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# Improving channel estimation for rapidly time-varying correlated underwater acoustic channels by tracking the signal subspace

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Multipath arrivals in many underwater acoustic channels are often cross-correlated and as a result, the path cross-correlation matrix shows a smaller rank than the number of multipath delay taps. Channel tracking error, measured in terms of the signal prediction error, can be significantly reduced by tracking the channel components in the signal subspace as previously demonstrated for a slowly varying channel in which the signal basis vectors can be assumed to be time-invariant. For a rapidly time-varying channel, one needs to track the time variation of the signal basis vectors. A subspace tracker is used in this paper to track the time variation of the signal basis vectors based on a coarse estimate of the channel impulse response (CIR). The signal amplitudes (channel components) are tracked using: (1) a recursive-least-square method and (2) a Kalman filter based on a state-space model. Performance of the proposed algorithms is demonstrated with real sea data. One finds that even for a rapidly time-varying channel, the channel impulse response can be tracked accurately. For the data analyzed, the signal prediction errors are reduced by ~12 dB using the algorithms proposed in this paper compared with that using the conventional approaches.


## 1. Introduction

It is recently shown that for many underwater acoustic channels, (1) the channel taps are often cross-correlated and the cross tap covariance is time varying [1,2] and (2) the signal prediction error (defined as the error between the received signal and the estimated signal, the latter calculated based on the convolution of the estimated channel impulse response (CIR) with the transmitted symbols) can be significantly reduced by tracking the signal subspace separately from the noise subspace in a noise-corrupted channel [2–4]. For correlated channels, the rank $r$ of the CIR covariance matrix is often (much) smaller than the number of taps $N$ used to model the CIR and can be represented by $r$ basis vectors and associated channel components. One observes experimentally that the basis vectors often vary much more slowly than the channel components [3,5]. For slowly time-varying channels, the basis vectors can be assumed time invariant (over the duration of a communication packet) and one need only to track the channel components. It was shown with real data that the channel can be estimated/tracked with high precision using a model based approach where the channel components are tracked using a Kalman filter – the signal prediction error using the model based approach can be as much

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as 10 dB smaller compared with the conventional recursive least square (RLS) or least mean square (LMS) method without exploring the signal subspace [2,3]. For rapidly time-varying channels, the basis vectors (of the signal subspace) cannot be assumed fixed. In this case, it is necessary to track the basis vectors as well as the channel components simultaneously. How to track the signal subspace basis vectors (and the associated channel components) is the subject of this paper. The question of interest is: how much improvement in the reduction of the signal prediction error can one expect for the rapidly time-varying case compared with the slowly time-varying case. Will one expect less improvement in the rapidly time-varying case due to the difficulty of tracking the channel basis vectors compared with the slowly time-varying case, or more improvement in the reduction of the signal prediction error compared with the conventional RLS algorithm due to the poor performance of the latter (conventional) approach in tracking the channel variation?

Traditional estimation techniques such as the RLS or LMS algorithms often fail to reconcile rapid channel variations due to the algorithm's limited tracking capability. Some improvements were obtained for sparse channels by reducing the degrees of freedoms, using matching pursuit or other compressive sensing methods [6,7]. Some advanced algorithms have been proposed to track the (time-varying) channel states. For example, the algorithm proposed by Iltis et al., estimates jointly the complex arrival gain and (bulk) delay using an Extended Kalman filter (EKF) [8,9]. In Ref. [10], Yang et al. proposed to explicitly estimate the multipath time delays by using a bank of delay locked loops (DLL), which is then followed by a MMSE multipath gain estimator. The common strategy of these methods is to break down the original optimization problem over the whole gains-delay space into a sequence of optimization problems with smaller parameter space. For example, in Ref. [11], this is done by optimizing over the gains first and then find the optimal delays. The adaptive delay filter [12] estimates the delay values of the filter and then adaptively determines the corresponding gain. The adaptive echo canceller [13] and the threshold RLS [14,15] are similar, in the sense that a full-tap adaptive filter is used as an auxiliary filter to provide tap location and then transfer the detected delay locations to a set of lower order filters to adapt those identified taps. In the context of multicarrier (i.e. OFDM) communications, the delay estimation problem is transformed to the direction-finding problem from the array processing literature, namely Root-MUSIC and ESPRIT, which are applied to identify the distinct path arrivals [7,10]. The direct computation of the delays is a nonlinear estimation problem and, as such, it suffers from the threshold effect at low signal-to-noise ratios (SNRs). The problem may be overcome by avoiding explicit estimation of the delays using, instead, an unstructured tracking of the variations of the signal subspace through one of the so called subspace tracking algorithms [16–18]. These algorithms are a class of adaptive filters based on sequential adaptive eigen-decomposition of the CIR covariance matrix and hence avoid direct eigenvector decomposition computation and associated estimation lag. Similar approaches were used in the context of OFDM communication systems, exploiting the frequency correlation of the channel, whose primary goal is to reduce complexity of the estimator [19,20]. Most of these works were carried out in the context of a radio frequency (RF) channel, where the channel taps are assumed wide-sense stationary and uncorrelated (the WSSUS condition). The calculations become very complicated and computationally intensive when the number of taps (the independent degrees of freedom) is large (>100) as is often the case for underwater acoustic channels.

For underwater acoustic channels where the taps are cross-correlated, it is important to exploit the channel (signal) subspace because it leads to not only improved performance but also much reduced computations [2–4]. In this case, the covariance matrix contains $r$ large eigenvalues assuming a high signal-to-noise ratio (SNR), with the rest of the eigenvalues determined by the noise variance. The eigenvectors associated with the $r$ large eigenvalues are the "eigenmodes" or basis vectors of the signal subspace. In this paper, we shall term "adaptive subspace tracking" to refer to tracking the $r$ basis vectors of the signal subspace as a function of time.[3] For that purpose, we shall adapt the projection approximation subspace tracking (PAST) method of [16]. To compare with the slowly time-varying cases where we studied the performance of the Reduced-rank Amplitude Estimation using the RLS (RAE-RLS) method [2], we present in this paper the Adaptive Subspace-tracking Reduced-rank Amplitude Estimation using the RLS method (ASRAE-RLS) for the rapidly time-varying channels. Likewise, for the slowly time-varying cases [2,3] where we presented the Reduced-rank Model-based Amplitude Estimation method (RMAE), we present in this paper the Adaptive Subspace-tracking Reduced-rank Model-based Amplitude Estimation method (ASRMAE) for the rapidly time-varying channels. We show for rapidly time-varying channels, by tracking the time-variation of the signal subspace simultaneously with the channel components, one can achieve as much as 12 dB improvement in signal prediction error compared with the conventional RLS applied to all taps. The main thrust of the subspace algorithms is the separation of the signal subspace from the noise subspace, allowing the algorithms to focus on tracking only the signal components and basis vectors. The assumption is that the stochastic channel fluctuation follows a state-space model and can be tracked accurately, which is not true for white noise. The reduced degrees of freedom (of the signal subspace) lead to significant saving in computational complexity.

The system model is presented in Section 2. Adaptive channel subspace tracking algorithms are presented in Section 3. First, we show that for rapidly time-varying channel, a significant reduction of the signal prediction error

[3] For a channel characterized by $k$ sparse arrivals out of $N$ taps, the signal is an $k$-sparse signal and can be pursued using compressive sensing. The signal subspace of dimension $k$ is in the delay domain. For correlated channels, the signal subspace (referred to in this paper) is in the eigenvector domain. If the $k$ sparse arrivals are correlated, the signal may have a subspace $r \ll k$. Whether the signal is continuous or spase in the delay domain has no direct bearing on the dimension of the signal subspace in the correlation eigenvector domain.