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► **To cite this version:**

Paul van Walree, François-Xavier Socheleau. Initial investigation of underwater acoustic channel replay errors. Underwater Communications and Networking Conference (Ucomms), Sep 2024, Sestri Levante, Italy. hal-04672794

HAL Id: hal-04672794

<https://hal.science/hal-04672794v1>

Submitted on 19 Aug 2024

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Initial investigation of underwater acoustic channel replay errors

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Abstract—Channel estimation plays an important role in underwater acoustic communications, with applications in phase-coherent modulation schemes and preparation of replay channels. Quantifying the estimation error is a challenge, however, as the true channel remains unknown. This paper introduces the channel replay error (CRE) as the difference between a test signal passed through an at-sea or synthetic ocean channel, and the same signal passed through the replay channel. The CRE is investigated for popular probing waveforms and estimation methods, including correlative channel sounders and (sparse) adaptive algorithms. By necessity, the test signal for at-sea data is the probing waveform. This potentially reproduces any type of in-band acoustic power, including noise, and can yield an overoptimistic CRE. Synthetic channels allow CRE computation for arbitrary reference waveforms, which yields valuable insights.

Index Terms—Channel estimation, channel replay, acoustic communication

I. INTRODUCTION

Channel estimation plays an important role in acoustic communications, where receivers require knowledge of the time-varying impulse response in order to compensate for the signal distortion. The output of a channel estimator can also serve as input to a replay channel simulator, allowing researchers to pass arbitrary waveforms through a replay channel without sea-going efforts of their own [1]. Acoustic channel simulation may be validated by comparing parameters computed from the simulator output with their corresponding ocean values [2]. Modem performance metrics like output signal-to-noise ratio (SNR) and bit error ratio are particularly useful, but do not explicitly quantify the difference between the measured channel and the true channel, which remains unknown.

Adaptive estimation algorithms come in many flavors. Their performance can be quantified through the mean square error (MSE) in the channel estimation process, also known as the signal (residual) prediction error (SPE) [3]. This prediction error is not available for the correlative channel sounder, which uses periodic probing waveforms with good autocorrelation properties and matched-filter processing.

Existing comparisons between channel estimation methods have focused on sparse and non-sparse algorithms, mostly adaptive, e.g. [3]–[5]. However, there is a literature gap regarding comparisons between these methods and correlative sounders. The present paper aims to address this gap,

especially investigating the suitability of the estimator outputs for channel replay. To this end, a channel replay error (CRE) is defined which incorporates the combined errors of the estimation algorithm and the replay convolution engine. The concept is applied to at-sea data and synthetic channels, and yields valuable insights.

The remainder of this paper is organized as follows. Section II briefly describes the waveforms and estimation algorithms. Detailed implementations are not provided, as the paper does not attempt to identify the best algorithms. Rather, it focuses on challenges associated with the CRE computation and different behaviors of the algorithms. Section III defines the CRE, and shows that channel replay can reproduce sea noise. Section IV examines synthetic channels, which are precisely known and allow CRE evaluation with a reference signal. Finally, Section V wraps up the findings.

II. CHANNEL ESTIMATION

A. Waveforms

The analysis uses the following channel probing waveforms:

- LFM — A linear frequency modulated chirp with a length $T = 62.5$ ms, repeated 512 times head to tail.
- mSeq — A binary phase-shift keyed (BPSK) modulated maximum-length (m) bit sequence of length $L = 255$, transmitted at a rate of $R = 4000$ bit s⁻¹. It is repeated 512 times, head to tail. The sequence length is $T = L/R = 63.75$ ms.
- PN — A single BPSK modulated m-sequence of length $L = 131071$, transmitted at a rate of $R = 4000$ bit s⁻¹.

All waveforms have a length between 32 and 33 s. Common parameters are a center frequency $f_c = 6$ kHz, and a root-raised-cosine (RRC) spectrum with roll-off factor $\beta = 1/8$. This yields a -3 dB bandwidth $B_{-3\text{dB}} = R = 4$ kHz and a 100% power bandwidth $B_{100\%} = (1 + \beta)R = 4.5$ kHz. The spectrum is flat over a width $B_{\text{flat}} = (1 - \beta)R = 3.5$ kHz.

B. Estimation algorithms

1) *Correlative sounders*: The LFM and mSeq processing is simple without user parameters. Received signals are brought to complex baseband, downsampled to $2B_{-3\text{dB}}$, and filtered with a copy of the transmitted chirp or m-sequence. The filter output is reshaped into a discrete-time matrix $\hat{h}(t, \tau)$ with a delay span T , which is also the sampling period in time.

2) *Sparse nonadaptive estimation*: The LFM waveform is processed in a similar way to correlative estimation except that matched filtering is replaced by orthogonal matching pursuit (OMP) [6], [7]. OMP is run with atoms made up of time-shifted replicas of the chirp stored in a dictionary. The size of this dictionary is set to $T \times 2B_{-3\text{dB}}$, the n -th atom being a replica shifted by n samples. The number of OMP iterations is set to 20. This corresponds to the maximum number of taps the estimator is able to detect.

3) *Nonsparse adaptive estimation*: The PN waveform is brought to complex baseband and downsampled to one sample per bit. Channel estimation is performed with standard LMS or RLS tap updates. The length of the channel vector is set to $T = 62.5$ ms, the LMS step-size parameter $\mu = 0.8/(TR)$, and the RLS forgetting factor $\lambda = 0.995$. The SPE is the difference between the received signal sample $\tilde{y}(n+1)$ at time $t(n+1)$, and the prediction of that sample based on the channel estimate at time $t(n)$ and the known transmitted signal. The tilde denotes that the SPE is relative to a root-mean-square (RMS) normalized signal: $\tilde{y}(n) = y(n)/\sigma_y$.

4) *Sparse adaptive estimation*: Channel estimation follows the same procedure as the nonsparse adaptive estimation, except that the tap updates are performed with the improved normalized least mean square (IPNLMS) algorithm [8]. The step-size constant is set to 1, and the degree of sparsity of the estimate is controlled by the parameter α [8, Eq. (14)], which balances the weight between the proportional and non-proportional tap adaptation. This parameter is set to 0.9.

III. CHANNEL REPLAY ERROR

A. Definition

In a linear time-variant channel, the acoustic field $a(t)$ at the receiver follows from the input signal $x(t)$ via the superposition integral

$$a(t) = \int_{-\infty}^{\infty} h(t, \tau) x(t - \tau) d\tau + n(t) = y(t) + n(t), \quad (1)$$

where $h(t, \tau)$ is the time-varying impulse response, $y(t)$ is the distorted output signal, and $n(t)$ is ambient noise. Channel replay is a numerical implementation of (1), substituting the true channel $h(t, \tau)$ by the estimator output $\hat{h}(t, \tau)$.

Let $y_{\text{sea}}(t)$ be the signal received over a (real or synthetic) ocean channel due to transmission of a waveform $x(t)$. The same $x(t)$ can be passed through a replay channel $\hat{h}(t, \tau)$, estimated from $a_{\text{sea}}(t)$, to yield $y_{\text{sim}}(t)$. The channel replay error (CRE) is defined as

$$\epsilon(t) \triangleq \tilde{y}_{\text{sea}}(t) - \tilde{y}_{\text{sim}}(t), \quad (2)$$

where the tilde denotes RMS-normalized signals. This error is computed after a dual synchronization procedure:

- 1) The instant x enters $\hat{h}(t, \tau)$ has to match the instant x entered $h(t, \tau)$;
- 2) Time and phase synchronization between y_{sim} and y_{sea} .

For a real ocean environment, the only choice of input signal for which the CRE can be computed is the probing waveform

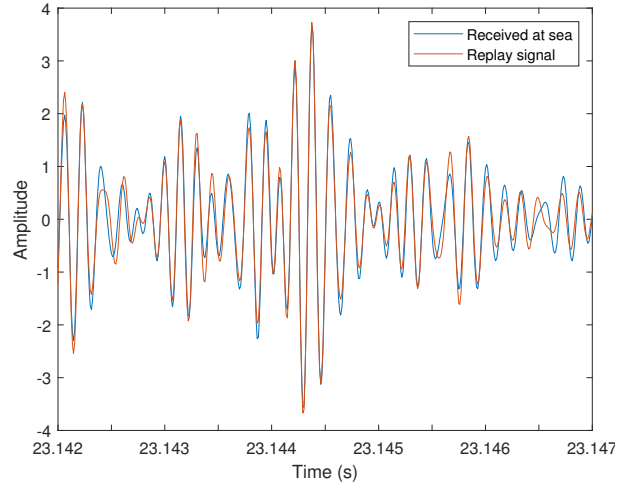


Fig. 1. At-sea data: A 5-ms passband time series segment of a PN waveform $a_{\text{sea}}(t)$, and the replay signal $y_{\text{sim}}(t)$.

x_{pr} . Furthermore, the received signal y_{sea} is not available and has to be replaced by a_{sea} . A synthetic ocean environment does not have these limitations. The signal y_{sea} is available, and the CRE can be computed for either $x = x_{\text{pr}}$ or arbitrary reference waveforms $x = x_{\text{ref}}$ propagated through the same channel realization.

B. Application to a real ocean environment

The CRE has been evaluated for data from several sea trials, and often it was suspiciously good. This happens with all the nonsparse algorithms (so far, the sparse algorithms have only been applied to the synthetic channels of Sec. IV). Figure 1 shows an example of a good match between a_{sea} and y_{sim} obtained with nonsparse RLS channel estimation. The SNR of a_{sea} used for this example is only 6 dB and the mean-square SPE is -2.4 dB, whereas the mean-square CRE is -12 dB. This is only possible if channel replay reproduces sea noise.

C. Signal spectrum and transfer function

In order to demonstrate that channel replay can reproduce sea noise, the correlative sounder is used as an example. Convolution and matched-filtering are straightforward operations in the frequency domain, and it is assumed that the channel is time-invariant over the duration T

$$H(t, f) \approx H(t_0, f) \quad \forall t \in [t_0, t_0 + T]. \quad (3)$$

An at-sea transmission of $x_{\text{pr}}(t)$ gives a received acoustic field whose spectrum is

$$A_{\text{sea}}(t, f) = H(t, f) X_{\text{pr}}(f) + N_{\text{sea}}(f). \quad (4)$$

The channel estimate is obtained by filtering $a_{\text{sea}}(t)$ by a replica of the LFM chirp (or m-sequence)

$$\begin{aligned} \hat{H}(t, f) &= C A_{\text{sea}}(t, f) X_{\text{pr}}^*(f) \\ &\approx C \left[H(t_0, f) |X_{\text{pr}}(f)|^2 + N_{\text{sea}}(f) X_{\text{pr}}^*(f) \right], \end{aligned} \quad (5)$$

where $C = B_{-3\text{dB}} / \int |X_{\text{pr}}(f)|^2 df$ is a normalization factor ensuring that $\hat{H}(t, f)$ has the same dimension and magnitude

as $H(t, f)$. The first term between brackets shows that the probing waveform has a bandlimiting effect: the transfer function is weighted by $|X_{\text{pr}}(f)|^2$, i.e., a full raised cosine.

The cascading continues with channel replay simulation, using an input signal $x_{\text{sim}}(t)$

$$\begin{aligned} Y_{\text{sim}}(t, f) &= \hat{H}(t, f) X_{\text{sim}}(f) \\ &\approx C \left[H(t_0, f) |X_{\text{pr}}(f)|^2 + N_{\text{sea}}(f) X_{\text{pr}}^*(f) \right] X_{\text{sim}}(f). \end{aligned} \quad (6)$$

Finally, if x_{pr} is substituted for x_{sim} in (6), the output signal becomes

$$Y_{\text{sim}}(t, f) \approx C [H(t_0, f) |X_{\text{pr}}(f)|^2 X_{\text{pr}}(f) + N_{\text{sea}}(f) |X_{\text{pr}}(f)|^2]. \quad (7)$$

The second term in (7) clearly shows that channel replay reproduces bandpass-filtered sea noise, regardless of the noise distribution. This expression is obtained for the correlative sounder, but adaptive estimation has the same potential, as the channel estimate can converge to the cross-correlation between x_{pr} and a_{sea} .

The replay also affects the signal spectrum: frequencies between B_{flat} and $B_{100\%}$ are attenuated by the factor $|X_{\text{pr}}(f)|^2$. This yields artificial signal distortion that affects the CRE. It can be mitigated by using a small value of β , yielding a large B_{flat} within which faithful replay is possible. Both a_{sea} and y_{sim} are bandpass-filtered to limit their spectrum to $B_{\text{flat}, \text{pr}}$ before computing (2). Synthetic channels permit the use of an x_{ref} whose spectrum is fully contained within $B_{\text{flat}, \text{pr}}$.

IV. PERFORMANCE ANALYSIS WITH A SYNTHETIC OCEAN ENVIRONMENT

The present objective is to study the behavior of, and differences between, the CRE and the SPE, and to quantify the error due to using the same waveform for channel estimation and computation of the CRE. In order to have full control over the parameters of the analysis and knowledge of the ground truth, a synthetic channel is used.

Figure 2 illustrates a Rician fading channel with a stable first arrival, followed by fluctuating paths whose power decreases with delay. All fading paths have a Gaussian Doppler spectrum with standard deviation σ . The stable path carries 40 % of the total power and the fading paths 60 %. Absorption is applied using the empirical equations of Van Moll *et al.* [9] over a range of 10 km for an ocean environment with a temperature of 20 °C, a modem depth of 100 m, a salinity of 35 g kg⁻¹, and pH = 8. Absorption skews the spectrum of y_{sea} ; for the chosen parameters the fall-off is 2.6 dB between 4 and 8 kHz. Absorption is of no consequence for the nonspare estimators, but sparse algorithms require more taps to represent a skewed signal spectrum. This synthetic channel has some aspects resembling an ocean channel, but is unrealistic in other aspects. Realistic simulation of ocean channels is a formidable task on its own, but is not required to study behavioral aspects of the CRE and the SPE.

Different probing waveforms x_{pr} and reference waveforms x_{ref} can be propagated through the same synthetic channel. All waveforms can also be propagated through the channel

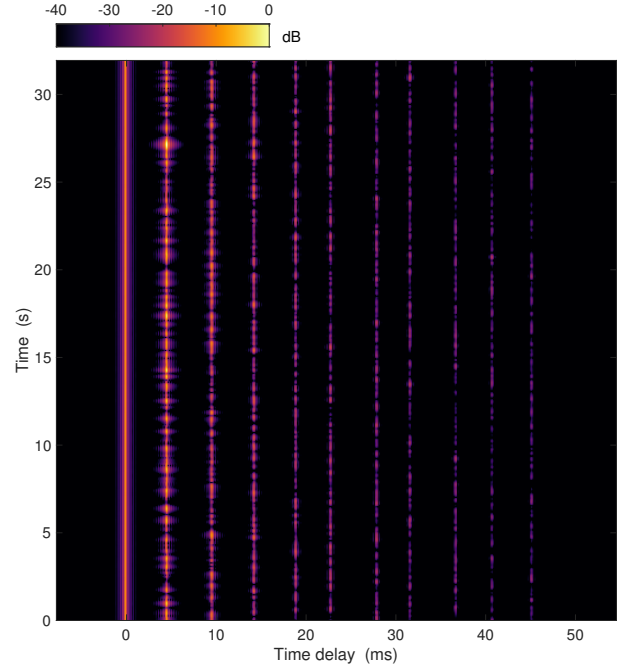


Fig. 2. Synthetic channel consisting of a stable first arrival followed by fluctuating paths, illustrated for $\sigma = 1$ Hz.

estimate $\hat{h}(t, \tau)$ obtained with $a_{\text{sea}, \text{pr}}$ and the estimation algorithms. The CRE (2) can be computed as $\tilde{y}_{\text{sea}, \text{pr}} - \tilde{y}_{\text{sim}, \text{pr}}$ or $\tilde{y}_{\text{sea}, \text{ref}} - \tilde{y}_{\text{sim}, \text{ref}}$. Alternatively it can be replaced by $\tilde{a}_{\text{sea}, \text{pr}} - \tilde{y}_{\text{sim}, \text{pr}}$, mimicking an at-sea scenario with an unknown noise term.

Figure 3 shows the result of $\tilde{y}_{\text{sea}, \text{ref}} - \tilde{y}_{\text{sim}, \text{ref}}$ CRE simulations. The Doppler spread σ of the fading paths is varied, and the SNR is set at 60 dB in order to concentrate on the impact of delay-Doppler spread. The CRE receives contributions from i) channel estimation errors, i.e., differences between $\hat{h}(t, \tau)$ and $h(t, \tau)$; ii) imperfections of the replay convolution tool, which performs linear interpolation between channel updates. These updates are spaced by $\Delta t = T \approx 62.5$ ms for the correlative sounders. The adaptive algorithms yield channel updates at the symbol rate, which yields an excessively large channel matrix. Only every 40th update is kept, which gives $\Delta t = 10$ ms. No CRE improvement is observed for smaller Δt .

The results in Fig. 3 show that IPNLMS achieves the best CRE, which is not surprising given the sparsity of the channel. The CRE is slightly worse than the SPE, and the difference increases with σ . This may be due to replay errors of rapidly fluctuating paths. The order is reversed for the nonspare adaptive algorithms, which yield a CRE that is several dB better than the SPE. The correlative LFM sounder has the best CRE of the nonspare algorithms. LFM OMP has the same performance at large σ , but reveals an error floor at small σ . This error floor is larger for mSeq, which has the highest (autocorrelation) sidelobes of all examined estimation methods. The sidelobes of a periodic m-sequence are flat, and the theoretical processing gain is $10 \log_{10} L = 24$ dB in a static or slowly varying channel (small σ). All sidelobes contribute

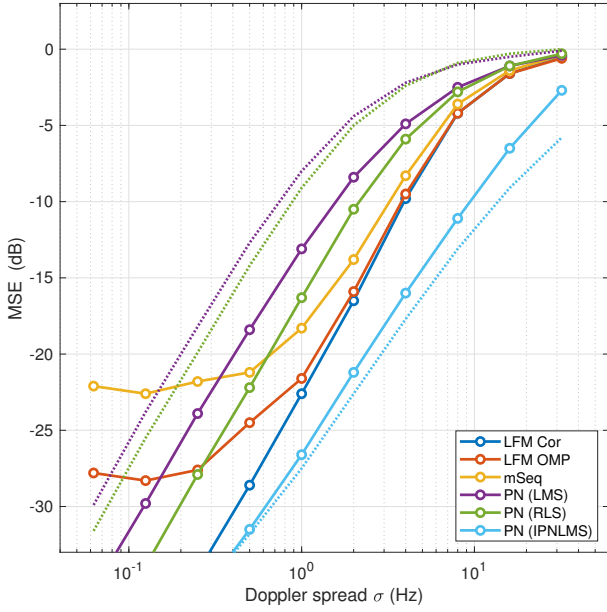


Fig. 3. Solid curves: CRE obtained with a reference waveform vs. the Doppler spread of the fading paths. The dotted curves give the SPE of the adaptive algorithms. All data points are 30 s averages.

power to y_{sim} in channel replay, which prevents the CRE from dropping below -24 dB.

The CRE drops if it is computed from the probe signal. Figure 4 gives the MSE difference with Fig. 3. The estimation algorithms behave in different ways, but have in common that the probing waveform CRE is more optimistic than the reference waveform CRE. The MSE difference is largest at large Doppler spread (except for mSeq), where the channel is overspread. Notice that the MSE improvement is not due to noise reproduction in this example, since the SNR is 60 dB. The same curves are obtained if $y_{sea,pr}$ is replaced by $a_{sea,pr}$.

Finally, an ideal (zero delay-Doppler spread) additive white Gaussian noise (AWGN) channel is considered to examine the impact of noise. The solid curves in Fig. 5 give the CRE difference between $\tilde{a}_{sea,pr} - \tilde{y}_{sim,pr}$ and $\tilde{y}_{sea,ref} - \tilde{y}_{sim,ref}$, while the dash-dot curves give the difference between $\tilde{y}_{sea,pr} - \tilde{y}_{sim,pr}$ and $\tilde{y}_{sea,ref} - \tilde{y}_{sim,ref}$. The use of $\tilde{a}_{sea,pr}$ instead of $\tilde{y}_{sea,pr}$ to compute (2) introduces a noise bias that yields big differences between estimation methods. By contrast, proper application of (2) gives the same CRE as the reference waveform, except for mSeq and nonsparse RLS.

V. DISCUSSION AND CONCLUSIONS

A channel replay error is defined which quantifies the similarity between a signal propagated through a (real or synthetic) ocean channel, and the same signal propagated through a replay channel. Computing the CRE from $a_{sea,pr}$ is the only option for at-sea data, but can yield optimistic results. All estimation methods considered in this paper have the ability to reproduce, to some extent, any in-band acoustic power, whether it concerns signal, noise, or interference.

The CRE has been computed for different reference waveforms in the synthetic channels, e.g. communication packets

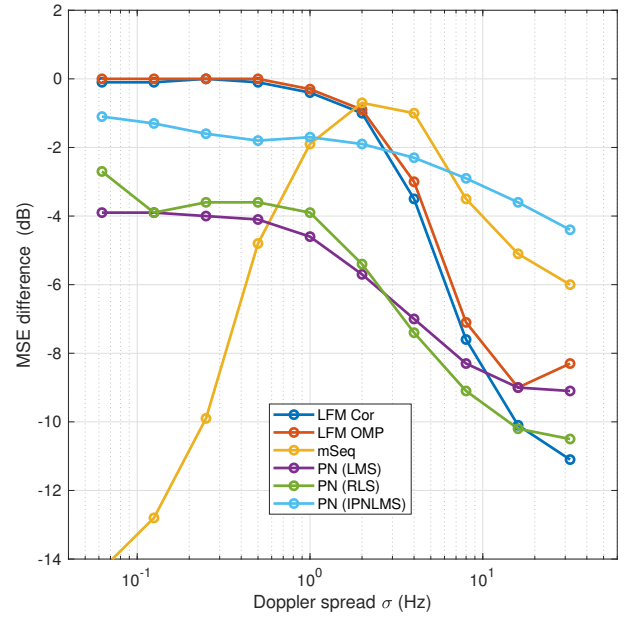


Fig. 4. CRE difference between $\tilde{y}_{sea,pr} - \tilde{y}_{sim,pr}$ and $\tilde{y}_{sea,ref} - \tilde{y}_{sim,ref}$.

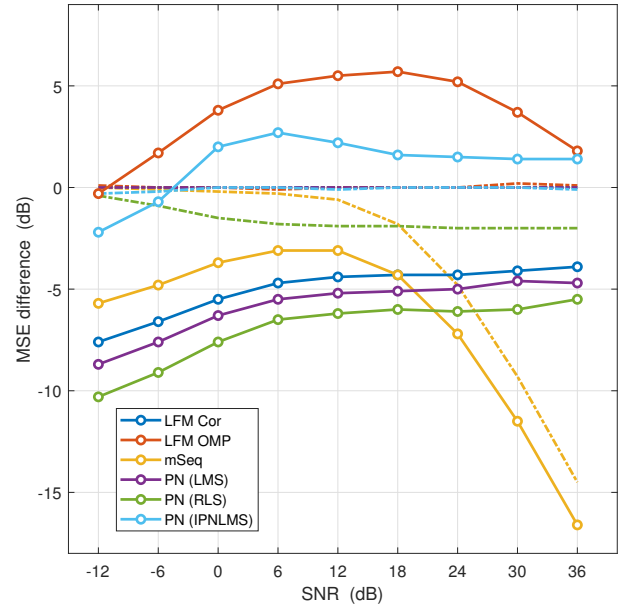


Fig. 5. AWGN channel. Solid curves: MSE difference between $\tilde{a}_{sea,pr} - \tilde{y}_{sim,pr}$ and $\tilde{y}_{sea,ref} - \tilde{y}_{sim,ref}$. Dash-dot curves: MSE difference between $\tilde{y}_{sea,pr} - \tilde{y}_{sim,pr}$ and $\tilde{y}_{sea,ref} - \tilde{y}_{sim,ref}$.

of various modulations or just bandpass filtered noise. The outcome is always the same so long as x_{ref} is uncorrelated with x_{pr} . Aberrant behavior is only observed when the CRE is computed from $a_{sea,pr}$ or $y_{sea,pr}$.

Future work will look further at the possibilities and impossibilities of applying the CRE to at-sea data. Dependencies between the CRE and the SPE will be investigated, and both metrics will be compared with the true channel estimation error $\hat{h} - h$.

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