Cross-Scenario Underwater Acoustic Channel-State Forecasting under Distribution Shift and Observation Noise

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***Abstract*—Reliable link adaptation in underwater acoustic networks depends on timely channel-state information. In practice, slow acoustic propagation, feedback latency, multipath variation, platform motion, and environmental noise can render estimated channel conditions obsolete before a transmission decision is applied. Forecasting from recent observations can mitigate this staleness, yet predictors trained in one deployment often generalize poorly when propagation geometry, scattering, dynamics, or signal-to-noise ratio change. This paper introduces a conceptual framework for transferring a compact, decision-oriented channel-state predictor across different environments. Temporal features are used to describe channel evolution, feature alignment reduces cross-environment mismatch, and noise-aware consistency training improves robustness to corrupted observations. The framework also clarifies target-data assumptions, uncertainty handling, and interfaces between channel estimation, forecasting, and link control.**

***Index Terms*—underwater acoustic communication, channel forecasting, domain adaptation, robust representation learning**

I. Introduction

Underwater acoustic communication supports ocean observation, environmental monitoring, resource exploration, and coordination among autonomous platforms. Its physical channel is difficult to track because propagation is slow, bandwidth is limited, and the received signal is shaped by multipath, Doppler effects, platform motion, boundary interactions, and environmental noise [1]–[3]. These mechanisms create temporal variation on several scales. As a result, channel information obtained through estimation or feedback may no longer describe the link when a transmission decision is made.

Short-term forecasting can help reduce the effect of this delay. By using recent observations, a predictor estimates the channel state expected at the next adaptation step. The predicted state can then support modulation, coding, power allocation, scheduling, or link selection. Earlier studies have shown the value of channel prediction for adaptive underwater links [4], [5], while recent reviews trace the development from linear and kernel methods to data-driven temporal models [6]. However, the problem is not limited to temporal prediction alone.

A model developed for one deployment may encounter a different seabed, water depth, geometry, motion pattern, or noise process after transfer [7]. The source and target observations can therefore follow different distributions even when the prediction task is unchanged. Simply pooling measurements may entangle environment-specific patterns with genuinely reusable dynamics [8], [9]. A second issue is observation quality. Even when the channel follows a similar evolution pattern, the model may receive observations under very different signal-to-noise ratios (SNRs). Therefore, channel forecasting needs to account for temporal dynamics, environmental variations, and observation noise at the same time.

This paper takes a system-level view of the problem and makes three main contributions: 1) a concise formulation of transferable channel-state forecasting; 2) an architecture that combines temporal modeling, feature alignment, and noise-aware consistency; and 3) practical deployment guidelines covering key assumptions, system interfaces, and remaining challenges. Instead of prescribing a particular model size, dataset, or training strategy, the framework emphasizes the main functional components and the connections among them.

II. Related Work

A number of earlier investigations into channel prediction have turned to models of growing nonlinearity, often supplemented by transfer learning and noise-mitigation techniques. Table I provides an overview of these representative studies and, more importantly, highlights that their primary goals are

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not aligned with the cross-scenario forecasting problem we tackle here [10].

III. Problem Perspective

The operational motivation is illustrated in Fig. 1. A surface transmitter and a mobile underwater receiver communicate through a channel shaped by direct, surface-reflected, and bottom-reflected propagation paths. Multipath, Doppler effects, platform motion, and ambient noise cause the channel quality to evolve while an estimate is being acquired and returned. Consequently, the observation available to the transmitter, denoted by q_t, may arrive after a propagation or feedback delay τ_d and no longer represent the channel quality q_{t+1} relevant to the next transmission decision. Rather than treating the delayed observation as current, the forecaster uses a history of channel-quality estimates to infer the next state. The figure therefore separates the physical source of channel staleness from the learning task that attempts to compensate for it.

A. A Decision-Oriented Channel State

Let $H(t,\tau)$ denote a time-varying channel impulse response at observation time t and delay τ. A complete prediction of all delay and Doppler components may be valuable for equalization, but it is also high dimensional and sensitive to estimation error. For many link-adaptation decisions, a compact state can be sufficient. One example is the channel energy

$$E(t) = \sum_{\tau} |H(t,\tau)|^2, \tag{1}$$

followed by a logarithmic transform and normalization. The resulting scalar s_t describes the broad strength of the observed channel while suppressing unnecessary tap-level detail.

Given a history of length L, the forecasting task is

$$\mathbf{x}_t = [s_{t-L+1}, \ldots, s_t], \qquad \hat{s}_{t+1} = f_\theta(\mathbf{x}_t), \tag{2}$$

where f_θ predicts the next channel state from recent observations. Prediction over longer horizons is also possible, although the uncertainty generally grows and a dedicated multi-step output may be needed.

B. Environmental Shift

Let $\mathcal{D}_s$ and $\mathcal{D}_t$ denote the source and target datasets. Both use the same channel-state representation and prediction task, but are collected under different operating conditions. In general,

$$P_s(\mathbf{x}, s) \neq P_t(\mathbf{x}, s). \tag{3}$$

Such differences may arise from changes in the observed data, temporal behavior, noise conditions, or the mapping from past observations to future states. Transfer learning offers a general way to reuse knowledge across these shifts [15], but effective transfer depends on separating common patterns from those tied to the source domain.

IV. Forecasting Framework

The proposed framework organizes the forecaster into four interacting functions: state construction, shared temporal encoding, cross-environment alignment, and noise-aware regularization. Fig. 2 shows their functional interfaces and information flow.

A. Temporal Representation and Cross-Environment Alignment

The temporal encoder transforms each history into a contextual representation. Self-attention can relate distant observations without recurrence [18], while recurrent, convolutional, state-space, or hybrid encoders can serve the same role. The essential capability is to separate short fluctuations from persistent evolution while preserving temporal order. Combining a final-step feature with pooled and adaptively weighted summaries allows the forecast head to use recency, global context, and selectively important events.

The adaptation module operates on the same fused feature used for prediction, ensuring that source–target alignment is applied directly to the predictor input. MMD compares source and target feature distributions in a reproducing-kernel Hilbert space [16], and using multiple kernels allows differences at several scales to be considered. Still, the alignment should retain information useful for prediction, since overly strong matching can blur domains with different mappings from past observations to future states.

B. Noise-Aware Consistency and Joint Learning

Observed histories can be distorted by estimation errors or environmental interference. The model therefore uses clean and perturbed target sequences as two versions of the same channel evolution. Perturbations are generated under realistic SNR conditions, and training encourages accurate predictions when labels are available while keeping the outputs of the two versions close. A practical perturbation model should also reflect estimator uncertainty, colored interference, missing samples, and impulsive disturbances instead of assuming simple random noise.

Prediction, alignment, and consistency are coordinated through

$$\mathcal{L} = \mathcal{L}_{\text{pred}} + \lambda_a \mathcal{L}_{\text{align}} + \lambda_c \mathcal{L}_{\text{con}}, \tag{4}$$

where the three terms correspond to prediction accuracy, cross-domain transfer, and robustness to observation noise. The auxiliary weights can be increased gradually so that training first learns the forecasting task before stronger invariance constraints are imposed.

V. Deployment Considerations and Research Directions

A. Deployment Assumptions and Safeguards

Because the forecast is used for link control, its horizon, state definition, normalization, and supervision must match the intended decision. Table II summarizes these assumptions and the safeguards needed for deployment.

TABLE I
REPRESENTATIVE APPROACHES RELATED TO UNDERWATER ACOUSTIC CHANNEL-STATE FORECASTING

Approach	Representative studies	Main focus	Limitation relative to the present problem
Linear prediction	[4], [11]	Low-complexity extrapolation and sparse delay–Doppler prediction.	Limited ability to describe nonlinear, non-stationary dynamics; distribution shift and observation noise are not modeled explicitly.
Kernel methods	[12]	Nonlinear prediction with online updates, sparse dictionaries, or adaptive forgetting.	Performance depends on kernel and dictionary design, and cross-scenario representation transfer is not addressed.
Deep temporal models	[13], [14]	CNN, recurrent, attention, and Transformer representations for complex temporal dependencies.	Training and deployment data are generally assumed to have similar distributions; robustness across SNR conditions is rarely coupled to transfer.
Domain adaptation	[15], [16]	Source–target representation alignment, including MMD-based distribution matching.	Application to underwater channel forecasting remains limited, and unconditional alignment can cause negative transfer when predictive dynamics differ.
Noise-robust learning	[17]	Channel estimators designed to remain stable across noise levels.	Robustness is applied mainly to the estimator rather than to the forecasting function and its cross-scenario representation.
Present framework	This paper	Temporal representation, predictive-feature alignment, and noise-aware consistency in one forecasting pipeline.	The formulation is conceptual; comparative and closed-loop validation remain necessary.

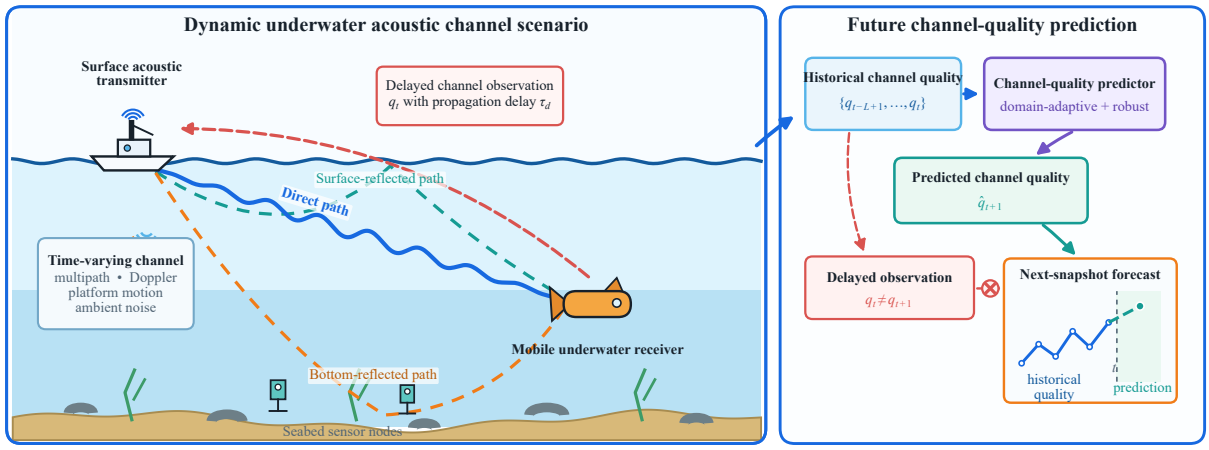


Fig. 1. Motivation for next-snapshot channel-quality forecasting in a dynamic underwater acoustic link. Historical observations may become stale because of propagation and feedback delay, while the underlying channel continues to vary under multipath, motion, Doppler effects, and noise.

Deployment can be organized into three stages: offline preparation defines the source operating range, target calibration determines normalization and noise characteristics, and limited online updates are used when persistent drift is observed. Post-deployment logs should connect forecasts and confidence with control actions and link outcomes.

B. Evaluation and Research Priorities

Future validation should compare transfer with a target-only model under the same label budget, examine multiple environments and transfer directions, and use augmentation-matched robustness baselines. WATERMARK supports reproducible scenario comparisons [19], while time-variation metrics characterize transfer difficulty [20]. Reporting should cover uncertainty, adaptation cost, and closed-loop communication outcomes in addition to forecasting error [21].

The scalar state in (1) is a research limitation. Hierarchical targets could connect coarse link quality with delay- or delay–Doppler-resolved structure for receiver configuration. Priorities include multi-source and online adaptation, conditional alignment under dynamics, calibrated abstention, and causal model compression for embedded acoustic modems.

VI. CONCLUSION

This paper considers underwater acoustic channel-state forecasting from three related aspects: temporal prediction, cross-scenario transfer, and robustness to uncertain observations. A channel estimate may become outdated before it is used for transmission decisions, while a predictor trained in one

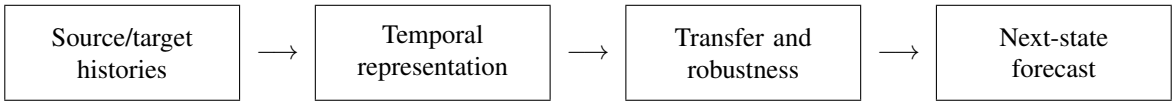


Fig. 2. Organization of transferable underwater acoustic channel forecasting.

TABLE II
DESIGN CHECKS FOR A TRANSFERABLE CHANNEL FORECASTER

Design element	Question to make explicit	Safeguard or evidence needed later
State interface	Which forecast horizon and channel summary drive the controller?	Verify that the representation preserves the physical quantity needed by the link decision.
Transfer regime	How much labeled or unlabeled target data are available?	Report the calibration resource and retain a conservative source-only or no-forecast fallback.
Feature alignment	Is the aligned representation the one consumed by the forecast head?	Check for negative transfer and condition alignment when predictive relationships differ.
Perturbation model	Does simulated corruption resemble uncertainty from channel estimation?	Include plausible SNRs, missing samples, colored interference, and impulsive disturbances.
Forecast output	Does the model expose confidence as well as a point estimate?	Calibrate uncertainty and define an abstention or conservative-control policy.
Online update	What triggers adaptation and how far may parameters move?	Bound memory and update magnitude, detect drift, and protect against catastrophic forgetting.

environment may degrade when propagation geometry, scattering, or noise conditions change. To address these issues, the proposed framework combines a decision-oriented channel representation, a shared temporal encoder, source-target feature alignment, and noise-aware consistency regularization. The forecasting model is placed between channel estimation and link control, making the prediction horizon, target-state definition, and target supervision explicit design choices.

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