize the weighting and assignment of pre-engineered features which are also based on problem domain knowledge. The finally classification system type is based on representation learning. Thereby, also the feature extraction is performed by self-optimization. Hence, representation learning systems eliminate any problem domain knowledge requirement and result in a full self-optimization classification system.

A well-known sub-type is called deep neural network (DNN), which is a multi-layer neural network for higher-order feature extraction. Another sub-type is a CNN, which utilizes convolution-related feature extraction layers. Hence, a deep CNN classifies with higher-order convolution-related features.

The self-optimization processing units in classification systems require a training phase. For the training phase, these systems require a set of input data, which contain specific objects, and the output labels of the object classes. Thereby, the data type, objects, and the labels depend on the application domain. Hence, classification systems assign input data objects to the label of the corresponding class. With multiple classes, classification problems can be divided into (i) single- and (ii) multi-label ones. In the former, only one out of several objects is present in the input data. Multi-label classification permits more than one object within the input data.

Within the problem domain of WII, an input data item is a sensing snapshot. Further, a contained object is a superimposed transmitted signal of a specific WCS. The particular frequency channel and WT of the transmitted signal express the object classes and therefore also the labels. The transmitted signals are distorted by the radio channel, e.g. attenuation and additive noise. Additionally, superposition of multiple signals impairs the classification task. Hence, WII in the presence of a utilized signal raises the multi-label requirement.

A. Neuro-Fuzzy Signal Classifier

The first system is called neuro-fuzzy signal classifier (NFSC). The NFSC is a rule-based system that was implemented and tested in [7]. The NFSC classifies frequency channels of IEEE 802.11 and IEEE 802.15.1 signals in six different industrial scenarios. The NFSC consists of six layers. In these six layers, the NFSC extracts feature from the input data. The extracted features are the center frequency, bandwidth, spectral pulse shape, time behavior, and spectral hopping behavior of the signals. Then, the features are assigned to the corresponding WT and frequency channel class. The NFSC can detect multiple signals in the input data and can, therefore, handle a multi-label classification problem. Nevertheless, the manual engineered heuristic functions lead to sub-optimal classification accuracies.

B. Convolutional Neural Network Classification

O’Shea et al. [8] introduce an approach based on CNNs. To recognize signal modulation types instead of WT or frequency channels. The approach differentiates between eleven modulation types. Thereby, the input data only contains the signal, and therefore it is a single-label classification problem. To train these systems, a dataset with 96,000 snapshots was used. For radio channel distortion, a variable-strength white Gaussian noise was added to the dataset. So, it consist of snapshots with a signal-to-noise ratio (SNR) of -20 dB to 20 dB. They show that CNN-based self-optimizing systems outperform rule-based systems and also other DNN-based
systems. CNN-based systems achieve the best classification accuracies of greater than 90% for a SNR of at least -2 dB.

In our previous work, Schmidt et al. [6] transferred the modulation recognition approach from O’Shea et al. to the problem domain of WII. The dataset was created using a vector signal generator (VSG) for signal generation and a real time spectrum analyzer (RSA) for data acquisition. The sensing bandwidth was limited to a bandwidth of 10 MHz and duration of 12.8 μs. The dataset includes signals from the WTs IEEE 802.11 b/g, IEEE 802.15.1, and IEEE 802.15.4 with there in-band frequency channels. They are divided into fifteen classes.

Schmidt et al. evaluated two different network architectures of CNNs. The first architecture was adapted from O’Shea et al. [8], while the latter one was a reduced variant to avoid overfitting. However the classification accuracy of the first architecture is higher during the training phase, there is hardly any difference in the validation phase. It results in classification accuracies of at least 95% at SNR of -5 dB. Additionally, the CNNs outperforms the NFSC regarding classification accuracy. It shows a processing gain of 5.32 dB and a classification accuracy improvement of 8.19%. But the CNNs is limited due to its single-label capability only to classify one signal from each sensing snapshot.

### III. Multi-Label Dataset Generation

The multi-label WII has to detect interference signals in the presence of a utilized signal of the WTs IEEE 802.15.1, IEEE 802.11 b/g, and IEEE 802.15.4. To approach real WCS capabilities, a limited sensing bandwidth of 10 MHz was assumed. Hence, eight simultaneous operating instances are required for loss-less WII within the 2.4 GHz band. Each sensing band covers ten, three and two frequency channels of the WTs IEEE 802.15.1, IEEE 802.11 b/g, and IEEE 802.15.4, respectively. Thereby, the frequency channels of the WT IEEE 802.11 are only partially within the sensing bandwidth.

The training and validation dataset for the multi-label WII was derived from the one of Schmidt et al. [6] as illustrated in Fig. 4. They generated a synthetic dataset \( D_{\text{single}} \) with VSG stimulation and RSA recording. \( D_{\text{single}} \) consists of several snapshots \( x_{\text{single},i} \) and labels \( y_{\text{single},i} \). Each snapshot \( x_{\text{single},i} \) is represented by complex 128 IQ samples and contains one of fifteen different classes. The classes represent the ten, three and two frequency channels of the WT IEEE 802.15.1, IEEE 802.11 b/g, and IEEE 802.15.4, respectively. Additionally, \( D_{\text{single}} \) utilized additive white Gaussian noise (AWGN) such that the SNR varies between -20 dB up to 20 dB with a step size of 2 dB. In total, \( D_{\text{single}} \) contains 225,225 snapshots, with 715 snapshots per class and SNR combination.

The multi-label dataset \( D_{\text{multi}} \) requires snapshots with several classes. Thereby, one class is the utilized signal, and the remainders are interfering signals. Since it is not likely that all fifteen classes occur in a snapshot simultaneously, it is limited to the utilized signal an up to six interfering signals. Additionally, despite the varying number of interfering signals the signal-to-interference ratio (SIR) remains constant. Hence, the results depend only on the amount of interfering signals. Furthermore, classification of an increasing number of interfering signals with a fixed SIR is more challenging.

Fig. 4 shows the multi-label generation signal flow with the combination of the single-label snapshots. Each resulting snapshot \( x_{\text{multi},j} \) contains a single utilized signal and \( N \) interfering signals. Hence, the corresponding label is the union of the labels of the contained classes. For input single-label snapshots with a SNR of 20 dB are used. Furthermore, the interfering signals were weighted with the factor \( 1/N \) to keep the SIR constant with the value one. Resulting same- and cross-technology interference (STI, CTI) snapshots are illustrated in Fig. 5 and Fig. 1 respectively.

The entire dataset \( D_{\text{multi}} \) consists of 450,000 snapshots and labels. These are divided into 360,000 snapshots for training and 90,000 snapshots for validation purposes.
Fig. 5. Exemplary same-technology interference snapshots with a utilized signal and an increasing number of interfering signals with same WT IEEE 802.15.1

IV. NEURAL NETWORK DESIGN

The CNN utilizes some pre-processing for the input data. Schmidt et al. [6] and Danev et al. [9] have shown that the classification of the frequency representation of radio signals increases the classification accuracy. Therefore, the snapshots are transformed with the fast fourier transform (FFT). Then, the resulting 128 complex values have been translated into a $128 \times 2$ matrix with the extracted real and imaginary parts. Thereby, real values are in the first column and the imaginary values in the second one.

The CNN output is a vector with 15 elements with the value range $[0, 1]$. Thereby, each element represents a class. For validation, a threshold is applied to result in binary output.

A. Network Architecture

The network architecture of the CNN is shown in Tab. I. It is derived from the CNN architectures of Schmidt et al. [6] and O’Shea et al. [8]. Thereby, Schmidt et al. have used a softmax activation function at the output of the last layer for optimal single-label classification. However, softmax activation function is not suitable for a multi-label classification problem. Therefore, it has been replaced by a sigmoid activation function. The sigmoid activation function enables the independent output calculation for each a class.

B. Network Training

The CNN was trained in 200 epochs. The Adam optimization was used with the standard default parameters and a learning rate of 0.001 [10]. As a cost function, the binary cross entropy was used as which is the optimal choice for sigmoid output activation functions. The batch size of 256 has been adjusted to the limitations of the computing platform. Additionally, no hyperparameter optimization was applied.

C. Implementation Aspects

The CNN was implemented in the programming language Python with the libraries Keras [11] and Tensorflow [12]. A high end platform with an Intel XENON E5-1660 v3 central processing unit (CPU), 16 GB RAM and a Nvidia GTX 960 graphics processing unit (GPU) was used. During the training process a CNN, an epoch took 390 s, resulting in a duration of 21.6 h for training.

V. RESULTS

For evaluation, we use a metric called true positiv rate (TPR), which is proposed by Godbole and Sarawagi [13]. TPR evaluates the outcome of a single class. Thereby, all data items which contain the distinct class are considered. TPR expresses the proportion of the actual correct classified ones, as illustrated in Fig. 6.

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TPR = \frac{TP}{TP + FN}
\]

It is important to note, that WII targets the classification of the interfering signals. The known utilized signal is, therefore, an unwanted one and therefore distorts the snapshots.

A. Single-Label Classification

First, the proposed multi-label WII approach was compared with single-label WII one from Schmidt et al. [6]. Therefore, the same single-label validation dataset from Schmidt et al. was utilized. The resulting averaged TPR is shown in Fig. 7 with the varying SNR. Thereby, the proposed approach only
differs for a SNR below -8 dB. Below, the multi-label WII approach is up to 10.14% worse and subtracts a processing gain of up to 1.1 dB. Hence, the single-label WII approach from Schmidt et al. [6] results in slightly better performance with the assumption of single-label data, and therefore without any utilized signal.

B. Same-Technology Interference Classification

The results of the multi-label WII approach with STI are shown in Fig. 8. Thereby, the snapshots contain a utilized signal and a varying number of interfering signals of the same WT.

The classification of STI with the narrow-band WTs IEEE 802.15.1 and IEEE 802.15.4 approach a TPR of one. The optimal behavior results from the limited spectral overlapping of the superimposed signals. Another reason is that the sensing bandwidth entirely covers signals from both WTs IEEE 802.15.1 and IEEE 802.15.4. Additionally, the TPR of IEEE 802.15.1 STI interferences is independent of the number of interfering signals, and therefore also it is independent of the frequency channel of the utilized signal.

In contrast, the TPR of a wide-band IEEE 802.11 b/g STI signal is worse and drops even further with multiple signals. Such signals are only partially within the sensing bandwidth of a snapshot. Another reason is that the inter-signal overlapping is significant. Therefore, the differentiation between interfering signals and the utilized signal is more difficult. Additionally, the high variation of the TPR indicates the frequency channel dependency of the utilized signal.

C. Cross-Technology Interference Classification

Figure 9 shows the evaluation for CTIs. It is noticeable, that the TPR for three IEEE 802.11 b/g interfering signals increases. This unexpected behavior may result from the combinatoric property that for three possible options the probability for one or three correct ones is higher than two correct ones. It is also possible that the CNN is overfitting for three IEEE 802.11 b/g interferers.

For CTI with an IEEE 802.11 b/g utilized signal the proposed approach results in a slightly better TPR. This is because the bandwidth of the IEEE 802.15.1 and IEEE 802.15.4 signals are narrow compared to the snapshot bandwidth and therefore less overlapping interference occurs.

In case of a wide-band IEEE 802.11 b/g utilized signal the narrow-band interfering signals suffer from the spectral intersection. It results in a decrease of the TPR. Additionally, the high variation of the TPR indicates the frequency channel dependency of the utilized signal.

VI. Conclusion

The steadily growing use of license-free frequency bands requires reliable coexistence management and therefore proper wireless interference identification (WII). In this work, we propose a WII approach based upon deep convolutional neural network (CNN) which extends our work [6]. The CNN naively learns its features through self-optimization during an extensive data-driven training process. In contrast to our previous work, we target coexistence management for cooperative utilized wireless communication system (WCS) which are interfered by non-cooperative WCSs. We analyzed WCSs with the wireless technologies (WTs) IEEE 802.15.1, IEEE 802.11 b/g and IEEE 802.15.4. Hence, our approach classifies multiple interfering signals in the presence of a utilized signal. Therefore, it is multi-class and multi-label classification problem.

For multi-label dataset generation, the single-label one from Schmidt et al. [6] has been combined. They are frequency- and time-limited with the bandwidth of 10 MHz and duration of 12.8 µs, respectively. Therefore, the 2.4-GHz-ISM band is divided into eight spectral non-overlapping sensing sub-bands. Each sub-band contains fifteen frequency channels of the WTs, and therefore also fifteen classes. The multi-label dataset contains in total 450,000 snapshots. Each snapshot combines one utilized signal with up to six interfering signals with a signal-to-interference ratio (SIR) of one.
The approach shows promising results for same- as well as for cross-technology interference (STI, CTI). The same-technology interference (STI) classification accuracies of spectral non-overlapping narrow-band IEEE 802.15.1 and IEEE 802.15.4 are approximately 100%. In contrast, spectral overlapping wide-band IEEE 802.11 b/g suffers from low accuracy of at least 78%.

For cross-technology interference (CTI) IEEE 802.15.1 and IEEE 802.15.4, the accuracy slightly drops down to at least 95%, because the utilized and interfering signals are partly spectral overlapping. However, for IEEE 802.11 b/g the accuracy even increases with at least 90%. It takes advantage of the narrow-band utilized signal.

For future work, the evaluation has to be experimentally validated within industrial environments.

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