

Prototyping of a wireless communication system with channel estimation based on quantum support vector machines

Caio N. Silva and João T. Dias

Abstract—This work presents an over-the-air (OTA) OFDM software-defined radio (SDR) prototype using GNU Radio and two HackRF One devices to evaluate classical and quantum-kernel channel estimation. LS, LMMSE, Support Vector Regression (SVR), and quantum-kernel SVR (QSVR) are compared on identical received IQ samples under controlled Gaussian and impulsive noise. BER, packet recovery, latency, and processing throughput are evaluated. Results show that the kernel-based estimators remain competitive with conventional approaches, demonstrating the feasibility of quantum-kernel channel estimation in a complete over-the-air SDR receiver.

Keywords—SDR, OFDM, channel estimation, quantum ML.

I. INTRODUCTION

Orthogonal Frequency Division Multiplexing (OFDM) is widely used because of its efficient implementation and robustness against frequency-selective channels [8], [9]. Its performance, however, strongly depends on channel estimation, since estimation errors directly affect equalization and BER [1]. LS offers low complexity, whereas statistical and learning-based methods may improve robustness under adverse channel conditions.

In a previous study by the authors [11], Support Vector Regression (SVR) and quantum-kernel SVR were investigated for OFDM channel estimation in a simulated environment under impulsive noise. The present work addresses the experimental gap by investigating their integration into a complete over-the-air GNU Radio/HackRF receiver, where synchronization errors, RF impairments, multipath propagation, and computational constraints are also present. We investigate whether classical and quantum-kernel regression can provide competitive communication performance relative to conventional LS and LMMSE estimators. The main contributions are: (i) the implementation and validation of SVR and QSVR channel estimators in an SDR receiver; (ii) a paired comparison with LS and LMMSE using identical received IQ samples; and (iii) an evaluation of BER, packet recovery, latency, and processing throughput under controlled Gaussian and impulsive noise.

II. SYSTEM MODEL

The prototype uses GNU Radio and two HackRF One devices for over-the-air transmission and reception. The devices

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TABLE I
MAIN EXPERIMENTAL PARAMETERS.

Parameter	Value
Sampling rate / carrier	8 MHz / 907.98 MHz
FFT / cyclic prefix	64 / 16 samples
Subcarrier spacing	125 kHz
Data / pilot carriers	48 / 4
Occupied / pilot indices	$[-26, 26] / \{-21, -7, 7, 21\}$
Header / payload	BPSK / QPSK
Packets / payload	200 / 50 bytes
Fig. 2: SNR / A_{imp}	20 dB / 5
Fig. 2: p_{imp}	$[10^{-4}, 2.5 \times 10^{-3}]$
Realizations / point	8
TX RF / IF / scale	14 dB / 40 dB / 0.03
RX RF / IF / BB	14 / 32 / 22 dB
TX/RX bandwidth	7 MHz
TX–RX distance	≈ 1.9 m

were kept stationary at approximately 1.9 m in a furnished indoor environment with fixed antenna orientation. Table I summarizes the configuration. The OFDM carrier allocation was adapted from IEEE 802.11a [7], while RF gains and bandwidth were fixed through a separate calibration campaign. The 907.98-MHz carrier and antenna were selected from NanoVNA impedance measurements.

The receiver follows the general GNU Radio OFDM architecture. Its native OFDM Channel Estimation block uses synchronization symbols to estimate the coarse carrier offset and the initial equalizer taps, which are propagated as stream tags to the OFDM simple DFE equalizer [5]. Custom Python blocks preserve the same interface for LMMSE, SVR, and QSVR. Figure 1 summarizes the implemented SDR chain. The source code, and experimental scripts are available from the authors by e-mail upon reasonable request.

For paired comparison, each OTA capture is retained in a shared in-memory IQ buffer before estimator processing. Synthetic noise is then applied and all four branches consume identical samples, verified by hash validation. This also decouples HackRF acquisition from the larger computational cost of the learning-based estimators.

A. Channel Estimators

The native GNU Radio estimator provides the LS reference. LMMSE regularizes these observations using a 16-tap exponentially decaying power-delay profile (decay 0.7) and relative noise regularization 0.03 [1].

For a known synchronization symbol, the conventional LS

channel observation at active subcarrier k is

$$\hat{H}_{LS}[k] = \frac{\hat{s}[k]}{s[k]}, \quad (1)$$

where $s[k]$ and $\hat{s}[k]$ are the transmitted and received synchronization symbols, respectively.

The SVR and QSVR estimators operate on the second known synchronization symbol. Their reference-corrected observation is

$$Z[k] = s^*[k]\hat{s}[k]. \quad (2)$$

Since the second synchronization symbol is unit-modulus BPSK, $s[k] \in \{-1, +1\}$, $Z[k] = H[k] + \tilde{W}[k]$. Unlike the previous simulation formulation [11], the present estimators use these reference-corrected observations directly as regression targets.

The learning model maps the normalized subcarrier index x_k to the real and imaginary parts of $Z[k]$. Since the channel response is complex-valued, two regressors are used:

$$\begin{aligned} \Re\{Z[k]\} &\approx f_R(x_k), \\ \Im\{Z[k]\} &\approx f_I(x_k). \end{aligned} \quad (3)$$

Both learning-based estimators use every fourth active carrier and employ robust support-vector regression motivated by impulsive-noise OFDM channel estimation [2]. Separate models are fitted to the real and imaginary channel components with $C = 100$, $\epsilon = 0.01$, $\delta = 0.2$ and $\gamma = (n_f \text{Var}(\mathbf{X}))^{-1}$, where n_f is the number of input features. These SVR hyperparameters were selected in a preliminary paired search before the final experimental campaign.

The QSVR retains the same regression structure but replaces the classical RBF kernel by a quantum state-fidelity kernel [3], [4], [13],

$$K_Q(\mathbf{x}_i, \mathbf{x}_j) = |\langle \phi(\mathbf{x}_i) | \phi(\mathbf{x}_j) \rangle|^2. \quad (4)$$

A circular positional encoding is adopted for the subcarrier coordinate:

$$\mathbf{x}_k = \frac{\pi}{4} \left[\sin\left(\frac{2\pi k}{N}\right), \cos\left(\frac{2\pi k}{N}\right) \right], \quad (5)$$

This periodic representation parameterizes a two-qubit Rx-Ry feature map with one repetition and linear entanglement. Because carrier coordinates and the reference subset are fixed, the exact-statevector training and prediction Gram matrices are computed once and reused across frames; only the regression targets change.

III. RESULTS

Global BER is adopted as the primary end-to-end performance metric because it accounts for both bit errors in recovered packets and packets that are not successfully recovered. Conditional BER, PER, and detection rate were also recorded as diagnostic metrics, but are omitted from the main figure for clarity.

Additional synthetic noise is applied after the over-the-air capture according to

$$y[n] = \bar{y}[n] + w[n] + b[n]i[n], \quad (6)$$

where $\bar{y}[n]$ is the HackRF received signal, $w[n] \sim \mathcal{CN}(0, P_{\text{ref}}10^{-\text{SNR}/10})$, $b[n] \sim \text{Bernoulli}(p_{\text{imp}})$, and $i[n] \sim \mathcal{CN}(0, A_{\text{imp}}^2 P_{\text{ref}})$. The reference power was measured and calibrated before the campaign and kept fixed for all synthetic-noise realizations. The reported SNR therefore represents the target SNR of the software-injected AWGN and not the absolute SNR of the physical radio link.

All estimators process the same IQ and noise realization within each trial, resulting in a paired comparison. Only runs satisfying capture-integrity, buffer, and shared-IQ consistency checks are included. The BER curves report the mean across valid realizations, while error bars indicate one standard deviation.

Figure 2 shows the mean global BER as the impulsive-noise probability increases; error bars denote one standard deviation over eight independent realizations.

As the impulsive-noise probability increases, the global BER increases for all four estimators. LMMSE achieves the lowest mean BER over most of the evaluated range, confirming it as a strong conventional reference. RBF-SVR and QSVR remain close to LMMSE and exhibit a modest tendency toward lower mean global BER than LS as the impulsive contamination becomes stronger. The dispersion of the learning-based estimators remains comparable to that of LS across the evaluated conditions.

The differences are small relative to the run-to-run experimental variability and therefore should not be interpreted as statistical evidence of superiority. For now, the results indicate that kernel-based regression can preserve, and under some degraded conditions slightly improve, the end-to-end performance of the conventional LS receiver. The experimental QSVR results should therefore be interpreted as evidence of implementation feasibility and competitive robustness rather than as evidence of quantum advantage.

TABLE II
COMPUTATIONAL PERFORMANCE OVER VALID EXPERIMENTAL RUNS.

Estimator	Time [s]	Throughput [MS/s]	Estimator RTF
LS	1.52 ± 0.14	32.77 ± 3.04	–
LMMSE	1.66 ± 0.21	30.25 ± 4.01	7.93 ± 1.10
RBF-SVR	3.72 ± 1.30	16.33 ± 9.25	179.70 ± 13.87
QSVR	3.44 ± 1.15	17.24 ± 9.07	153.76 ± 12.66

The computational results also show that BER alone does not characterize the feasibility. LS and LMMSE exhibit substantially lower processing cost than the kernel-based estimators. Although both RBF-SVR and QSVR process the buffered experimental capture at an average throughput above the 8-MS/s acquisition rate, their estimator real-time factor (RTF) values are substantially greater than one, indicating that the channel-estimation operation itself would not keep pace with a continuously occupied OFDM frame stream.

IV. CONCLUSIONS

This work experimentally evaluated LS, LMMSE, RBF-SVR, and QSVR channel estimation in an over-the-air GNU Radio/HackRF OFDM receiver. A shared-IQ architecture enabled paired comparisons under identical physical captures and

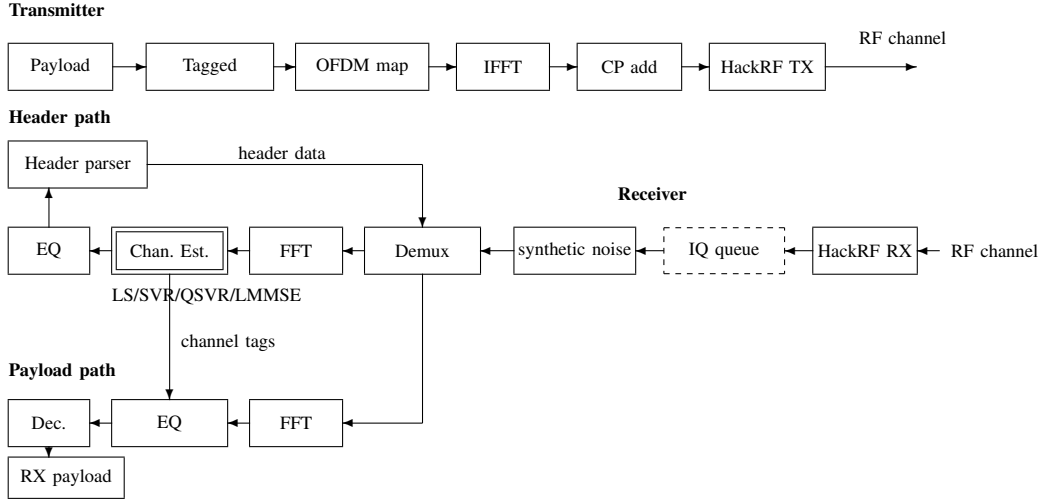
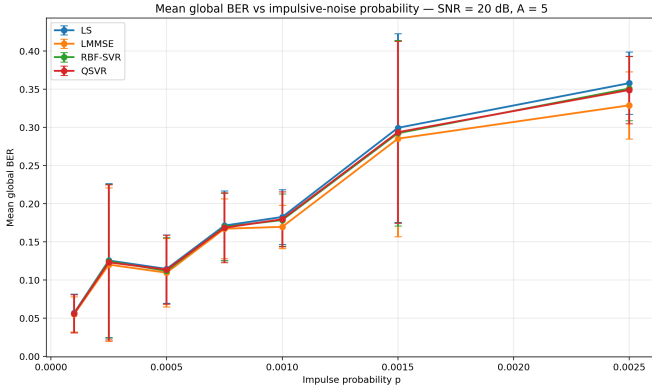


Fig. 1. Simplified GNU Radio OFDM SDR prototype.


 Fig. 2. Mean global BER versus impulsive-noise probability at a target injected AWGN SNR of 20 dB and $A_{\text{imp}} = 5$. Error bars denote one standard deviation across valid independent realizations.

synthetic-noise realizations. Although the SVR- and QSVR-based estimators remain under active development and further refinement is expected in future iterations of this work, the proposed implementation provides a solid experimental foundation for the development, prototyping, and evaluation of data-driven channel estimators in real SDR-based OFDM systems.

Under increasing impulsive-noise contamination, the kernel-based estimators already remain competitive with the conventional references and showed a modest tendency toward lower mean global BER than LS in the more degraded operating region. LMMSE provided the strongest conventional performance over most conditions, whereas QSVR closely followed its classical RBF-SVR counterpart.

Nevertheless, the results demonstrate the feasibility of integrating a quantum-kernel channel estimator into a complete over-the-air SDR receiver. These results constitute a proof of concept and should not be interpreted as evidence of quantum advantage.

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