# AUTOREGRESSIVE MODELING OF MOBILE UNDERWATER ACOUSTIC COMMUNICATIONS CHANNELS

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**Abstract:** *The cost and logistics to deploy experimental underwater acoustic networks remains high and is beyond the reach of many researchers. Even researchers who can perform at-sea experiments, they often have limited time and control over the natural environment. Consequently, there is an imperative need to develop accurate underwater acoustic channel models to test network performance in simulation. Although sophisticated physics-based channel models have been developed, these models are computationally infeasible for large-scale (space, time, and frequency) simulations. In addition, they are less realistic than stochastic replay methods since not all physics is included in the channel model as well as complete knowledge about the environment is often unavailable. In this paper, we propose a computationally efficient stochastic model for replaying mobile underwater acoustic communication channels. The simulator includes non-stationary effects resulting from non-constant platform motion. In addition, environmental temporal fluctuations are captured via locally stationary autoregressive (AR) processes. The accuracy of the model is validated based on at-sea measurements.*

**Keywords:** *Stochastic replay, channel simulation, adaptive channel estimation, adaptive resampling, motion-induced Doppler compensation.*

## 1. INTRODUCTION

Underwater acoustic communications is the core enabling technology for developing distributed sensor networks for monitoring the maritime environment. To allow interoperability between sensors from different vendors, communication standards for modulation, coding and medium access protocols must be designed. Candidate standards should be examined based on their performance on various underwater acoustic environments. However, the cost to conduct extensive sea experiments remains high and is beyond the reach of many researchers. Hence, it is plausible to assess candidate standards via reliable computer simulations, which in turn require accurate channel models.

At frequencies of interest (> 5 kHz), ray theory provides the foundation of underwater sound propagation. An approximate prediction of the channel impulse response is computed from a ray tracing software by exploiting any available information about the physical environment, namely, link geometry, ocean bathymetry, seabed acoustic properties, sea state, to name a few [1]-[3]. Yet, an accurate channel prediction is nontrivial since complete knowledge of the environment as well as positions and velocities of the network nodes are often unavailable. For this reason, compound models for which coarse multipath delays are computed from ray tracing and multipath gains are modeled as stochastic processes are proposed in the literature ([4] and references therein). The plethora of the proposed statistical models, however, imply that there is no consensus as to which model is more appropriate for simulating underwater acoustic channels.

A more realistic way to simulate underwater acoustic channels is based on stochastic replay methods [5], [6]. According to these methods, time-varying impulse responses with identical statistical properties as the at-sea measured impulse response are generated in a computationally efficient manner. The accuracy of the channel estimation depends on the probe signal, the employed estimation algorithm and the environmental conditions. Any replay method faces two limitations. Firstly, the simulated impulse response must lie within the frequency band and time duration of the probe signal. Secondly, environmental parameters (e.g., sea state, sound speed profile, etc.) cannot be changed during simulations.

This work proposes a computationally efficiency stochastic replay method for simulating mobile underwater acoustic communications channels. A multipath channel is modeled as a tapped-delay line with taps being realizations of various stochastic processes with certain power spectral densities. A key issue is to provide the simulator with reliable channel estimates in the presence of non-constant motion. That is achieved by employing a novel receiver structure that performs Doppler resampling, channel estimation and decision feedback equalization in a closed-loop fashion. Treating slow fading as deterministic and focusing on fast fading, we use locally stationary autoregressive (AR) processes to capture temporal correlations of each channel tap. The validity of the proposed model is demonstrated for three different signal bandwidths using data from a mobile shallow-water experiment.

## 2. EXPERIMENTAL PROCEDURE

The experiment took place in the sea of Selat Pauh, Singapore, on October 21st and 23rd, 2013. Two vessels were used as two nodes of a mobile point-to-point link. One vessel carried the transmitter (projector) and the other the receiver (hydrophone). Both the transmitter and the receiver were submerged about 3 m below the sea surface. The sea depth along the link varied about 15-20 m and the sound speed profile was isovelocity (1540 m/s). The sea state was calm but ship wakes were often encountered during the course of the experiment.

The multipath acoustic channel is mathematically modeled as a linear time-varying filter with tap spacing equal to the reciprocal of the channel bandwidth. The important issue is to capture the time scale of variation of individual filter taps. To achieve this, the channel response must be estimated at a rate greater than twice the channel Doppler spread. The channel probing signal was a continuous transmission of uncorrelated quadrature phase-shift keying (QPSK) symbols at a rate of 1000 symbols/s. The QPSK symbols were pulse-shaped via a raised cosine filter (roll-off factor 0.7) and then multiplexed in frequency occupying three subbands: 14.4-16.1 kHz (subband A), 16.1-17.8 kHz (subband B) and 17.8-19.5 kHz (subband C). This signal structure allowed us to obtain channel estimates at every millisecond, which is sufficient for most practical scenarios. In addition, the signal subband structure makes possible to check the model variation in frequency domain.

The received signal that occupies the three aforementioned subbands can be seen in Figure 1(a). Each subband is shifted to baseband, low-pass filtered and coarsely synchronised with a known chirp pulse. The proposed receiver structure (as seen in Figure 1(b)) detects the QPSK data by dividing the demodulation process into three major subsections: (a) motion compensation via adaptive resampling; (b) inter-symbol interference (ISI) mitigation based on channel estimation; (c) adaptive linear equalization.

To compensate for any time dispersion/compression due to motion, the sampling rate of the incoming baseband signal is adjusted during each symbol interval by using linear interpolation [7]. The interpolation factor is computed from the extracted phase rotation of the QPSK symbol received at the previous symbol interval. Next, the resulting signal is used to produce an estimate of the channel impulse response based on the improved-proportionate normalized least mean square (IPNLMS) algorithm [8]. Combining past channel estimates with past transmitted symbols, an estimate of the post-cursor intersymbol interference (ISI) is subtracted from the received signal. Then, the ISI-free signal is equalized by a linear filter producing a soft estimate of the transmitted QPSK symbol. The difference between the soft estimate and the actual transmitted QPSK symbol is used to optimise the feedforward filter through the exponentially-weighted recursive least-squares (RLS) algorithm. Note that the novelty in our approach is that the proposed receiver performs symbol-by-symbol adaptive resampling with symbol-by-symbol adaptive channel estimation in a closed-loop fashion. Consequently, fast platform motion is decoupled from slow environmental fluctuations leading to better channel estimates. In addition, the channel impulse response can be estimated for arbitrary long periods without any interruption for explicit synchronization.

Figure 2(a) illustrates the transmit/receive positions based on GPS recordings. The range of the link was about 2.7 km. Figure 2(b) shows the mean Doppler shift that each subband experiences due to platform motion. The positive Doppler indicates that the transmit vessel was propelling towards the receiver at a varying speed of about 0.5-1.5 m/s. In addition, the wavy pattern of fluctuation is indicative of surface waves-induced motion. Figure 2(c) shows the time evolution of the amplitude of the channel impulse response. As expected, the responses are different for different subbands. This is explained by noting that different subbands undergo different frequency fading and Doppler spread. The filter tap at the 0 ms delay corresponds to the strongest signal arrival. Due to the limited signal bandwidth as well as the link geometry, the tap temporal correlation is dictated by the interference of the direct path and the first surface bounce. Moreover, transmitter motion gives rise to a prominent Lloyd's Mirror Effect [9] and therefore this tap value rapidly fluctuates in time.

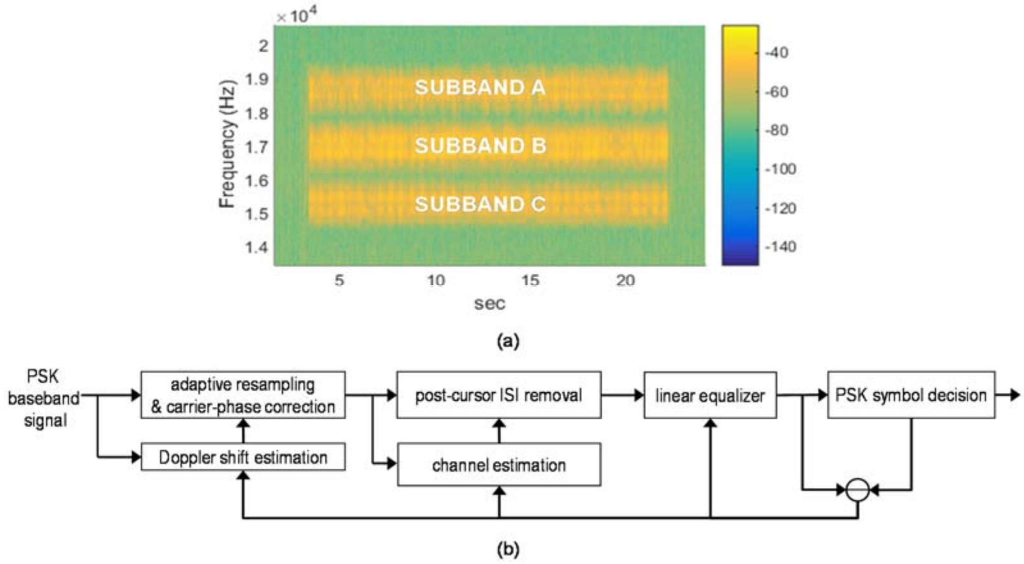


*Figure 1: (a) Spectrogram of the received signal. The amplitude scale is in dB. (b) The receiver block diagram.*

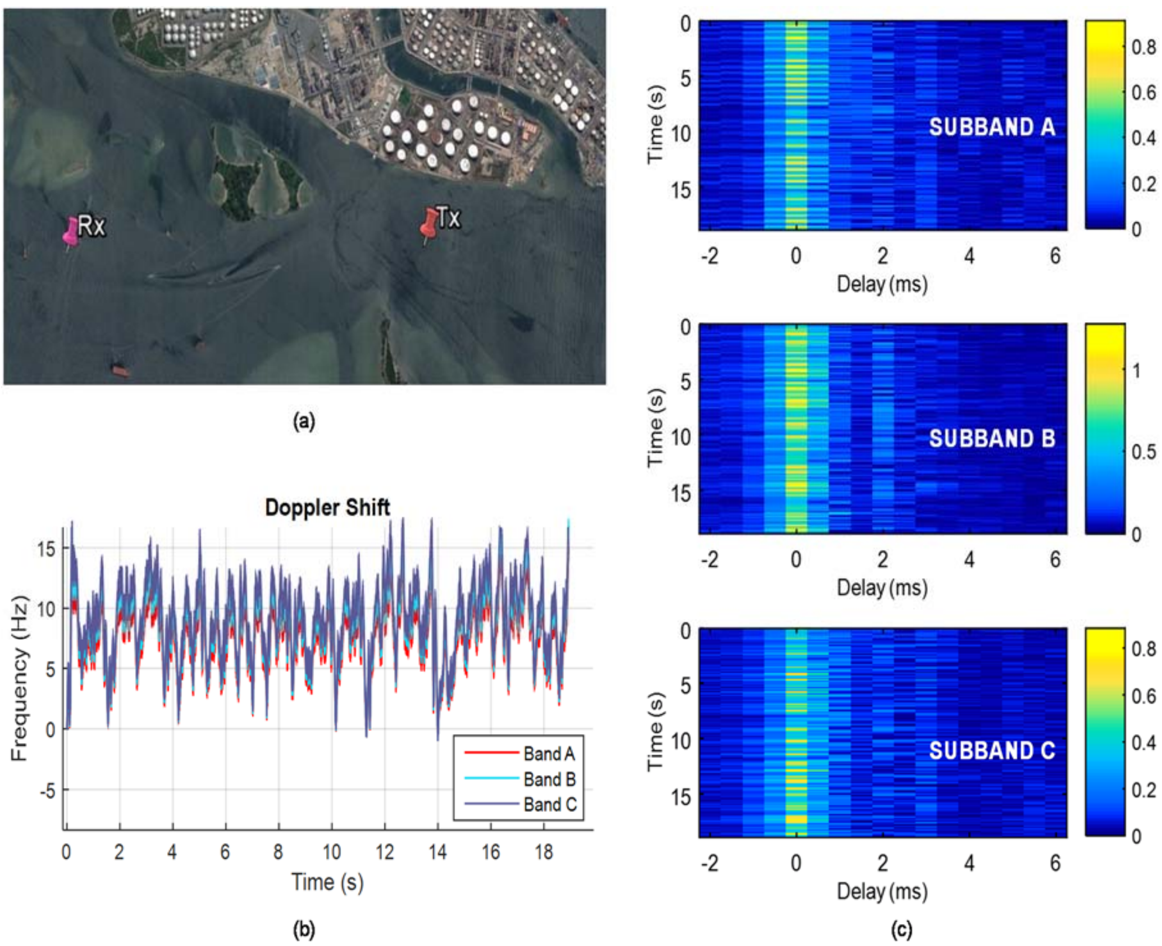


*Figure 2 (a) Transmitter and receiver locations. (b) Time evolution of the mean Doppler frequency shift for each sub-band. (c) Snapshots of the amplitude of the baseband impulse response for different subbands. The snapshots are taken every millisecond. The colorbar in linear scale.*

## 3. MODELING PROCEDURE

To implement a stochastic replay simulator for an underwater acoustic channel response, we are interested in a statistical characterization of each channel filter tap. Here, we derive a statistical model for the 0-ms tap of the channel response that corresponds to subband A (see Figure 2(a)). The same procedure can be followed for any of other channel tap as well as for different subbands (omitted for brevity). We also stress that ambient noise simulation is not addressed in this paper.

Let $h(n)$ denote the tap value at discrete time $n$. Figure 3(a) (black dashed line) shows its amplitude variation. Deriving a statistical model for $h(n)$ is tedious because variation at different time scales is observed. That is the case for most underwater acoustic communication channels [4]-[6]. One can typically divide the tap's temporal variability into two types: (a) *slow fading*, due to the link geometry and slow environmental fluctuations (seasonal changes in temperature profile, tidal changes, internal waves, to name a few); (b) *fast fading*, due to multipath constructive and destructive interference, scattering off rough surfaces and Doppler effects. Following this line of thought, we start our stochastic model by decomposing $h(n)$ into its time-varying mean (local average) and a residual (noise-like) signal. By using an averaging window of 100 ms (i.e., 100 signal samples since the baud rate is 1000 symbols/s), we have

$$h(n) = \bar{h}(n) + r(n) \qquad (1)$$

where $\bar{h}(n)$ stands for the time-varying mean and $r(n)$ denotes the residual signal. The amplitude of the slow fading signal can be seen in Figure 3(a) (green line). This signal is treated as deterministic in our model. The amplitude of the fast fading signal can be seen in Figure 3(a) (red dashed line). Typically, $r(n)$ is considered as a wide sense stationary (WSS) process [4]-[5], yet, this may not be accurate for mobile channels where abrupt changes may occur. Our approach here is to model $r(n)$ as a WSS process only within the 100 ms averaging interval. This is well justified based on the following numbers. Let us assume that the platform motion is 1 m/s, then the change in the link geometry during 100 ms is about 10 cm (order of one wavelength at 17 kHz), which is typically less than the expected ocean spatial variability. Splitting the total measurement interval into 100-ms non-overlapping sub-intervals, we can write

$$r(n) = \sum_{m=1}^{M} r(n,m) \qquad (2)$$

where $r(n,m)$ is an AR process. For every $m^{th}$ sub-interval, $m$=1… $M$, the AR process can be expressed as

$$r(n,m) = \sum_{i=1}^{K} a(i,m)r(n-1,m) + w(n,m) \qquad (3)$$

where $a(i,m)$ are the (complex-valued) filter parameters and $w(n,m)$ is a zero-mean Gaussian noise with variance $\sigma^2(m)$. The AR model parameters are estimated by solving the Yule-Walker equations.

The validity of the aforementioned AR model can be seen in Figure 3(a). This figure illustrates the average power spectral density (PSD) of $r(n)$ over the entire duration of the probe signal (18.5 s). For comparison purposes, the PSD of one realization of the simulated process (18.5 s) is also presented. The order of the employed AR filters is 30. Note that good agreement between real and simulated $r(n)$ is observed. A similar result (agreement) is shown for the other subbands as well (Figure 3(b) and (c)).

The complete stochastic replay simulator first generates each $r(n, m)$ to compose $r(n)$ and then includes $\bar{h}(n)$ creating the final tap value. Hence, the simulated channel not only is easy to generate but also has the same statistical properties as the measured channel. To include platform motion (for each subband), the channel output signal is symbol-by-symbol resampled according to the estimated Doppler of Figure 2 (b).

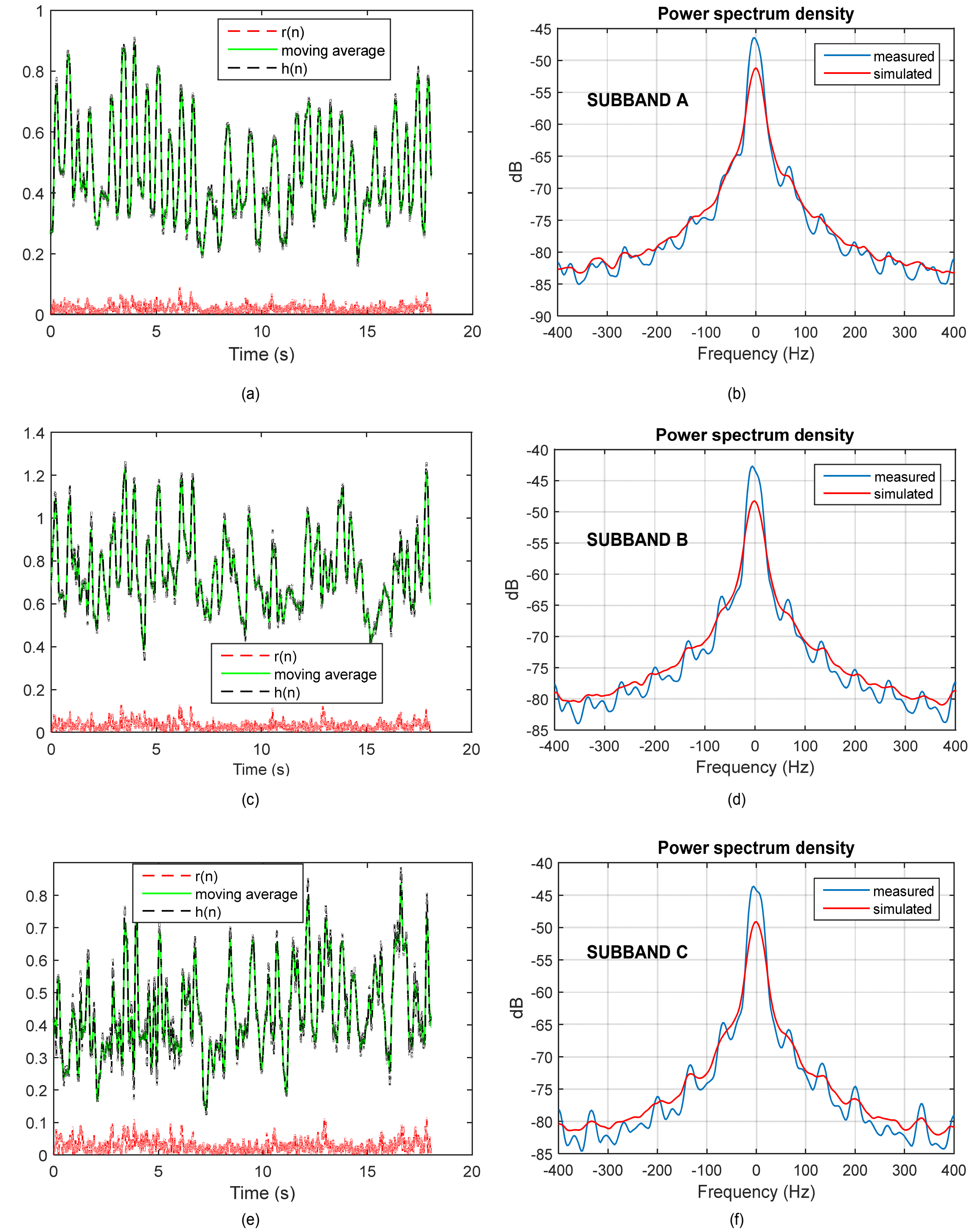


*Figure 3 (a) Amplitude decomposition of $h(n)$ into a moving average and a residual signal $r(n)$ for subband A. (Similarly, (c) and (e) correspond to subband B and C, respectively) (b) Average power spectral density of the process $r(n)$ for real and simulated data for subband A. (Similarly, (d) and (f) correspond to subband B and C, respectively).*

## 4. CONCLUSION

A stochastic model for simulating mobile underwater acoustic channels is presented. This model relies upon acquiring reliable channel estimates in the presence of non-constant motion. This is accomplished by employing a communications receiver that performs symbol-by-symbol Doppler compensation and channel estimation in a closed-loop with a decision feedback equalizer. Having the channel impulse response at hand and after removing its slow fading component, the fast fading (noise-like) signal can be treated as a locally stationary AR process. Our results validate this claim based on at-sea data from a mobile shallow water link. The low computational complexity of this stochastic model renders it handy for large scale simulations of underwater acoustic networks. Future work will showcase this possibility by comparing the bit error rate performance of a receiver in real and simulated data.

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