Soft Direct-Adaptive Turbo Equalization for MIMO Underwater Acoustic Communications

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***Abstract*—A Soft Direct-Adaptive Turbo Equalization (Soft DA-TEQ) is proposed for robust MIMO UWA communications. The proposed Soft DA-TEQ is derived under on the general frame of Expectation Maximization (E.M.) algorithm, which utilize the *a priori* soft decisions from the decoder to direct the equalizer's coefficients adaptation. The *a priori* soft decisions directed adaptation effectively lower the error propagation, which often cause catastrophic performance degradation in Hard DA-TEQ. Besides, in each iteration of the E.M. based soft adaption, the reliability of the symbol estimation is updated and used in the next iteration of soft adaption, which further enhances the convergence of the DA-TEQ. Experimental results show that the proposed Soft DA-TEQ is capable of robust detection in fast time varying MIMO UWA channels, even with low pilot overhead.**

***Index Terms*—Adaptive equalization, turbo equalization, multiple-input multiple-output (MIMO), underwater acoustic communications.**

I. Introduction

High data-rate multiple-input multiple-output (MIMO) underwater acoustic (UWA) communications is very challenging due to severe inter-symbol interference, strong spatial correlation and fast channel variation. Turbo equalization is considered as a promising detection scheme to achieve satisfactory performance in MIMO UWA communications. However, due to the large delay spread of UWA channels, it is desirable to design efficient low-complexity minimum mean square error (MMSE) turbo equalizers for real-time applications.

Currently, two classes of MMSE turbo equalizers are commonly used in UWA communications: channel estimation based MMSE turbo equalizer (CE MMSE-TEQ) [1] and direct adaptive turbo equalizer (DA-TEQ) [2]. In CE MMSE-TEQ, the UWA channel is explicitly estimated and incorporated into the calculation of MMSE equalizer coefficients. The performance of the CE MMSE-TEQ has been verified by many oceans experiments. However, due to the typically long channel impulse response, the large-dimension matrix inversion involved in the equalizer coefficients computation contributes to the high complexity. Alternatively, the DA-TEQ uses adaptive algorithms to directly equalize the received symbols without the knowledge of the UWA channel. Most existing DA-TEQs use either the Recursive Least Square (RLS) or Least Mean Square (LMS) algorithm to adjust the equalizer coefficients [2]–[5]. The RLS based DA-TEQ has faster convergence but higher complexity due to matrix inversion at each time step. In contrast, the LMS based DA-TEQ enjoys low-complexity at the cost of slow convergence. Hence the conventional LMS based DA-TEQ requires long training sequence to converge, which greatly reduced the spectral efficiency.

Most existing DA-TEQs use hard-decision to direct the coefficient adaptation at data-directed (DD) mode, which often suffer from error propagation. To lower the error propagation effect in coefficients adaptation, a soft-decision directed RLS algorithm named RELS is recently used in turbo equalization for UWA communications, where the *a priori* information from the decoder is incorporated into the adaptation [6]. Experimental results show that the RELS based DA-TEQ outperforms the hard-decision directed RLS based DA-TEQ in single input multiple output (SIMO) systems, but it still needs long training sequence for initial convergence and has much higher complexity than the LMS based DA-TEQ.

In this paper, we propose a Soft Direct-Adaptive Turbo Equalization (Soft DA-TEQ) with high spectral efficiency for MIMO UWA communications. We derive the soft direct adaptation in DA-TEQ with the the general frame of Expectation Maximization (E.M.) algorithm [7]. The reliability of the adaptive symbol estimation increases in the E.M. iteration process, which greatly speed the overall convergence of the turbo detection. The low-complexity gradient based NLMS algorithm are embedded into the E.M. loop to adjust the equalizer coefficients. Experimental results show that the proposed Soft DA-TEQ greatly enhances the convergence of the iterative detection, even with low pilot overhead.

Throughout this paper, superscripts $(\cdot)^T$ and $(\cdot)^H$ represent matrix transpose and conjugate transpose, $E\{\cdot\}$ denotes statistical expectation.

II. System Model

Consider an $N \times M$ MIMO UWA communication system depicted in Fig. 1, where N and M are the numbers of transducers and hydrophones, respectively. At the transmitter, N parallel information bit streams $\{\mathbf{b}^{(n)}\}_{n=1}^{N}$, are independently encoded and interleaved. The nth branch of the interleaved coded bits are then grouped as a block $\mathbf{c}^{(n)} = \left[\mathbf{c}_1^{(n)} \;\; \mathbf{c}_2^{(n)} \cdots \mathbf{c}_{K_c}^{(n)}\right]$, where $\mathbf{c}_k^{(n)}$ represents the kth bit vector $\left[c_{k,1}^{(n)} \;\; c_{k,2}^{(n)} \cdots c_{k,q}^{(n)}\right]$ with $c_{k,j}^{(n)} \in \{0,1\}$. Each bit vector $\mathbf{c}_k^{(n)}$ is mapped into a specific symbol $x_k^{(n)}$ from the 2^q-ary constellation set $S = \{\alpha_1, \alpha_2, \cdots, \alpha_{2^q}\}$, where α_i corresponds to the deterministic bit pattern $\mathbf{s}_i = [s_{i,1} \; s_{i,2} \cdots s_{i,q}]$ with $s_{i,j} \in 0,1$. After symbol mapping, the baseband signal is partitioned into blocks and modulated with a single carrier, then transmitted to the MIMO UWA channel.

At the receiver side, after front end processing such as synchronization, demodulation and down sampling, the received passband signals are converted into the symbol rate baseband

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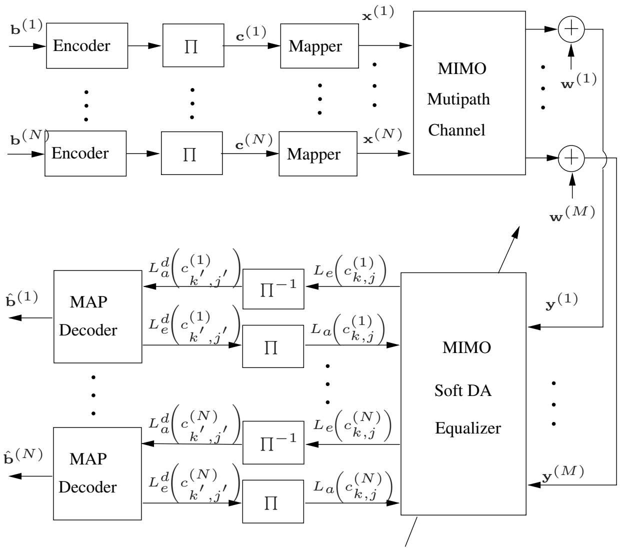


Fig. 1. Structure of a MIMO communication system with turbo equalizer.

signals. The mth branch of the received baseband signal at time instant k is written as

$$y_k^{(m)} = \sum_{n=1}^{N} \sum_{l=0}^{L-1} h_l^{(m,n)} x_{k-l}^{(n)} + w_k^{(m)} \tag{1}$$

where $x_{k-l}^{(n)}$ denotes the symbol transmitted by the nth transducer at time instant $k-l$ and $\{h_l^{(m,n)}\}_{l=1}^{L}$ is the baseband equivalent channel between the nth transducer and the mth hydrophone, where L is the length of the baseband equivalent channel. In addition, $w_k^{(m)}$ represents the noise sample at the mth receiver, which is modeled as additive white Gaussian noise (AWGN) with zero mean and variance σ_w^2.

We stack up the received symbols from all the M receive elements as $\mathbf{y}_k = [y_k^{(1)}, y_k^{(2)}, \ldots, y_k^{(M)}]^T$

$$\mathbf{y}_k = \sum_{l=0}^{L-1} \mathbf{h}_l \mathbf{x}_{k-l} + \mathbf{w}_k \tag{2}$$

where

$$\mathbf{x}_k = [x_k^{(1)}, x_k^{(2)}, \ldots, x_k^{(N)}]^T \tag{3}$$
$$\mathbf{w}_k = [w_k^{(1)}, w_k^{(2)}, \ldots, w_k^{(M)}]^T \tag{4}$$

and

$$\mathbf{h}_l = \begin{bmatrix} h_l^{(1,1)} & h_l^{(1,2)} & \cdots & h_l^{(1,N)} \\ h_l^{(2,1)} & h_l^{(2,2)} & \cdots & h_l^{(2,N)} \\ \vdots & \vdots & \ddots & \vdots \\ h_l^{(M,1)} & h_l^{(M,2)} & \cdots & h_l^{(M,N)} \end{bmatrix}. \tag{5}$$

The structure of MIMO direct adaptive turbo receiver is depicted in Fig. 1, which is consist of a soft-input soft-output MIMO adaptive equalizer and a maximum *a posterior* probability (MAP) decoder. The MIMO adaptive equalizer directly estimates the transmitted symbols $\hat{x}_k^{(n)}$ and outputs the corresponding bit extrinsic information $L_e\left(c_{k,j}^{(n)}\right)$. The detailed mapping operation between $\hat{x}_k^{(n)}$ and $L_e\left(c_{k,j}^{(n)}\right)$ is provide in [8]. The extrinsic information is then de-interleaved and passed to the decoder as the *a priori* information $L_a^d\left(c_{k',j'}^{(n)}\right)$ for MAP decoding. The MAP decoder outputs the extrinsic information $L_e^d\left(c_{k',j'}^{(n)}\right)$, which is interleaved and fed back to the equalizer as the new *a priori* information $L_a\left(c_{k,j}^{(n)}\right)$ for symbol detection. Based on the turbo principle, the extrinsic information are iteratively exchanged between the equalizer and decoder, which increase the reliability of the soft information in each iteration. The final hard decision $\hat{b}_k^{(n)}$ is made after multiple iterations or after the decoder output converges.

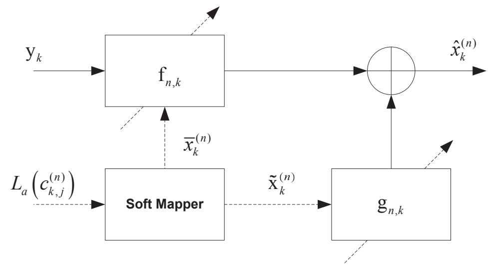


Fig. 2. Structure of adaptive linear turbo equalizer.

III. Proposed Soft Decision Directed Direct-Adaptive Turbo Equalizer

A. Structure of Adaptive Linear Turbo Equalizer

The structure of the adaptive linear turbo equalizer is depicted in Fig. 2. The transmitted symbol $x_k^{(n)}$ is estimated by a linear combining of the received signals and the *a prior* soft decisions

$$\hat{x}_k^{(n)} = \mathbf{f}_{n,k}^H \mathbf{y}_k + \mathbf{g}_{n,k}^H \tilde{\mathbf{x}}_{n,k} \tag{6}$$

where $\tilde{\mathbf{x}}_{n,k} = [\bar{\mathbf{x}}_1^{(n)}, \bar{\mathbf{x}}_2^{(n)}, \ldots, \bar{\mathbf{x}}_K^{(n)}]^T$. Here $\bar{\mathbf{x}}_j^{(n)} = [\bar{x}_{1,j}, \bar{x}_{2,j}, \ldots, \bar{x}_{N,j}]^T$ when $j \neq k$, and $\bar{\mathbf{x}}_j^{(n)} = [\bar{x}_{1,j}, \ldots, \bar{x}_{n-1,j}, 0, \bar{x}_{n+1,j}, \ldots, \bar{x}_{N,j}]^T$ when $j = k$.

The *a prior* soft decision $\bar{x}_{n,k}$ is computed based on the *a prior* soft information from the decoder

$$\bar{x}_{n,k} = \sum_{\alpha_i \in S} \alpha_i P\left(x_{n,k} = \alpha_i\right) \tag{7}$$

where

$$P\left(x_{n,k} = \alpha_i\right) = \prod_{j=1}^{q} \frac{1}{2}\left(1 + \tilde{s}_{i,j} \tanh\left(L_a\left(c_{k,j}^{(n)}\right)/2\right)\right) \tag{8}$$

and

$$\tilde{s}_{i,j} = \begin{cases} +1 & \text{if } s_{i,j} = 0 \\ -1 & \text{if } s_{i,j} = 1. \end{cases}$$

To simplify the notations for the following algorithm derivation, equation (6) can be further written as

$$\hat{x}_k^{(n)} = \mathbf{G}_{n,k}^H \mathbf{U}_k \tag{9}$$

where $\mathbf{G}_{n,k}^H$ and $\mathbf{U}_k$ are the overall equalizer coefficient vector and overall input vector at time instant k, which are defined as

$$\begin{aligned}\mathbf{G}_{n,k} &= [\mathbf{f}_{n,k}^T\, \mathbf{g}_{n,k}^T]^T & (10)\\ \mathbf{U}_k &= [\mathbf{y}_k^T\, \tilde{\mathbf{x}}_{n,k}^T]^T & (11)\end{aligned}$$

The adaptive algorithms are used to adjust the equalizer's coefficients to minimize the MSE $E[|\hat{x}_k^{(n)} - x_k^{(n)}|^2]$ between the estimated symbol and transmitted symbol.

Conventional adaptive equalizer consider training symbols insertion at the beginning of a data frame. In the training phase, the adaptive algorithm updates the equalizer coefficients based on received signal and the known training symbols. However, in fast time varying channels, like underwater acoustic channels, the equalizer's coefficients should be updated during symbol detection, which is after the training phase. Since the transmitted symbols are unknown at the receiver, the adaptive algorithms work in a decision directed (DD) mode, where the adaptation of the equalizer coefficients is driven by the decisions of the detected symbols.

B. Soft Decision Directed Adaptation

Most existing DA-TEQs use hard decisions of the estimated transmitted symbols to drive the coefficients adaptation in DD mode. The main drawback of the hard decision directed adaptation is the error propagation, which may results into a catastrophic failure of the convergence. Especially in fast time varying MIMO UWA channels, due to the higher probability of incorrect symbol decision and extremely long equalizer length, the error propagation effect is further amplified.

To lower the error propagation in adaption during the DD mode, we propose a soft decision directed-adaptive (SD-DA TEQ) turbo equalizer for MIMO UWA communication systems. Take advantage of the *a prior* information fed back from the soft-input soft-output decoder, the *a prior* soft decision is naturally incorporate into the equalizer's coefficients adaption to lower the error propagation. In the following, we derive our soft adaptation method in DD mode under the frame of E.M. algorithm. In DD mode, the transmitted symbol $x_{n,k}$ is unavailable, which is treated as unobserved latent data. The received signal is the incomplete observed data. Repeatedly applying the following two steps, Expectation step and Maximization step, gives us the maximum likelihood (ML) estimation of the equalizer's coefficients. Note that in the following derivation, the subscript k in $\mathbf{G}_{n,k}$ is dropped for notation simplification.

The maximum likelihood estimation of $\mathbf{G}_n$ is given by

$$\begin{aligned}\hat{\mathbf{G}}_n &= \arg\max_{\mathbf{G}_n} \log p(\mathbf{U}_k, x_k^{(n)}; \mathbf{G}_n) & (12)\\ &= \arg\max_{\mathbf{G}_n} l(\mathbf{G}_n) & (13)\end{aligned}$$

In DD mode $x_k^{(n)}$ is unavailable, the objective function to be maximized is given by

$$\begin{aligned}\bar{l}(\mathbf{G}_n) &= \log p(\mathbf{U}_k; \mathbf{G}_n) & (14)\\ &= \log \sum_{x_k^{(n)} \in S} p(\mathbf{U}_k, x_k^{(n)}; \mathbf{G}_n) & (15)\\ &= \log \sum_{x_k^{(n)} \in S} p(x_k^{(n)}) \frac{p(\mathbf{U}_k, x_k^{(n)}; \mathbf{G}_n)}{p(x_k^{(n)})} & (16)\\ &\geq \sum_{x_k^{(n)} \in S} p(x_k^{(n)}) \log \frac{p(\mathbf{U}_k, x_k^{(n)}; \mathbf{G}_n)}{p(x_k^{(n)})} & (17)\\ &= \sum_{x_k^{(n)} \in S} p(x_k^{(n)}) \log p(\mathbf{U}_k | x_k^{(n)}; \mathbf{G}_n) & (18)\\ &= \hat{l}(\mathbf{G}_n) & (19)\end{aligned}$$

Here $\hat{l}(\mathbf{G}_n)$ is the lower bound of the original objective function $\bar{l}(\mathbf{G}_n)$. Note that $\bar{l}(\mathbf{G}_n)$ is a concave function, hence the inequality in (17) follows the Jensen's Inequality.

In turbo equalization, the estimated symbol $\hat{x}_k^{(n)}$ is commonly treated as the output of an equivalent Gaussian channel

$$\hat{x}_k^{(n)} = A_n x_k^{(n)} + \eta_n \qquad (20)$$

where $\eta_n \sim \mathcal{N}(0, A_n(1-A_n))$. With this Gaussian approximation, $\hat{l}(\mathbf{G}_n)$ is further expressed as

$$\begin{aligned}\hat{l}(\mathbf{G}_n | A_n) &= \sum_{x_k^{(n)} \in S} p(x_k^{(n)}) (C_n - \frac{|A_n x_k^{(n)} - \hat{x}_k^{(n)}|^2}{2A_n(1-A_n)})\\ &= C_n - \frac{|A_n \bar{x}_k^{(n)} - \mathbf{G}_n^H \mathbf{U}_k|^2}{2A_n(1-A_n)} & (21)\end{aligned}$$

where $C_n = \log\left(1/2\pi\sqrt{A_n(1-A_n)}\right)$.

The parameter A_n is estimate by time averaging

$$\hat{A}_n = \frac{1}{K_c} \sum_{k=1}^{K_c} \frac{\hat{x}_k^{(n)}}{Q(\hat{x}_k^{(n)})} \qquad (22)$$

where $Q(\cdot)$ is a slicer operation. Note that we only use the estimated transmitted symbols to estimate A_n and the training symbols is not applied for this parameter estimation. Since $\hat{A}_n$ is estimated with $\hat{x}_k^{(n)}$ and $\hat{x}_k^{(n)}$ is determined by the received signal and the estimated equalizer's coefficients $\hat{\mathbf{G}}_n$, $\hat{A}_n$ can be further expressed as a function of $\hat{\mathbf{G}}_n$

$$\hat{A}_n \triangleq F(\hat{\mathbf{G}}_n) = \frac{1}{K_c} \sum_{k=1}^{K_c} \frac{\hat{\mathbf{G}}_n^H \mathbf{U}_k}{Q(\hat{\mathbf{G}}_n^H \mathbf{U}_k)} \qquad (23)$$

Then the lower bounded objective function $\hat{l}(\mathbf{G}_n | \hat{A}_n)$ can be presented as $\hat{l}(\mathbf{G}_n | F(\hat{\mathbf{G}}_n))$.

Now, we can use the E.M. algorithm to iteratively estimate the equalizer's coefficients

Expectation step: At the q_{th} iteration, the average log-likelihood of the complete data is given by $\hat{l}(\mathbf{G}_n | F(\hat{\mathbf{G}}_n^q))$. Here q is the E.M. iteration index and $\hat{\mathbf{G}}_n^q$ is the estimated channel coefficient vector at the q_{th} iteration.

Maximization step: The equalizer's coefficient vector is updated with $\hat{\mathbf{G}}_n^{(q+1)}$ through maximizing $\hat{l}(\mathbf{G}_n|F(\hat{\mathbf{G}}_n^q))$

$$\hat{\mathbf{G}}_n^{(q+1)} = \arg\max_{\mathbf{G}_n} \hat{l}(\mathbf{G}_n|F(\hat{\mathbf{G}}_n^q)) \tag{24}$$

which is equivalent to minimize the following objective function

$$\begin{aligned}\hat{\mathbf{G}}_n^{(q+1)} &= \arg\min_{\mathbf{G}_n} \mathbf{Q}(\mathbf{G}_n|F(\hat{\mathbf{G}}_n^q)) \\ &= \arg\min_{\mathbf{G}_n} |F(\hat{\mathbf{G}}_n^q)\bar{x}_k^{(n)} - \mathbf{G}_n^H\mathbf{U}_k|^2 \end{aligned}\tag{25}$$

Considering the fast time variations of the UWA channels, we use the low complexity adaptive algorithm to implement the above minimization problem, and the previous simplified notation $\mathbf{G}_n$ for coefficient vector is recovered as $\mathbf{G}_{n,k}$ in the process of adaptation. To adaptively find the minimum point of $\mathbf{Q}(\mathbf{G}_{n,k}|F(\hat{\mathbf{G}}_{n,k}^q))$, we take the partial derivative

$$\frac{\partial J}{\partial \mathbf{G}_{n,k}^H} = -2(A^{(q)}\bar{\mathbf{x}}_k^{(n)} - \mathbf{G}_{n,k}^H\mathbf{U}_k)\mathbf{U}_k \tag{26}$$

where $J = \mathbf{Q}(\mathbf{G}_{n,k}|F(\hat{\mathbf{G}}_{n,k}^q))$. Consider the gradient $\mathbf{G}_{n,k} = \mathbf{G}_{n,k-1} - \mu\frac{\partial J}{\partial \mathbf{G}_{n,k}^H}$, we get the LMS coefficients adaptation:

$$\hat{\mathbf{G}}_{n,k}^{q+1} = \hat{\mathbf{G}}_{n,k-1}^{q+1} + 2\mu(\hat{A}^{(q)}\bar{\mathbf{x}}_k^{(n)} - (\hat{\mathbf{G}}_{n,k-1}^{q+1})^H\mathbf{U}_k)\mathbf{U}_k \tag{27}$$

where the μ is the step size.

To achieve faster convergence, we use the Normalized LMS algorithm

$$\hat{\mathbf{G}}_{n,k}^{q+1} = \hat{\mathbf{G}}_{n,k-1}^{q+1} + 2\frac{\mu}{\epsilon + \mathbf{U}_k\mathbf{U}_k^H}(\hat{A}^{(q)}\bar{\mathbf{x}}_k^{(n)} - (\hat{\mathbf{G}}_{n,k-1}^{q+1})^H\mathbf{U}_k)\mathbf{U}_k \tag{28}$$

where the ϵ is a small number for regularizing the adaptation at the initial stage.

IV. Experimental Results

The proposed MIMO Soft DA-TEQ has been tested by ocean data collected in the SPACE08 experiment, which is conducted at the coast of Martha's Vineyard, Edgartown, MA, in October 2008. In this experiment, a MIMO single carrier acoustic communication system was tested with 60 m, 200 m and 1000 m transmission distances respectively. A $rate = 1/2$ convolutional code with generator polynomial in octal notation $G = [17, 13]$ was chosen as the channel code. The signal format are detailed in Fig. 3, where K_p and K_d are the size of pilot and information blocks, respectively.

During the soft adaptation, we set the number of iteration in the E.M. based adaptation as 5, *i.e.*, $q_{max} = 5$. The step size for the NLMS algorithm is chosen as 1 and 0.1 at training mode and DD mode, respectively. Note that in the initial stage of turbo detection, the *a prior* information from the decoder is unavailable, therefore the hard directed adaptation is adopted.

We present two typical channels observed during one data payload transmission in Fig. 4. The channel impulse responses (CIR) are non-minimum phased with time variation, which is challenging for symbol detection.

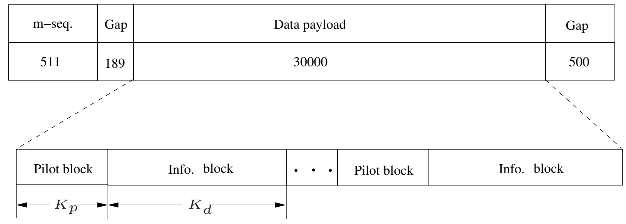
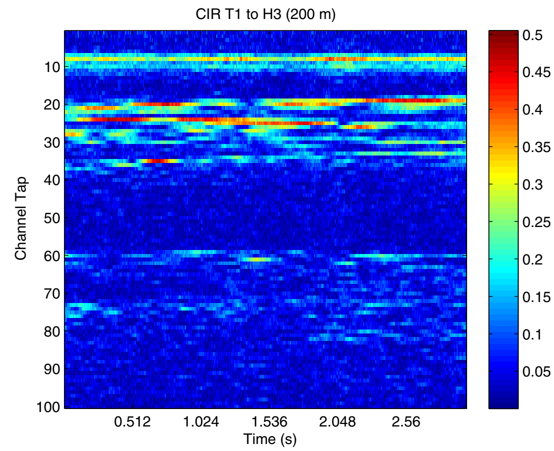
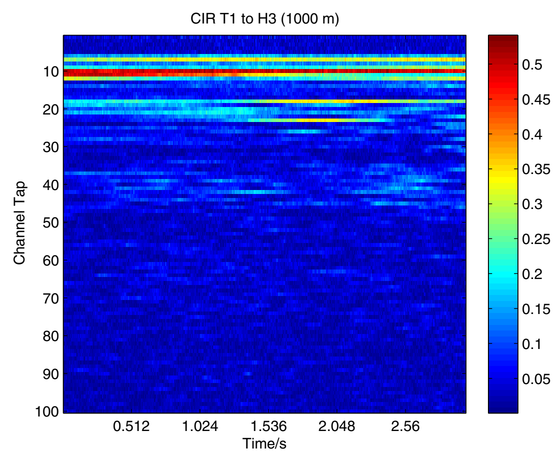


Fig. 3. Signal format in SPACE08 experiment.



(a)

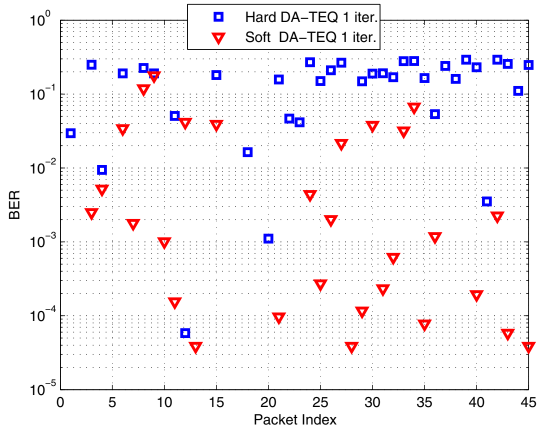


(b)

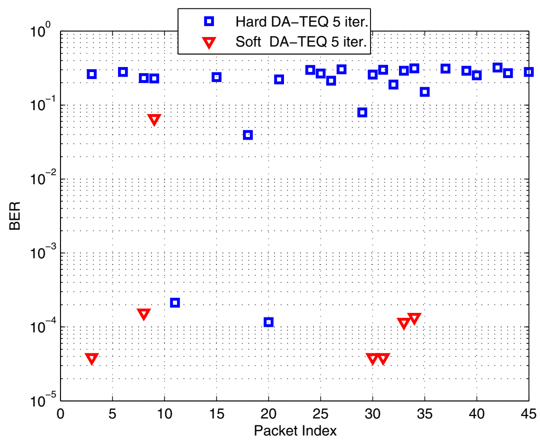
Fig. 4. Examples of channel impulse response over long term observation.

Figure 5 shows the BER comparison between the Soft DA-TEQ and the Hard DA-TEQ in each packet. The detection result is also summarized in Fig. 6 in terms of the percentages of different BER ranges. After 1 iteration, most packets achieved BER below 10^{-2} using the Soft DA-TEQ. After multiple iterations, the Soft DA-TEQ successfully detected 91.1% of packets with BER less than 10^{-4}. However, with the Hard DA-TEQ, there are still 48.9% packets failed with BER larger than 10^{-1}.

For 1000 m transmission, the BER comparison between the Soft DA-TEQ and the Hard DA-TEQ in each packet



(a)



(b)

Fig. 5. Performance comparison between Soft DA-TEQ and Hard DA-TEQ for 2×6 MIMO over 200 m UWA channels (QPSK modulation). (a)BER comparison after 1 iteration. (b) BER comparison after 5 iteration.

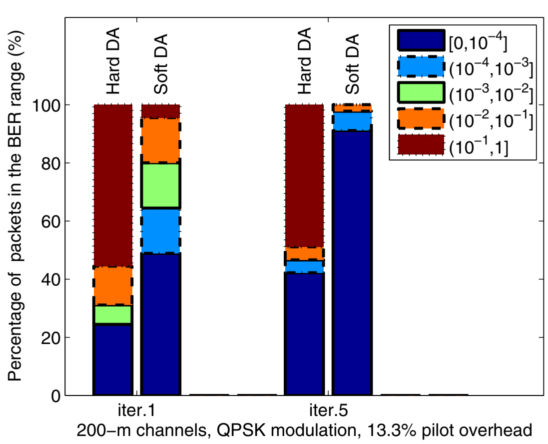
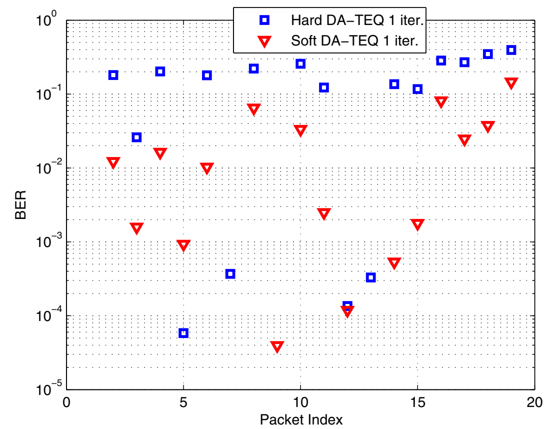
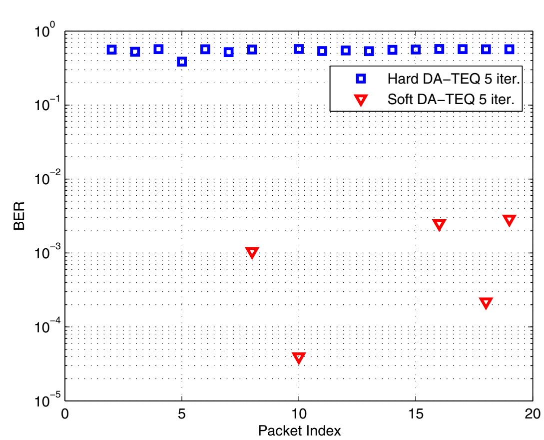


Fig. 6. BER ranges comparison between Soft DA-TEQ and Hard DA-TEQ for 2×6 MIMO over 200 m UWA channels.

is presented in Fig. 7. The overall detection result is also



(a)



(b)

Fig. 7. Performance comparison between Soft DA-TEQ and Hard DA-TEQ for for 2×6 MIMO over 1000 m UWA channels (QPSK modulation). (a)BER comparison after 1 iteration. (b) BER comparison after 5 iteration.

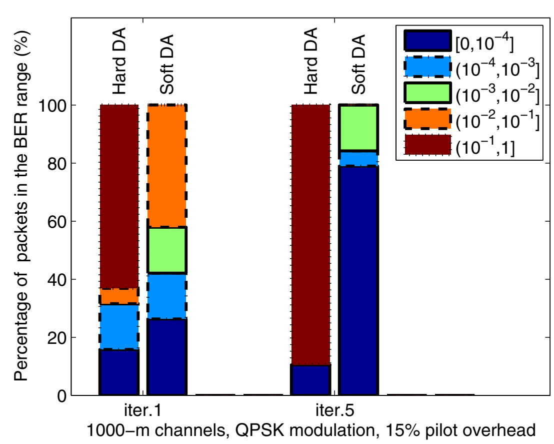


Fig. 8. BER ranges comparison between Soft DA-TEQ and Hard DA-TEQ for 2×6 MIMO over 1000 m UWA channels.

summarized in Fig. 6. The results of the 1000 m share the same trend in performance gap between the Soft DA-TEQ and the Hard DA-TEQ. After 1 iteration, 57.9% of packets achieved BER below 10^{-2} using the Soft DA-TEQ. After 5 iterations, 84.2% of packets are successfully detected by the Soft DA-TEQ with BER less than 10^{-4} . Moreover the minimum BER among all packets is on the level of 10^{-3}, which is lower the case of 200 m transmission. However, compared with the 200 m transmission, the Hard DA-TEQ experienced more severe catastrophic error propagation, which make the adaptive equalizer incapable of convergence, i.e., the adaptation stops.

The obvious performance gap between the Soft DA-TEQ and Hard DA-TEQ demonstrates that the Soft DA-TEQ exhibits faster convergence and robust performance in time varying UWA MIMO channels. Besides, the experimental results verified that our proposed Soft DA-TEQ can work with low pilot overhead (13.3% and 15% pilot overheads are used in the 200 m and 1000 m transmission), which greatly enhanced the system's spectral efficiency.

V. Conclusion

A Soft DA-TEQ with robust performance and high spectral efficiency is proposed for MIMO UWA communications. The proposed Soft DA-TEQ is derived based on the frame of E.M. algorithm, which utilize the *a priori* soft decisions from the decoder to adjust the equalizer coefficients. The *a priori* soft decisions directed adaptation effectively lower the error propagation, which often results into catastrophic performance degradation in hard directed DA-TEQ. Experimental results show that the proposed Soft DA-TEQ greatly enhances the convergence of the iterative detection and works robustly in fast time varying MIMO UWA channels, even with low pilot overhead.

References

[1] Z. Yang and Y. R. Zheng, "Iterative channel estimation and turbo equalization for multiple-input multiple-output underwater acoustic communications," *IEEE J. Ocean. Eng.*, vol. 99, Feb. 2015.

[2] J. W. Choi, T. J. Riedl, K. Kim, A. C. Singer, and J. C. Preisig, "Adaptive linear turbo equalization over doubly selective channels," *IEEE J. Ocean. Eng.*, vol. 36, no. 4, pp. 473–489, Oct. 2011.

[3] P. A. Van Walree and G. Leus, "Robust underwater telemetry with adaptive turbo multiband equalization," *IEEE J. Ocean. Eng.*, vol. 34, no. 4, pp. 645–655, 2009.

[4] C. Laot, N. Beuzeulin, and A. Bourre, "Experimental results on mmse turbo equalization in underwater acoustic communication using high order modulation," in *OCEANS 2010-Seattle*, 2010, pp. 1–6.

[5] M. Qingwei, H. Jianguo, H. Jing, H. Chengbing, and M. Chuang, "An improved direct adaptive multichannel turbo equalization scheme for underwater communications," in *OCEANS, 2012-Yeosu*. IEEE, 2012, pp. 1–5.

[6] A. Yellepeddi and J. C. Preisig, "Soft-adaptive turbo equalization: Using soft information in adaptation," in *Signals, Systems and Computers (ASILOMAR), 2012 Conference Record of the Forty Sixth Asilomar Conference on*. IEEE, 2012, pp. 1541–1546.

[7] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the em algorithm," *Journal of the royal statistical society. Series B (methodological)*, pp. 1–38, 1977.

[8] M. Tuchler, A. C. Singer, and R. Koetter, "Minimum mean squared error equalization using *a priori* information," *IEEE Trans. Signal Process.*, vol. 50, no. 3, pp. 673–683, Mar. 2002.