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# Free Space Optical Communication Cooperative Diversity

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**ABSTRACT**

**In this paper, I investigate the cooperative diversity technique as a candidate solution for combating turbulence-induced fading over Free-Space Optical (FSO) links. In particular, a one-relay cooperative diversity scheme is proposed and analyzed for non-coherent FSO communications with intensity modulation and direct detection (IM/DD). The error performance is derived in semi-analytical and closed-form expressions in the presence and absence of background radiation, respectively. Results show the enhanced diversity orders that can be achieved over both Rayleigh and lognormal fading models.**

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## I. INTRODUCTION

The adaptive least mean square (LMS) algorithm is of interest with its simple first order update equation Unfortunately, tracking performance of the LMS algorithm de-Teri orates dramatically in fast time-varying environments A recent bidirectional estimation strategy, which is pioneered by and further elaborated in and offers an improved tracking performance for fast-time varying channels, but this time, at the expense of a severe computational complexity. In this paper, we consider a bidirectional LMS algorithm over fast frequency-selective time-varying channels with an increased but still practical level of complexity. The tracking performance of the proposed algorithm at the steady-state is very close to that of the optimal minimum mean-square error (MMSE) filter in some settings of practical interest in terms of communication systems and is remarkably better than that of the conventional LMS.

Although there are various work present in the literature on other forms of bidirectional estimation none of them provide a theoretical analysis on the mean-square error (MSE) behaviour. Therefore, as a major contribution of this paper, we analyse the tracking performance of the bidirectional LMS algorithm by deriving a novel step-size dependent steady-state MSE and optimal step-size expressions over fast frequency-selective time-varying channels. This derivation is applicable to many communication scenarios in the sense that it does not depend on the channel characteristics and the modulation scheme in use. The numerical evaluations show a very good match between the theoretical and the experimental results most of the time. The robustness of the algorithm to the imperfect initialization and noisy Doppler and signal-to-noise ratio (SNR) values is also verified with the associated mean square identification error (MSIE) statistics. Finally, the promised performance is also investigated through BER results in a coded scenario as a more realistic application.

## II. TIME-VARYING CHANNELS

An adaptive coding scheme for digital communication over time-varying channels is presented. The scheme is based on a finite-state Markov channel

 

model. Emphasis is on the adaptation of the error protection to the actual channel state. The throughput gains that are achieved by the adaptive scheme relative to the conventional non adaptive coding methods are demonstrated by several examples. Of special interest is the use of punctured convolutional codes with maximum-likelihood Viterbi algorithm to enable adaptive encoding and decoding without modifying the basic structure of the encoder and the decoder

The idea of using knowledge of the current channel fading values to optimize the transmitted signal in wireless communication systems has attracted substantial research attention. However, the practicality of this adaptive signalling has been questioned due to the variation of the wireless channel over time, which results in a different channel at the time of data transmission than at the time of channel estimation. By characterizing the effects of fading channel variation on the adaptive signalling paradigm, it is demonstrated here that these misgivings are well founded, as the channel variation greatly alters the nature of the problem. The main goal of this paper is to employ this characterization of the effects of the channel variation to design adaptive signalling schemes that are effective for the time-varying channel. The design of encoded adaptive quadrature amplitude modulation (QAM) systems is considered first, and it demonstrates the need to consider the channel variation in system design. This is followed by the main contribution of this paper; using only a single out dated fading estimate when neither the Doppler frequency nor the exact shape of the autocorrelation function of the channel fading process is known, adaptive trellis-coded modulation schemes are designed that can provide a significant increase in bandwidth efficiency over their no adaptive counterparts on time-varying channels

The presence of reflectors in the environment surrounding a transmitter and receiver create multiple paths that a transmitted signal can traverse. As a result, the receiver sees the superposition of multiple copies of the transmitted signal, each traversing a different path. Each signal copy will experience differences in attenuation, delay and phase shift while travelling from the source to the receiver. This can result in either constructive or destructive interference, amplifying or attenuating the signal power seen at the receiver. Strong destructive interference is frequently referred to as a deep fade and may result in temporary failure of communication due to a severe drop in the channel signal-to-noise ratio.

A common example of multipath fading is the experience of stopping at a traffic light and hearing an FM broadcast degenerate into static, while the signal is re-acquired if the vehicle moves only a fraction of a meter. The loss of the broadcast is caused by the vehicle stopping at a point where the signal experienced severe destructive interference. Cellular phones can also exhibit similar momentary fades.

Fading channel models are often used to model the effects of electromagnetic transmission of information over the air I cellular networks and broadcast communication. Fading channel models are also used in underwater acoustic communications to model the distortion caused by the water. Mathematically, fading is usually modelled as a time-varying random change in the amplitude and phase of the transmitted signal

## III. LEAST-MEAN-SQURE METHODS

Least mean squares (LMS) algorithms are a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and the actual signal). It is a stochastic gradient descent method in that the filter is only adapted based on the error at the current time.

The combination of the famed kernel trick and the least-mean-square (LMS) algorithm provides an interesting sample-by-sample update for an adaptive filter in reproducing kernel Hilbert spaces (RKHS), which is named in this paper the KLMS. Unlike the accepted view in kernel methods, this paper shows that in the finite training data case, the KLMS algorithm is well posed in RKHS without the addition of an extra regularization term to penalize solution norms as was suggested by Kivinen [Kivinen, Smola and Williamson, ldquo Online Learning With Kernels, rdquo IEEE Transactions on Signal Processing, , Aug. 2004] and Smaller [Smale and Yao, ldquo Online Learning Algorithms ,rdquo Foundations in Computational Mathematics, This result is the main contribution of the paper and enhances the present understanding of the LMS algorithm with a machine learning perspective. The effect of the KLMS step size is also studied from the viewpoint of regularization. Two experiments are presented to support our conclusion that with finite data the KLMS algorithm can be readily used in high dimensional spaces and particularly in RKHS to derive nonlinear, stable algorithms with comparable performance to batch, regularized solutions.

## IV. MEAN SQUARED ERROR METHOD

In statistics, the mean squared error (MSE) of an estimator is one of many ways to quantify the difference between values implied by an estimator and the

 

true values of the quantity being estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the squares of the "errors." The error is the amount by which the value implied by the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance of the estimator. Like the variance, MSE has the same units of measurement as the square of the quantity being estimated. In an analogy to standard deviation, taking the square root of MSE yields the root mean square error or root mean square deviation (RMSE or RMSD), which has the same units as the quantity being estimated; for an unbiased estimator, the RMSE is the square root of the variance, known as the standard deviation.

This paper describes a practical method for estimating the mean square error (MSE) given a finite amount of sample data. The new estimator is applied to the critical problem of rank selection for reduced rank adaptive filters by selecting the rank that minimized the MSE estimate. Since this approach estimates the optimum filter rank, independent of the signal rank, it will work for any reduced rank algorithm, and in particular offers a working solution for nonagon based reduced rank techniques. The estimator's performance is simulated for the problem of detecting the optimum rank for identifying plane waves impinging a line array.

We consider the problem of estimating an unknown parameter vector x in a linear model that may be subject to uncertainties, where the vector x is known to satisfy a weighted norm constraint. We first assume that the model is known exactly and seek the linear estimator that minimizes the worst-case mean-squared error (MSE) across all possible values of x. We show that for an arbitrary choice of weighting, the optimal mini max MSE estimator can be formulated as a solution to a semi definite programming problem (SDP), which can be solved very efficiently. We then develop a closed form expression for the mini max MSE estimator for a broad class of weighting matrices and show that it coincides with the shrunken estimator of Mayer and Willke, with a specific choice of shrinkage factor that explicitly takes the prior information into account. Next, we consider the case in which the model matrix is subject to uncertainties and seek the robust linear estimator that minimizes the worst-case MSE across all possible values of x and all possible values of the model matrix. As we show, the robust mini max MSE estimator can also be formulated as a solution to an SDP. Finally, we demonstrate through several examples that the mini max MSE estimator can significantly increase the performance over the conventional least-squares estimator, and when the model matrix is subject to uncertainties, the robust mini max MSE estimator can lead to a considerable improvement in performance over the mini max MSE estimator.

## V. SYSTEM MODEL AND THE BIDIRECTIONAL LMS ALGORITHM

We consider an unknown time-varying frequency-selective communication channel represented by anLc-tap fading vec-tor fk =[fk,0... fk,Lc−1]T with uncorrelated entries and assume the following discrete-time complex baseband model at an epoch given as

$$y_k = \sum_{l=0}^{L_c-1} f_{k,l}\, a_{k-l} + n_k = \mathbf{f}_k^T \mathbf{a}_k + n_k \qquad \textbf{(1)}$$

Where yk is the observation symbol,

ak=[ak... ak−Lc+1] T is the vector of data symbols chosen from a finite alphabet A in an independent and identical fashion, and nk is a circularly symmetric complex white Gaussian noise with zero-mean and varianceN0.

The bidirectional LMS algorithm is basically an extension of the conventional unidirectional LMS that operates both in the forward and the backward directions along an observation block. Defining ˆffk andˆfbk to be the channel estimates in the forward and the backward directions, respectively, the algorithm is given as

$$\hat{\mathbf{f}}_{k+1}^f = \hat{\mathbf{f}}_k^f + 2\mu e_k^f \mathbf{a}_k \qquad \textbf{(2)}$$

$$\hat{\mathbf{f}}_{k-1}^b = \hat{\mathbf{f}}_k^b + 2\mu e_k^b \mathbf{a}_k \qquad \textbf{(3)}$$

where μ is the step-size, efk = yk −(ˆffk)Tak and ebk=yk −(ˆfbk)T ak are the forward and the backward errors, respectively. The arithmetic average operation is preferred among various choices as a simple yet efficient combining strategy to obtain the final coefficient estimates ˆfkas follows

 

$$\hat{\mathbf{f}}_k = \frac{\hat{\mathbf{f}}_k^f + \hat{\mathbf{f}}_k^b}{2}. \quad (4)$$

The bidirectional LMS algorithm requires (3Lc+2) complex additions and(5Lc+4)complex multiplications in esti-mating each fading vector while these numbers areLc+1and 2(Lc+1)for the conventional LMS algorithm and Lc(K−1) and LcK for a K-tap MMSE filter respectively. Note that the MMSE filter also requires a matrix inversion of complexity O(K3) and a matrix multiplication of complexity O(LcK2) to compute optimal filter coefficients. As a result, the overall complexity of the bidirectional LMS is approximately twice that of the conventional LMS and significantly lower compared to the optimal MMSE estimation.

## VI. NUMERICAL RESULTS

Without any loss of generality, a frequency-selective channel with Lc ={2,4} taps is assumed with wide-sense stationary uncorrelated scattering (WSSUS) Rayleigh fading generated according to the well-known Jakes' model .The channel has a fast time variation with the maximum normalized Doppler frequency of fdTs ={0.01,0.02}.In each trial, a set of L= 100information symbols are chosen independently from the the BPSK alphabet A={−1,+1}so that Es=E4=1, and the observations are produced according to the system model given in (1). We accordingly assume constant average SNR and maximum normalized Doppler frequency over a data block due to the transmission of short data blocks.

In Fig. 1, we plot theoretical and experimental normalized MSIE, i.e ,JMSIE/Lc, results for the bidirectional LMS (Bi LMS) algorithm by using (5) and (20) for varying μ and at γ Es/N0 =10dB forfdTs =0.01and γ =4Db for fdTs=0.02whereγdenotes the average received SNR. The experimental normalized MSIE results associated with the conventional unidirectional LMS (Uni LMS) and MMSE filter are also provided. We observe a very good match between the theoretical and the experimental results for the bidirectional LMS for any choice of μ. The tracking ability of the bidirectional LMS is also verified by achieving a minimum MSIE which is close to that of the MMSE filter which is far.

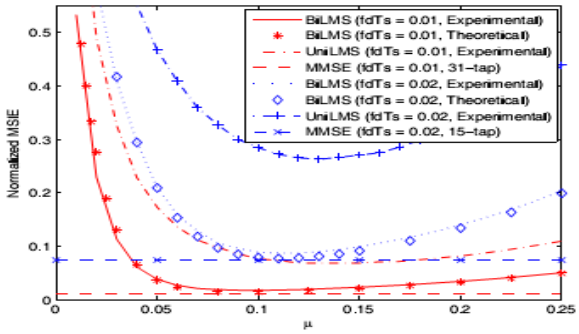


Fig.5. 1. Theoretical and experimental normalized MSIE over a frequency-selective Rayleigh fading channel of length L= 100withLc =2tap at γ=10dB forfdTs=0.01andγ=4dB forfdTs=0.02.

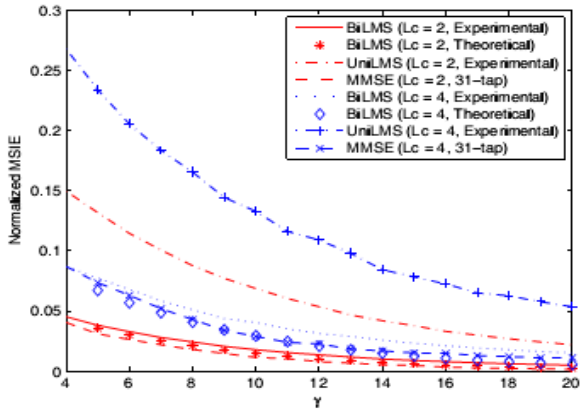


Fig.5 .2. Theoretical and experimental normalized MSIE associated with the optimal step-size over a frequency-selective Rayleigh fading channel of length L= 100withLc={2,4}tap and fdTs=0.01.

beyond that of the conventional LMS. We should also report that no significant performance improvement is observed in MMSE filter when K>31for fdTs=0.01andK>15for fdTs=0.02.

In Fig. 2, the MSIE results are presented for varying with the optimal step-size values (μopt) over a frequency-selective channel with Lc ={2,4}taps. The experimental and the theoretical MSIE results for the bidirectional LMS algorithm are again observed to exhibit a very good match for various γ choices. The theoretical μ opt's computed according to (21)-(22) in Table I together with the experimental values produced.

Table I
Theoretical And Experimental optimal step-Size (Mopt)Values F Or The bidirectional LMS Algorithm]

| SNR | | 0 dB | 2 dB | 4 dB | 6 dB | 8 dB | 10 dB |
|---|---|---|---|---|---|---|---|
| $f_dT_s = 0.01$ | Experiment | 0.060 | 0.060 | 0.070 | 0.080 | 0.090 | 0.100 |
| | Theory | 0.056 | 0.062 | 0.069 | 0.076 | 0.084 | 0.092 |
| $f_dT_s = 0.02$ | Experiment | 0.090 | 0.100 | 0.110 | 0.130 | 0.140 | 0.150 |
| | Theory | 0.089 | 0.100 | 0.110 | 0.122 | 0.134 | 0.146 |

 

through exhaustive search with 0.01 increments which are observed to be very close to each other for various fdTs choices. Because the large step-size values contribute to the self-noise part and the small ones amplify the lag part of the associated MSIE, the optimal step-size appears to be a compromise to obtain the best performance in accordance with the results of Fig. 1 and should be greater to track much faster channels.

## VII. CONCLUSION

A bidirectional LMS algorithm is considered and analysed over fast frequency-selective time-varying channels. The tracking performance of the bidirectional LMS is shown to be very close to that of the optimal MMSE filter in some settings of practical interest, and remarkably better than that of the conventional LMS algorithm. A step-size dependent steady-state MSE together with the optimal step-size expressions are derived in order to provide a theoretical analysis, and the corresponding theoretical results show a good match to the experimental ones most of the time. The algorithm is also shown to be robust to imperfect initialization together with noisy Doppler and SNR information, and achieves BER results very close to that of the MMSE filter in various scenarios.

## REFERENCES

[1]An Analysis Of The Bidirectional Lms Algorithm Over Fast-Fading Channels, Yavuz Yapıcı And A. Özgür Yılmaz, Ieee Transactions On Communications, Accepted For Publication.

[2] B. Widrow and S. Stearns, Adaptive Signal Processing. Prentice Hall,1985.

[3] C. Komninakis, C. Fragouli, A. Sayed, and R. Wesel, “Multi-input multi-output fading channel tracking and equalization using Kalman estimation,”IEEE Trans. Signal Process., vol. 50, no. 5, pp. 1065–1076,May 2002.

[4] A. Anastasopoulos and K. Chugg, “Adaptive soft-input soft-output algorithms for iterative detection with parametric uncertainty,” IEEE Trans. Commun., vol. 48, no. 10, pp. 1638–1649, Oct. 2000.

[5] A. Hansson and T. Aulin, “Generalized APP detection of continuous phase modulation over unknown ISI channels,”IEEE Trans. Commun.,vol. 53, no. 10, pp. 1615–1619, Oct. 2005.

 