Simulating the Physical Layer of Body-Coupled Communication Protocols

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***Abstract*—Modeling, simulating, and testing communication links are core components of telecommunication research. However, novel communication methods such as Body-Coupled Communication (BCC) do not currently have readily available protocol implementations. In this extended abstract, we present a Python module that implements the BCC physical layer (PHY). Furthermore, we demonstrate how to use this simulator in conjunction with a machine learning model that estimates signal loss in a human body. This work enables researchers to obtain bit-error rate estimates for communication through various human body types, depending on parameters such as data rate, noise level, and carrier frequency.**

***Keywords*—BCC, physical-layer, software-defined radio, modulation**

I. INTRODUCTION

Radio Frequency (RF) telecommunication research relies on the support of many existing network simulators such as ns-3 and scientifically validated signal propagation models. RF links can also be experimentally realized in the real world with the help of commodity hardware, or with software-defined radios (SDR). In contrast, the state of research of BCC is at a low technology readiness level (TRL), and very few tools are available for BCC protocol researchers. Work towards a more mature BCC research ecosystem is needed.

This extended abstract introduces a new simulator for the BCC physical layer. We describe its components and show how it can be integrated with a human body model to simulate communication performance depending on various parameters of the human, the connection setup, and the protocol itself.

II. NUMERICAL SIMULATOR

The goal of the simulator is to enable experimentation in BCC protocol research and prototyping, without the need to be restricted to real-world setups. To this end, we implement a simulator that, at its current form, takes a stream of input bits ("tx data") and turns them into output bits ("rx data"). The discrepancies between the inputs and outputs correspond to the *bit error rate* (BER) of the communication channel, and can be used to evaluate the suitability of a given communication protocol and its parameters for a given channel. The target communication protocol for this study is the one from the IEEE 802.15.6 standard [1], which defines the so-called Human Body Communication (HBC) PHY and MAC layers.

The simulator is implemented using the Python programming language, with NumPy and SciPy libraries. The main blocks of the simulator module are shown in Fig. 1.

A key block of the simulator is the modulation function. As defined in IEEE 802.15.6, it uses binary frequency shift keying (FSK). The default value of the center frequency F_{center} is set to 21 MHz, as in the standard, and the constant modulation index h is set to one. The deviation frequency $F_{deviation}$ therefore depends on the datarate R_{data}, as the simulator automatically switches to a wider channel (larger bandwidth) to transmit higher rate data, and keep the index h constant.

The default sampling rate R_{sample} is set to 52.5 MHz. This datarate value was chosen to prevent spectral leakage and comply with the Nyquist criteria that is given as a solution to the equation

$$2 \times (F_{center} + h \cdot R_{data}) = R_{sample} \tag{1}$$

When solving this equation using the numbers from above, the maximum R_{data} is equal to 5.25 Mbit per second. This is more than sufficient to simulate the maximum bitrate of 1.3125 Mbit per second from the IEEE 802.15.6 standard.

After modulation and upsampling, the signal is divided by a constant signal loss parameter, obtained either directly from configuration settings, or from a signal loss model (Section III). More specifically, for a given value of signal loss L in dB, the signal S is divided by $10^{\frac{L}{20}}$.

Subsequently, the signal is mixed with noise. We use Additive White Gaussian Noise (AWGN) with zero mean μ and fixed standard deviation σ, given as a configuration parameter.

As a next step, the signal is filtered using 5-th order Butterworth bandpass filter with constant bandwidth of 5.25 MHz. This number is defined in the IEEE 802.15.6 standard as the spectral mask; Fig. 2 shows the shape of the mask. This ensures that the simulation adheres to the standard and produces results that are comparable with results obtained in real-world experiments.

Finally, the signal is demodulated and downsampled in order to obtain a stream of bits to be received. We use the Hilbert transform on the signal, and multiply it with $-F_{center}$ in order to remove carrier frequency. To demodulate the baseband signal, phase is first extracted for each sample. The difference between the latest and previously extracted phases is then calculated and classified as either 0 or 1, resulting in a stream of bits as the final output.

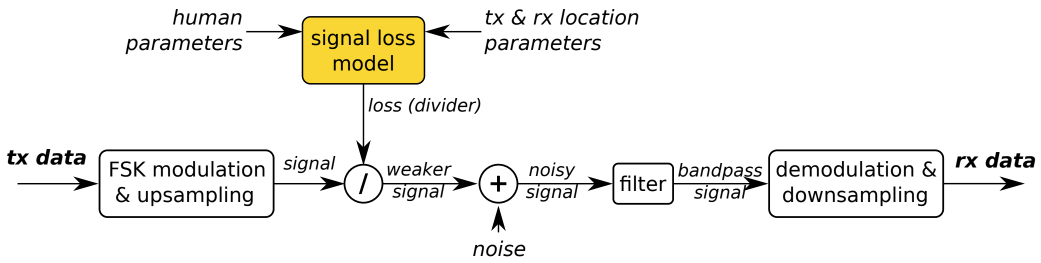

Fig. 1. Overview of the simulation of PHY layer BCC.

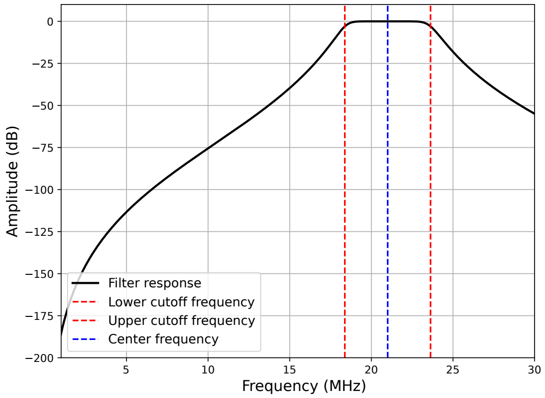

Fig. 2. Spectral mask of the simulated channel filter.

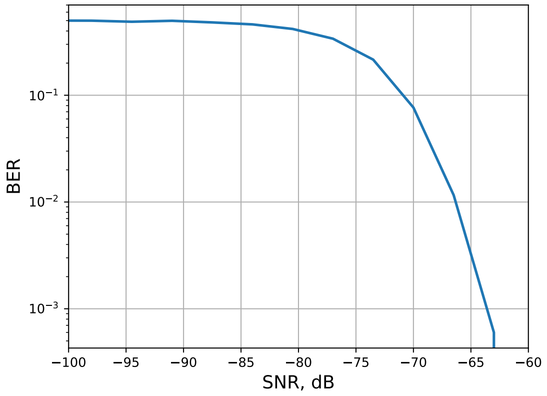

Fig. 3. Bit error rate (BER) depending on the signal-to-noise ratio (SNR).

To test the accuracy of the simulations, we evaluate the BER depending on the signal-to-noise ratio (SNR). Fig. 3 shows the results. The shape of the BER curve matches the expected shape for binary FSK modulation, providing evidence that the simulation is accurate.

III. INTEGRATION WITH A SIGNAL LOSS MODEL

Based on dataset collected from more than 20 volunteers, we implement several signal loss models that allow to predict the signal loss in a human body. The first is a mathematical model based on approximating the human body as a schematic from electronic components [2]. This model offers a good level of insight on where does the loss comes from, but is not accurate or easy to use. Therefore we additionally developed a number of machine learning models. We investigate both parametric and non-parametric options: linear regression and random forests, respectively, and look at both multi-frequency and single-frequency models. The former have signal frequency as one of the parameters to use in prediction; the latter are fine-tuned to a specific frequency. The results show that random forests (RF) have the best predictive accuracy ($> 0.72 R^2$ score for a multi-frequency model), even though they offer the least level of insight compared with the other types of models.

The PHY simulator module is then integrated with the RF-based signal loss model. The resulting simulation enables researchers to obtain bit-error rate estimates for communication through various human body types. At the first level, it takes the following inputs: human-specific parameters (weight, BMI, sex etc.); connection-specific parameters such as distance between communication points and body composition at the points. Based on these inputs, it estimates the signal loss, and uses this signal loss along with signal-specific parameters such as the data rate and noise level, in order to estimate the BER.

IV. CONCLUSION

We believe that our implementation of a PHY layer simulation using elements from the IEEE 802.15.6 standard offers a reliable and accurate approach for studying Body-Coupled Communication. It includes signal propagation, modulation/demodulation, filtering, as well as allows to use a human body model as an input component in order to determine the signal loss in the communication channel.

Our future plans envision extending this work along two different directions. The first is implementation of the missing elements such as framing, check-summing, and MAC-layer functionality from the IEEE 802.15.6 standard. The second is our work-in-progress on a software-defined radio (SDR) library that uses Python components for the BCC-specific details, and can be run on physical SDR such as HackRF. Once completed, the SDR code will be used in demonstrators, and to test BCC protocol performance on real test subjects.

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