WLAN Interference Identification Using a Convolutional Neural Network for Factory Environments

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\textbf{Abstract}—Factory communication systems require highly reliable links with predictable performance and quality of service in order to avoid outages that can damage the production-line process. Communication anomalies can be caused by narrowband interference which is difficult to identify and track from the time-domain information only. This paper describes a methodology for classifying increasing severity and types of interference in order to improve throughput prediction. Received signal strength (RSS) data is collected from both a ray-tracing simulation and a Wireless Local Area Network (WLAN) measurement campaign with a transmitter mounted on an actual automated guided vehicle (AGV). Scalogram time-frequency images are computed from the RSS signal and a convolutional neural network (CNN) is then trained to recognize the spectral features and enable the interference classification. The block random interference could be correctly classified on over 65\% of the occasions in the ray-traced channel at 30 dB SNR.

\textbf{Index Terms}—WLAN, CNN, deep-learning, interference, scalogram, ray-tracing, factory communications

I. INTRODUCTION

Communication infrastructure in factory and industrial settings still use fixed-wire links such as Ethernet or proprietary-based technology to a considerable extent. Recently there has been a growing trend to employ wireless technology in factory systems [1] thanks to the continual improvement in data-rate, multi-user support and robustness. These systems include IEEE 802.11 wireless local area network (WLAN) [2] and wireless personal area networks such as IEEE 802.15.1 or IEEE 802.15.4 [3]. Factory communication infrastructure needs to support transmission of time critical data at sufficient rate to avoid control instability and ultimately failure. With evermore complex systems, increasingly higher bandwidth signals need to be transported such as from multiple surveillance cameras on the production floor. Meanwhile there are many potential sources of electromagnetic interference such as wireless communication devices for wireless LAN, Bluetooth and ZigBee, cordless phones and microwave ovens in the unregulated 2.4-2.5 GHz industrial, scientific and medical (ISM) band. There are also many physical obstructions such as workers, robots or equipment that can potentially block or degrade the communications links.

In order to improve the reliability of a factory communication link, prediction of received signal strength (RSS) and throughput is required enabling advanced warning of pending anomalies. There have been a number of researches towards this goal in the literature. Future RSS samples were predicted at multiple receivers (Rx) for a transmitter (Tx) placed on an automated guided vehicle (AGV) using a probabilistic neural network (PNN) in [4]. Transmission control protocol (TCP) throughput prediction using support vector regression was made in [5]. Improvements in the quality of adaptive video using wireless traffic prediction using [Fractional] Auto-Regressive Integrated Moving Average ([F]ARIMA) time-series models were described in [6]. Recently we described methodologies to predict throughput using the PNN for time-series prediction providing optimized weights for a convolutional neural network (CNN) in [7] and for predicting anomalies in throughput using a kernel density estimation technique for multiple bandwidths in [8]. It is considered that the reliability of throughput prediction systems could be further enhanced with reliable information provided on the type and severity of the interference present.

Radio frequency interference (RFI) detection using K-nearest neighbor and random forests were shown to outperform a Bayesian based detector in [9]. Sensing temporal and frequency interference characteristics was demonstrated by employing a semi-Markov chain and data with a Poisson-distribution arrival rate in [10]. A CNN was applied to detecting images generated from the FFT of the complex signal received by an astronomy

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array antenna in [11]. It was shown that RFI could be detected by the abrupt change in the amplitude of the signal likely to appear as high intensity pixels and distinguished from the noiseless data by the difference in statistical distribution. A narrow-band interference model specifically for an Orthogonal Frequency Division Multiplexing (OFDM) communication system operating over a power-line was described in [12]. We assume an energy detector Rx and simple model for the received signal after interference has been added and the proposed system is not restricted to any modulation scheme. Interference may appear random and unstructured when examined solely in the time-domain. The fast Fourier transform (FFT) is a most widely used function for analysis of the signals in the frequency domain. However, while the short-term Fourier transform, which divides a signal into small windows, can provide information with either good frequency resolution or good time resolution, it cannot provide both simultaneously with accuracy [13]. The scalogram on the other hand simultaneously provides time-frequency information using the wavelet transform. There are a number of articles in which wavelets have been applied to the classification of normal and irregular or interfering signals using pattern matching. For example, heartbeat irregularities have been successfully identified using the wavelet transform by examining the departure from regularly spaced signal pulses [14]. Epilepsy detection was demonstrated by applying deep learning to scalograms in [15] and the wavelet transform has also been used to identify problems in asynchronous machines [16].

Deep-learning can be applied to recognize features of the two-dimensional scalogram image as part of an automated system. Examples of applications include radiology [17] and earthquake detection [18]. It has also been demonstrated that the CNN trained using general images such as animals or cars for example can also perform well at detecting features from other types of images such as scalograms. This is because once-trained the network is able to detect edges, areas and features irrespective of the particular object.

In this work we employ ray-tracing to model the RSS data variation based on the constructive and destructive addition of multipath rays [19] and also record actual RSS data from an actual WLAN experiment.

A. Ray-tracing Simulation

A ray-tracing simulator generates RSS data variation based on the vector addition of multipath rays [19]. The factory room has dimensions of 20m-by-20m and two scatterers are randomly placed within this area. AGV are now common in warehouses such as those used by several well-known Internet shopping companies for collecting and transporting products to a dispatch area. The Rx are placed at fixed positions and the Tx is mounted on an AGV which moves along a known route at a fixed speed of 1 m/s following the black dashed line in Fig. 2. The simulation settings are summarized in Table I.

B. WLAN Measurement Campaign

A plan-view showing the layout of the experiment environment and measurement locations is depicted in Fig. 3. RSS measurements were recorded in an L-shaped corridor on the 3rd floor of a Japanese office building. The dimensions of the long corridor section
were 30m × 2.2 m and the short-section has dimensions 7m × 2 m. The corridor is surrounded by office rooms mainly comprising a metal floor and metal-backed or concrete wall contributing to a rich multipath scattering environment. The plasterboard ceiling was at a height of about 2.6 m and had metallic fixings of approximate dimensions 1m × 0.5 m containing fluorescent strip-lights at about 3 m intervals.

Fig. 3. Plan view of the experiment environment showing location of Tx, Rx, sniffing station and route of the AGV.

Fig. 4. Photograph of experiment environment showing (left) mobile Tx station, and (right) AGV loaded with metallic rack and case.

The Tx was first positioned in an adjoining room behind a door at Location-A at the top of the short-corridor section and then sequentially moved to measurement locations labeled A-F. A photograph of the experiment environment showing the mobile Tx station is shown in Fig. 4 (left). The unloaded AGV vehicle has a relatively low-profile at 30 cm height and to simulate a loaded vehicle a metallic trolley and suit-case were additionally placed on top of the AGV as seen in Fig. 4 (right). The AGV moved at a speed of about 0.3 m/s.

A PC running WLAN sniffing software with modified WLAN adapter card operating in promiscuous mode was placed half-way along the corridor opposite to Location-F. The Windows Media Player software was configured to stream 4K-video from the Tx to Rx which was placed on a chair 2.5 m from the west end of the corridor and at a height of 0.5 m. The WLAN packet data was recorded by the sniffing-PC over a duration of about 1 minute for each Tx position. The sniffer data file was imported into Matlab and 16 fields extracted including the packet number, time-stamp, data length, signal and noise power. As the packets arrive randomly and have different lengths the data is irregularly sampled and we processed this to provide estimated signal to noise ratio (SNR) at regular 1 ms intervals. The cumulative distribution function (CDF) of the RSS SNR at locations [A, B, C, D, E] is shown in Fig. 5. It can be seen that there was a variation of up to 30 dB in the SNR values (99% level) at the measured locations. The locations A-D have a non line-of-sight (NLOS) link while Location E has a line-of-sight (LOS) link of to the Rx and WLAN sniffer. A portion of the packets are therefore received at Location E with a higher average SNR compared to the other locations as expected.

Fig. 5. CDF of RSS SNR for Tx at locations A-F with moving AGV.

C. Addition of Interference

Distributed or block interference is added to the frequency domain RSS signal. For both interference types the total number of interfered samples is steadily increased from 50 to 1500 in steps of 50 samples. The RSS signal together with its mean-value from the ray-tracing simulation is depicted in Fig. 6(a). In this work we assume that the signal at the Rx is sampled by an energy detector and that the interference vector adds constructively or destructively on each sample such that the signal plus interference sums to the mean level. An example where the block interference for the first \( N_s = 100 \) samples are set to the average value is shown in Fig. 6(b). Similarly a case where 100 randomly distributed samples are set to the average value is shown in Fig. 6(c).

Fig. 6. Ray-tracing RSS waveform in frequency domain showing (a) average signal value indicated by the dashed line, (b) block interference with first \( N_s = 100 \) samples set to the average value, (c) 100 distributed random samples set to the average value.

III. SIGNAL PROCESSING

After generating the 2D scalogram images for each RSS signal with increasing amounts of interference, we first train the CNN to categorize each Red-Green-Blue (RGB) image in the absence of receiver noise. We then
add additive white Gaussian noise (AWGN) to the time-domain signal and compute the accuracy to which the CNN can correctly categorize the amount of interference for each type.

A. Time-Frequency Analysis

The 2D scalogram decomposes the signal in order to identify and detect periodic components. In contrast to the Fourier transform, wavelets can be used to classify arbitrarily small time-interval signals [21]. The scalogram is efficiently computed using the continuous wavelet transform (CWT) [22]. The CWT is expressed as the product of the information signal \( f(t) \) and wavelet function \( \phi(t) \) as:

\[
T(a,b;f(t),\phi(t)) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \phi \left( \frac{t-b}{a} \right) dt
\]

where \( \phi(t) \) is the mother wavelet, \( a \) is a scale parameter, and \( b \) is a translation (time) parameter. The analytic Morse wavelet is used as CWT in the filter bank. Morse wavelets are useful for analyzing modulated signals, transients, and short-duration signals [23]. There are two control parameters for Morse which allow increased control over, for example the Morlet wavelet which uses a single parameter.

The scalograms for increasing levels of randomly distributed interference are plotted in Fig. 7. The red region shows the strong time-frequency component of the RSS signal. The abrupt change in frequency at about one-third of the way across the time interval (x-axis) corresponds to the change in direction of the AGV by 90 degrees as indicated in the ray-tracing layout of Fig. 2. Increasing amounts of noise can be seen by the blurred white areas particularly in the high frequency regions i.e. top half of each figure. There is also progressively more noise seen within the signal itself i.e. on the red line. Similarly, scalograms corresponding to increasing amounts of block interference are shown in Fig. 8. It can be seen that as the number of interfered blocks increases sections of the strong red signal region are progressively removed. The distributed interference scalograms have similar features which become relatively hard to distinguish in noise. A block interferer on the other hand removes a large section of the well-defined signal (red colour) and each resulting scalogram can be easily discerned. The structure of the non-dominant signal (non-red) also becomes relatively stronger as seen in sub-figure 8 of Fig. 8. The scalograms for increasing levels of randomly distributed interference from the WLAN trials with the Tx at location B with moving AGV present are plotted in Fig. 9. Unlike in the ray-tracing simulation, the AGV does not move at a precise constant speed or course in part due to its heavy load and, also there are many more potential scatterers present. The walls, floor and ceiling in the trials environment contribute to a much richer multipath environment and together with random movement of people walking, this contributes to a less-defined signal with no dominant Doppler frequency present.

B. Convolutional Neural Network

The CNN calculates weights in order to minimize a loss function between trained and evaluation image data. The net-work comprises three principle layers: convolutional, pooling and fully-connected layers. A typical convolutional layer filter has dimensions 5x5x3 for detecting small features, edges and patterns in RGB images with 3-color depth. Pooling layers are inserted periodically to reduce the complexity by down-sampling the input data. Neurons in the fully-connected layer are connected to all activations in the preceding filter: their construction is similar to that in the convolutional layer but they are not confined to a local region. The rectified linear unit (ReLU) is gradually replacing use of the sigmoid for activation function computing \( \text{max}(0,k) \) which reduces the complexity as well as influence of low-value or noisy input data, \( k \).

GoogLeNet is a CNN that was trained using a subset of everyday images from the Open Source ImageNet database [20], [24]. It has been shown that although the CNN is trained on generic images the developed network structure is suit-able for classifying other input images, for example electro-cardiograms. The scalogram has the same dimensions as the everyday images used in the training and is treated as a normal RGB photo image. In this work the network settings were set as: dropout = 0.63, and initial learning-rate = 0.001.

IV. PERFORMANCE EVALUATION

The performance is evaluated through a Monte-Carlo software simulation comparing the accuracy between the actual and predicted number of interfering samples. A
Correct categorization is determined to be when the exact number of frequency domain interfering components is correctly estimated. For example, if the number of samples containing interference was 200 but the CNN classified the scalogram as having 250 interfering samples then this was classified as an error. A comparison of the classification accuracy for distributed versus block interference for the ray-tracing simulation is shown in Fig. 10. The results show that the random block interference could be correctly classified in over 65% of the trials at 30 dB SNR and rising to 78% in 50 dB SNR. The block interference in which 50 or more continuous frequency domain samples were adjacent to each other was more often correctly categorized by the CNN. The randomly distributed interference was more difficult to classify with success rate between 50–60%. The performance result for exactly classifying the size of distributed interference on the RSS signal collected at trials locations B, D, and E is summarized in Table II. The system works best where there are a certain number of strong time-frequency signature signals that could be generated by a moving transmitter with fairly constant speed. The categorization accuracy was observed higher in the NLOS channels where there was a large number of packets received by multipaths that could potentially aid the CNN in categorizing the interference.

![Fig. 9. Scalograms for increasing amounts of distributed random interference in experiment trials.](image)

**TABLE II: PERFORMANCE ACCURACY FOR TRIALS LOCATIONS**

<table>
<thead>
<tr>
<th>Location</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>50%</td>
</tr>
<tr>
<td>D</td>
<td>46%</td>
</tr>
<tr>
<td>E</td>
<td>33%</td>
</tr>
</tbody>
</table>

The requirement of estimating exactly the number of interfering samples was quite strict. As a typical narrowband interference signal such as from competing Wi-Fi or Bluetooth will generate a block of interference the proposed system with near 80% success rate is considered a suitable and promising method for its identification. There are 30 target values of increasing size for the interferer i.e. [50, 100, 1500] and therefore randomly guessing the number correctly would exhibit an average success rate of 3.33%. In this respect a 50% accuracy rate could be considered very good and should provide useful information to the higher layer anomaly prediction unit. It is also possible that the anomaly prediction unit would operate efficiently with fewer categories of the interference such as a 5-level scale and quantization of the interference feedback is a potential area for further work.

![Fig. 10. Comparison of the average classification accuracy for random block versus distributed interference from ray-tracing simulation.](image)

**V. FUTURE WORK**

The intensity scale used in generation of the RGB figure could potentially be optimized in order to use the full dynamic range of 256 values. Removal of low-value RSS samples by a moving-average filter prior to the scalogram could improve the performance. The current ray-tracing model could be enhanced by increasing the number of scatterers, adding information on the floor and wall reflectivity and include NLOS modeling. The size of the Monte-Carlo simulation could be enlarged by increasing the number of AGV routes, as well as the number and bandwidth of interfering signals. Further WLAN trials measurements could be conducted to collect an increased range of channel types. The study of scalograms in the presence of multipath-rich multiple input- multiple output (MIMO) channels is an interesting area for future research. The scalogram block-size and sampling-rate are also important parameters that should be optimized and may further improve the performance of the results. The size of the interfering blocks could be considered as a step-wise optimization exercise considering the size of the estimation error. Finally, the classification performance of time-varying interferers could potentially be improved by sampling the RSS at multiple Rx locations.

**VI. CONCLUSION**

We have demonstrated a machine learning based methodology enabling the classification of distributed and block interference of increasing severity through the spectral decomposition of RSS data collected from both a ray-tracing simulation and WLAN experiment. The CNN was able to categorize the RSS signals in the presence of block interference with higher success compared to the equivalent amount of distributed interference with nearly 80 percent accuracy achieved for the ray-traced channel. The actual WLAN channel is
complex with many scatterers present and this contributes to the reduced classification accuracy of 50% in the NLOS channel. It is envisaged that the proposed system can be utilized by a WLAN performance predictor unit in order to improve the reliability of pending outage prediction when in the presence of interference.

**CONFLICT OF INTEREST**

There are no conflicts of interest.

**AUTHOR CONTRIBUTIONS**

JW measured the channel, ran simulations, and wrote the paper. KY provided technical advice including on interference & WLAN, NS, EN advised on simulation, YH assisted with channel measurement, TH advised on network issues, AM advised on wavelets and CNN, and YS advised on system concept. All co-authors provided input to the paper through regular discussions. KY and YS directed the project part under JPJ000254.

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