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# MULTIPLE-TRAINING BI-DIRECTIONAL ADAPTIVE EQUALIZERS FOR TDMA DIGITAL CELLULAR SYSTEMS

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## SUMMARY

In this paper, two popular adaptive equalization methods, fractionally spaced decision feedback equalization (FSDFE) and maximum-likelihood sequence estimation (MLSE), are investigated for the design of digital mobile receivers for the IS-54 specifications of the NADC* system. A bi-directional equalization technique is incorporated and a multiple training LMS (MT-LMS) algorithm is used as the adaptive algorithm for both equalization methods. The results show that both MT-MLS and bi-directional techniques are effective in improving the receiver performance. However, the MT-LMS algorithm is more useful for MLSE than FSDFE whereas the bi-directional equalization technique improves FSDFE much more than MLSE.

KEY WORDS: TDMA cellular systems; adaptive equalization; least mean square; bi-directional equalization

## 1. INTRODUCTION

In recent years, mobile cellular systems have experienced very fast growth in most developed and developing countries. As a result of multipath propagation, the mobile communication channel will experience time dispersion and fast fading which is typically modelled as frequency selective multipath Rayleigh fading channel in urban and suburban areas. In addition, the received signal is subjected to random frequency shifts (Doppler) and the effects of a highly non-stationary channel, as direct consequences of vehicular motion. The above channel distortion results in severe intersymbol interference (ISI), which significantly degrades the digital transmission system performance if left uncompensated. The amount of time dispersion that must be handled by the receiver is specified to one symbol period, i.e. approximately 40 $\mu$s in the IS-54* specification. Furthermore, the receiver has to track the channel during the time division multiple access (TDMA) time slot duration. To handle this an adaptive equalizer is required.

There has been a wide range of publications pertaining to the subject of equalization. A survey of adaptive equalization techniques was given by Qureshi[1] and more specifically for TDMA mobile channels by Proakis.[2] We will give a brief review of decision feedback equalization (DFE) and the maximum likelihood sequence estimation (MLSE) in Section 3 after a brief description of the mobile channel model in Section 2.

The choice of adaptation algorithms and equalization techniques for mobile units depends mostly on the hardware complexity. As a result of the short training sequence in IS-54, the least mean square (LMS) adaptation algorithm[3] was considered inappropriate.[2] The recursive least square (RLS) algorithm[4] was recommended for its fast convergence and tracking capabilities, although requiring a higher hardware complexity.[2] In this paper we investigate the use of a multiple training LMS (MT-LMS) adaptation algorithm, which makes use of the training sequence multiple times, for our equalizers for the relatively lower complexity compared to RLS. MT-LMS was developed for fractionally spaced decision feedback equalization (FSDFE)[5] and we extended it to MLSE for comparison, where in FSDFE we train the equalizer itself and in MLSE we train the channel impulse response.

A bi-directional adaptive equalization technique, which includes an additional backward tracking using the training sequence of the following time slot, was proposed in Reference 6 for the DFE structure to combat the divergence problem when a deep fade occurs in the received time slot. In this paper we extended the bi-directional technique to FSDFE and MLSE for comparison. The multiple training adaptation algorithm and the bi-directional equalization technique will be explained in Section 4.

It should be pointed out that even though both the multiple-training and the bi-directional ideas introduce additional computations, if desired, such computations can be performed in a sequential manner, taking advantage of the frame separation in TDMA systems. As a result, little extra hardware is required. The additional latency from sequential processing is much smaller compared to that of de-interleaving and speech decoding. Therefore, we consider these techniques very attractive in achieving

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reasonable performance at a modest hardware complexity.

In Section 5 we show simulation results of FSDFE and MLSE for IS-54 mobile channels, using the multiple training adaptation algorithm and bi-directional equalization technique. To our knowledge such a study and comparison have not been reported in the literature previously. The results show that both MT-LMS and bi-directional techniques are effective in improving the receiver performance. However, the MT-LMS algorithm is more useful for MLSE than FSDFE whereas the bi-directional equalization technique improves FSDFE much more than MLSE.

## 2. THE MOBILE CHANNEL MODEL

The radio channel specified in the TIA requirement specification[7,8] is a two-ray (or selective) Rayleigh fading channel, as shown in Figure 1. This model was found to be a simple but good approximation of the real radio channel. It represents one direct path and one reflected path with a given delay and attenuation. In the requirement specification there is no attenuation of the reflected ray ($r = 1$), which can be viewed as a worst case in propagation conditions. In the simulations of this thesis the fading signal for each ray is produced by taking the complex signal input and multiplying it by a complex time-varying weight. The weight for each ray is independent. Each is generated by passing complex white Gaussian noise through a fading filter and then interpolating the output of the fading filter. The fading filter, also known as the spectrum shaping filter, is based on Jake's model[9] which has the frequency response as follows:

$$|H(f)| = \begin{cases} \dfrac{1}{\sqrt{1-\left(\dfrac{f}{f_D}\right)^2}} & , |f| < f_D \\ 0 & , |f| > f_D \end{cases} \qquad (1)$$

The maximum Doppler frequency $f_D$ is defined as

$$f_D = V/\lambda \qquad (2)$$

where $V$ is the vehicle speed and $\lambda$ is the carrier wavelength. If the carrier frequency is 900 MHz, the maximum Doppler frequencies corresponding to vehicle speeds of 20 kmph, 60 kmph and 100 kmph are 16·7 Hz, 50·0 Hz and 83·3 Hz, respectively.

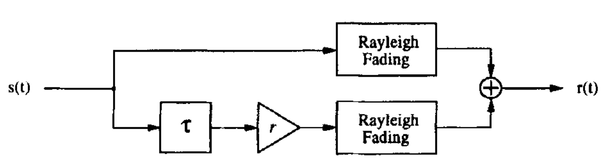


Figure 1. The two-ray Rayleigh fading channel model

## 3. EQUALIZATION TECHNIQUES

### 3.1 *Decision feedback equalization*

The decision feedback equalizer, as shown in Figure 2 for the $\pi/4$-DQPSK case, consists of two filters, a feedforward filter and a feedback filter. The input to the feedforward section is the square root raised cosine (SRRC) filtered signal sequence $\{x_k\}$. The feedforward filter is identical to a linear transversal equalizer. The input to the feedback filter is the sequence of decisions $\{u_k\}$ on previously detected symbols. Functionally, the feedback filter is used to estimate the intersymbol interference caused by previously detected symbols and to subtract it out prior to symbol detection. The equalizer output taps DFE can be expressed as

$$y_k = \sum_{i=0}^{K_1-1} c_{k+i}x_{k+i} + \sum_{j=1}^{K_2} b_{k-j}u_{k-j} \qquad (3)$$

where $y_k$ is an estimate of the $k$th information symbol, and $\{c_i\}$, $\{b_j\}$ are the tap coefficients of the feedforward and feedback filters, respectively. The equalizer is assumed to have $K_1$ taps in its feedforward section and $K_2$ taps in its feedback section. In every iteration, the tap coefficients are adaptively updated to minimize the mean square error (MSE) between the desired equalizer output and the actual equalizer output. The input to the feedback section could be a short known sequence of symbols named 'training sequence' during the start-up period or the decision data during the tracking period. The adaptive update algorithm of the filter coefficients will be described in Section 4.1.

The equalizer structure described above has the taps spaced at the symbol rate $T_s$. This tap spacing is optimum if the equalizer is preceded by a filter matched to the channel distorted transmitted pulse. When the channel characteristics are unknown, such as with the mobile radio channel, the receiver filter is usually matched to the transmitted signal pulse and the sampling time must be optimized for this suboptimum filter. In general, this approach leads to an equalizer performance that is very sensitive to the choice of sampling time. A fractionally spaced equalizer (FSE) based on sampling the incoming signal at least as fast as the Nyquist rate will outperform the symbol-spaced equalizer, in that the FSE is equivalent to the optimum linear receiver consisting of the matched filter followed by a symbol rate equalizer.[4] In a digital implementation, the fractionally spaced equalizer has tap spacing or $\tau = MT_s/N$ where $M$ and $N$ are integers and $N > M$. In practice, it is more convenient to choose $\tau = T_s/N$ and especially the $T_s/2$-spaced equalizer which is used in many applications. An FSDFE has a fractionally spaced filter in its feedforward section.

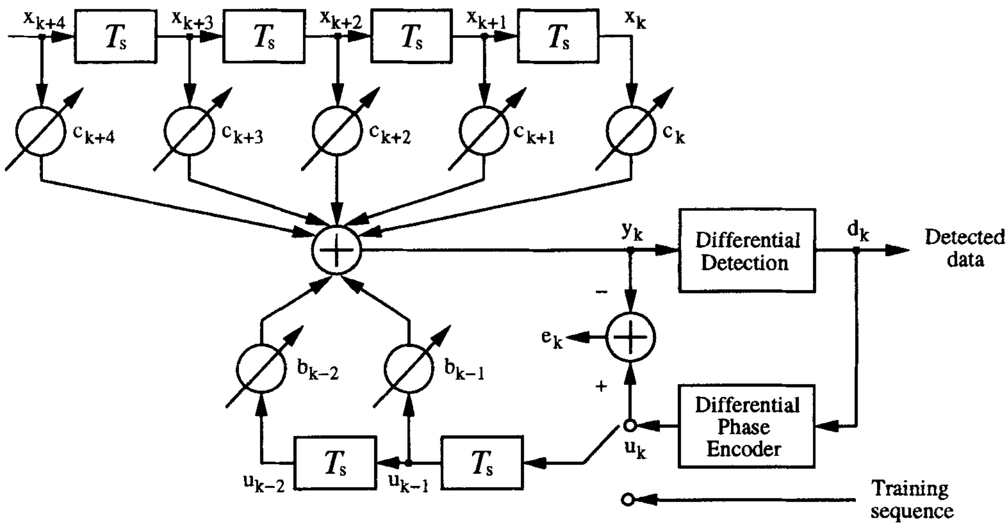


Figure 2. An example of (5,2) taps DFE for the $\pi/4$-DQPSK case

### 3.2. *Maximum likelihood sequence estimation*

The adaptive maximum likelihood sequence estimator, as shown in Figure 3, consists of a channel estimator and a maximum likelihood sequence estimator implemented by means of the Viterbi algorithm.[10,11] In the Figure, $\{x_k\}$ is the filtered and sampled data streams and $\{I_{k-L}\}$ is the estimated information sequence where $L$ is the truncation path length in the Viterbi algorithm. The Viterbi algorithm forms the main processing portion of this estimator and it is optimum in the sense that it is the maximum-likelihood estimator of the entire received sequence. In the case of the additive white Gaussian noise, the Viterbi algorithm requires knowledge only of the channel impulse response. When the channel impulse response is unknown, such as in the mobile radio channel, an adaptive estimator must be provided that operates on the estimated information sequence and the received signal sequence to provide a measurement of the channel impulse response. The channel estimator structure is shown in Figure 4. It is similar to a linear equalizer. This linear finite-state machine approximates its tap gains $\{c_i\}$ to the actual channel impulse response, where $i = 0, 1 \ldots, M - 1$, and $M$ is tap length chosen to approximate the channel impulse response. The adjusted tap gains are then used by the Viterbi ML sequence estimator to compute the trellis metrics and to choose the maximum likelihood sequences transmitted.

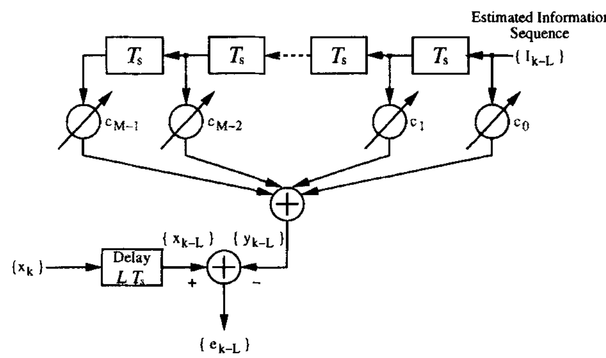


Figure 4. The channel estimator

A delay equal to the decision delay, i.e., the truncation path length $L$ of the Viterbi algorithm, is required to make time consistent between the input sequence $\{x_k\}$ and the estimated information sequence $\{I_{k-L}\}$. Therefore the error sequence $\{e_{k-L}\}$ could be formed correctly by taking the difference between these two sequence.

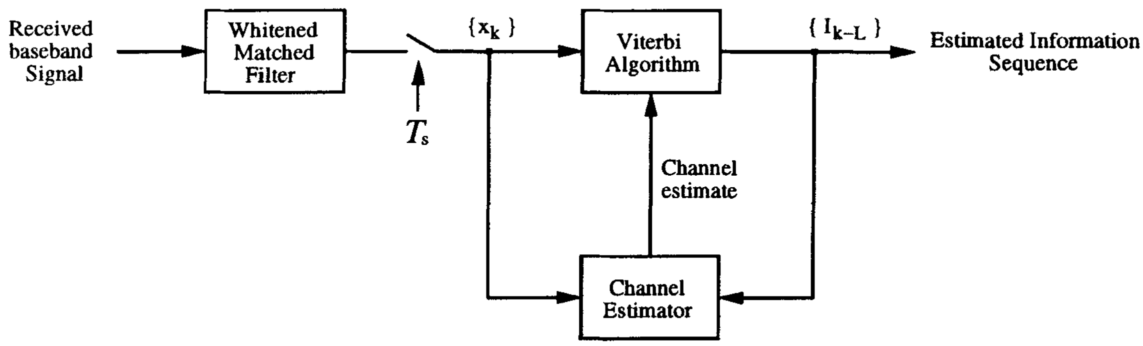


Figure 3. Adaptive maximum likelihood estimator block diagram

## 4. MULTIPLE-TRAINING ADAPTIVE ALGORITHM AND BI-DIRECTIONAL EQUALIZATION TECHNIQUE

### 4.1. *Multiple training LMS adaptive algorithm*

The adaptive algorithm for training and updating the tap coefficients of the equalizer is an important issue. In the IS-54 TDMA system each slot uses 14 symbols for training. It is reported that the short training sequence of 14 symbols cannot make the LMS DFE converge in the start-up training period of each slot.[2] In this paper we investigate the use of a multiple training LMS (MT-LMS) adaptation algorithm[5] for our equalizers for the relatively lower complexity.

The proposed MT-LMS scheme uses the same training sequence to train the tap weights $N_T$ times. After the tap weights are well initialized, the equalizer then processes the received data sequence in the tracking mode. Figure 5 shows the overall sequence processed by the MT-LMS DFE which can be viewed as a cascade of $N_T$ training sequences of 14 symbols and one data sequence of 148 symbols.

The computational complexity ratio of the MT-LMS algorithm over the LMS algorithm can be given by

$$R(N_T) = \frac{14N_T + 148}{162} = 1 + \frac{14(N_T - 1)}{162} \tag{4}$$

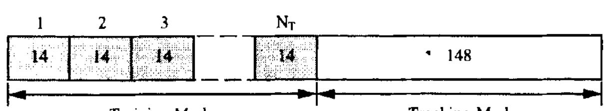


Figure 5. Multiple training scheme for LMS DFE

When $N_T = 12$, the computational complexity of the MT-LMS algorithm is approximately twice as that of the LMS algorithm.

The LMS algorithm[3] adapts the filter tap weights $\mathbf{W} = [W_0 \ldots W^{N-1}]^T$ so as to minimize the mean square error (MSE) between the filter output $\mathbf{W}_k^T\mathbf{X}_k$ and the desired signal $d_k$. The adaptive equation is as follows

$$e_k = d_k - \mathbf{W}_k^T\mathbf{X}_k$$
$$\mathbf{W}_{k+1} = \mathbf{W}_k + \mu e_k \mathbf{X}_k^* \tag{5}$$

where $\mathbf{X}_k = [x_k \; x^{k-1} \ldots x^{k-N+1}]^T$ is the input signal vector buffered in the filter, $N$ is the tap length and $\mu$ is the adaptation gain or step size.

In the LMS algorithm, the step size should be taken as inversely proportional to the input signal variance $\sigma_x^2$ for stability reasons and determined by $\mu_k = \mu_0/\sigma_x^2$. A normalized LMS algorithm (NLMS)[12,13] estimates the input signal variance online with $\sigma_x^2(k) = \|\mathbf{X}_k\|^2/N$. In the simulations of this thesis, $\mu_0$ is chosen as $2^{-n}$ and $n$ is empirically determined as 4. The input signal variance is estimated as the following equation:[5]

$$S_k = \frac{1}{2N}\sum_{i=0}^{N-1} (|Re\{x_{k-i}\}| + |Im\{x_{k-i}\}|) \tag{6}$$

The computational complexity of this estimate is reduced significantly, whereas comparing it with the NLMS algorithm it is found to perform as well.

### 4.2. *Bi-directional equalization technique*

The conventional equalizer processes the receiving data in the forward direction. This one-directional

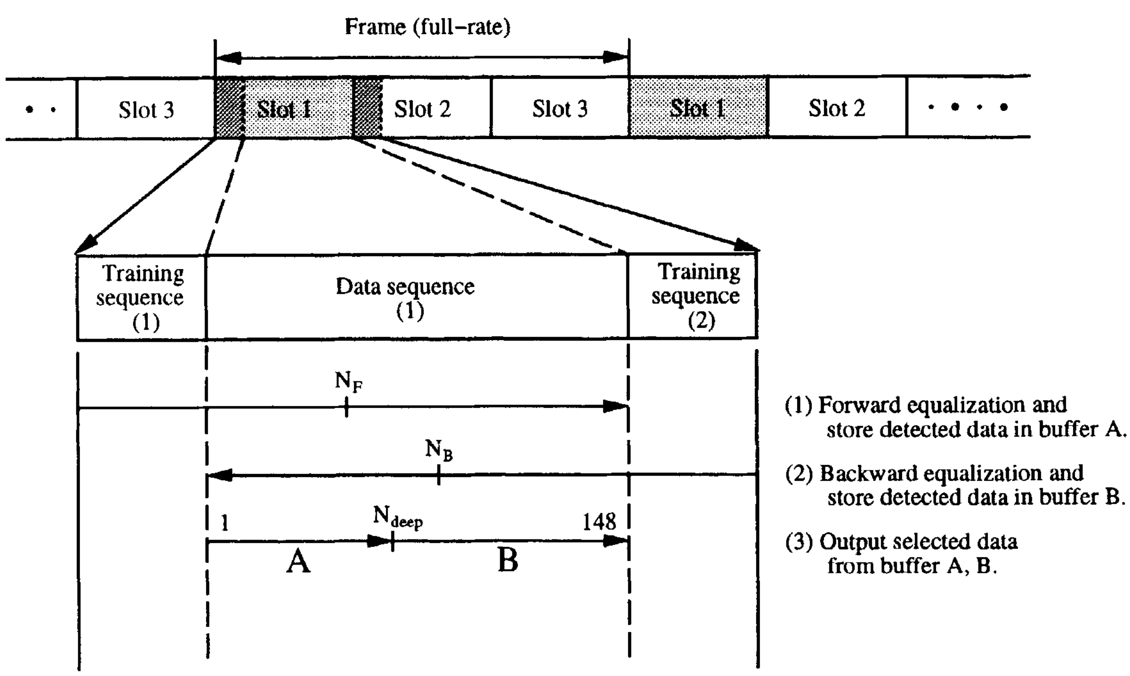


Figure 6. Bi-directional equalization procedure for IS-54 full-rate TDMA system

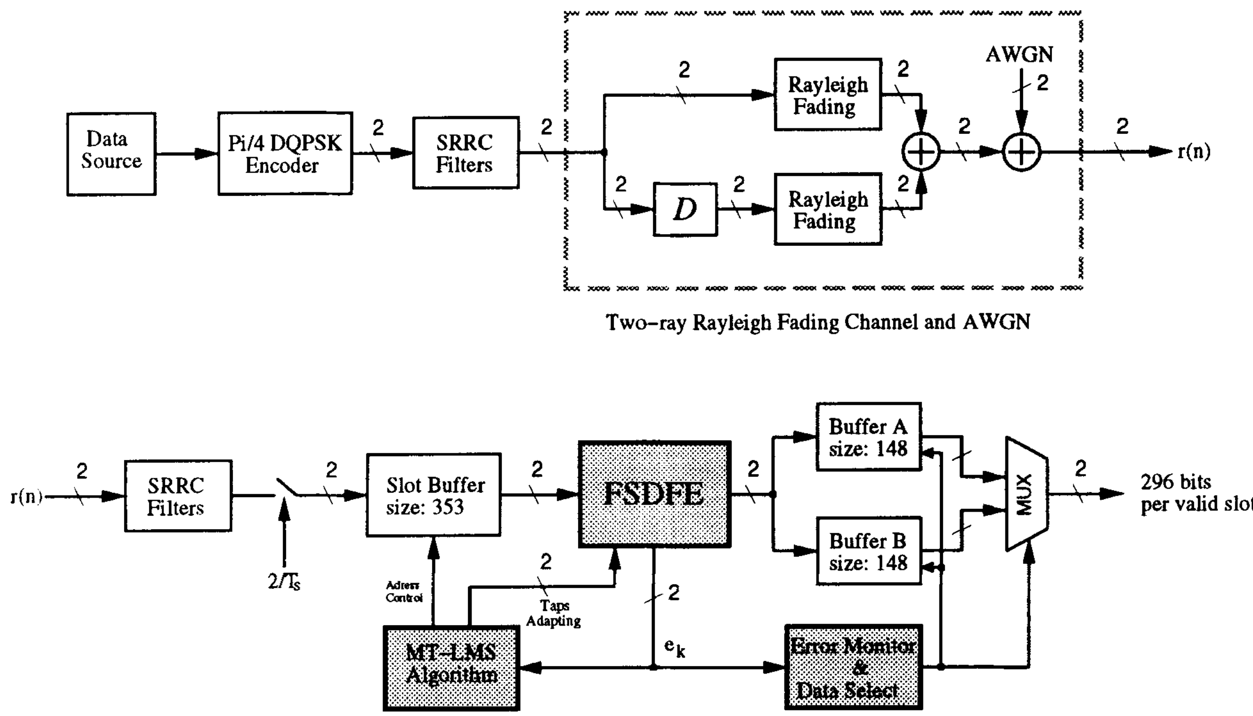


Figure 7. The simulation model for MT-LMS bi-directional FSDFE

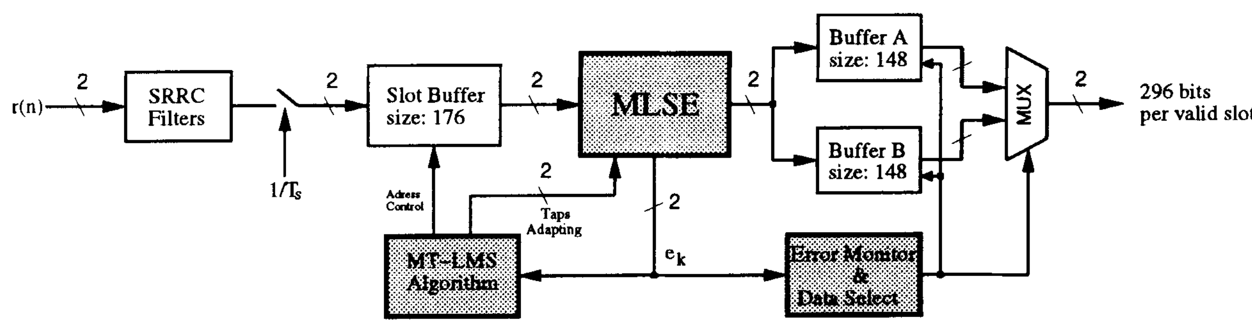


Figure 8. The simulation structure for MT-LMS bi-directional MLSE

equalization technique suffers from fast fading in the mobile radio channel in that the equalizer may diverge due to the deep fade or the very fast variation of the channel. The data after the divergence of the equalizer cannot be recovered until the next sequence of the training symbol is received.

A bi-directional equalization technique which is able to estimate the location of a deep fade within a time slot is proposed in Reference 6. In addition to forward equalization, the bi-directional equalization technique borrows the training sequence from the next time slot and equalizes the data in the backward direction. A control mechanism is added to monitor the error signal, providing information on the tracking status and the decision selecting of the forward and backward equalization. An error monitoring function $E_k$ is defined as

$$E_k = \frac{1}{N_w} \sum_{i=0}^{N_w-1} \|e_{k-i}\|^2 \qquad (7)$$

where $E_k$ is a short-time average of the error signal power in DFE and $N_w$ is the window length for average. The equalizer identifies a deep fade if $E_k$ is greater than an empirical error monitoring threshold $T_E$.

The sample sequence of the current time slot and the training sequence of the next time slot are first stored in a buffer to allow for forward and backward equalization. The bi-directional equalization scheme which is modified in the simulations is listed as follows (see Figure 6):

1. Start forward equalization, store the decision data (symbols 1–148) in buffer A and latch the position $N_F$ if $E_k \geq T_E$.
2. Start backward equalization, store the decision data (symbols 148–1) in buffer B and latch the position $N_B$ if $E_k \geq T_E$.
3. Compute the location of the deep fade as

$$N_{deep} = \left\lfloor \frac{N_F + N_B}{2} \right\rfloor *$$

Then output the decision data symbols by the following rules:

(a) If $N_F$ = 148 and $N_B \neq 1$ (meaning that the backward equalization diverges but the forward equalization does not) then output symbol 1 to 148 from buffer A.

(b) If $N_F \neq 148$ and $N_B$ = 1 (meaning that the forward equalization diverges but the backward equalization does not) then output symbol 1 to 148 from buffer B.

(c) else (meaning that both equalizations diverge or both not) output symbol 1 to $N_{deep}$ from buffer A and symbol $N_{deep}$ + 1 to 148 from buffer B.

## 5. SIMULATION RESULTS

### 5.1. *Simulation structure*

The block diagram of the entire simulation system is shown in Figure 7. The data source generates a

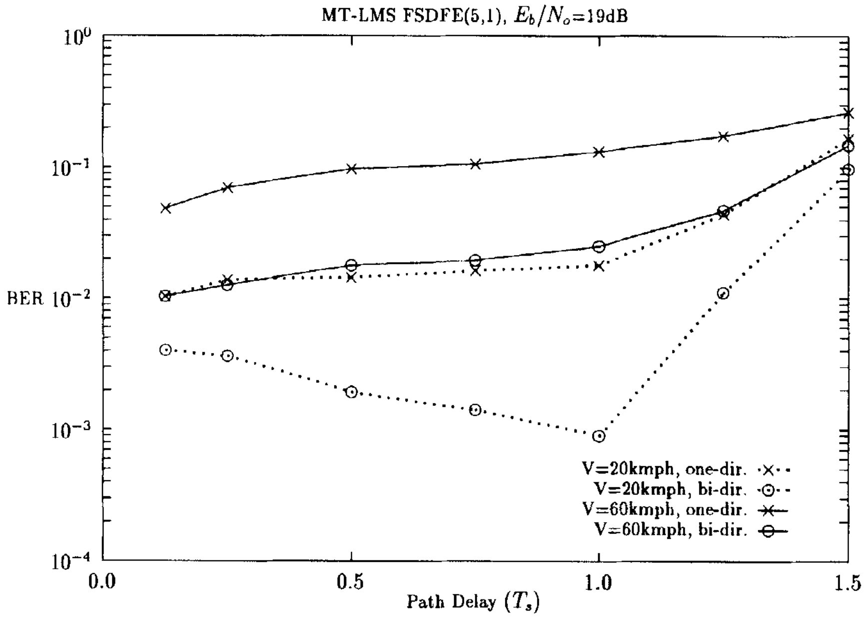


Figure 9. The BER performance of one-directional and bi-directional FSDFE equalizations

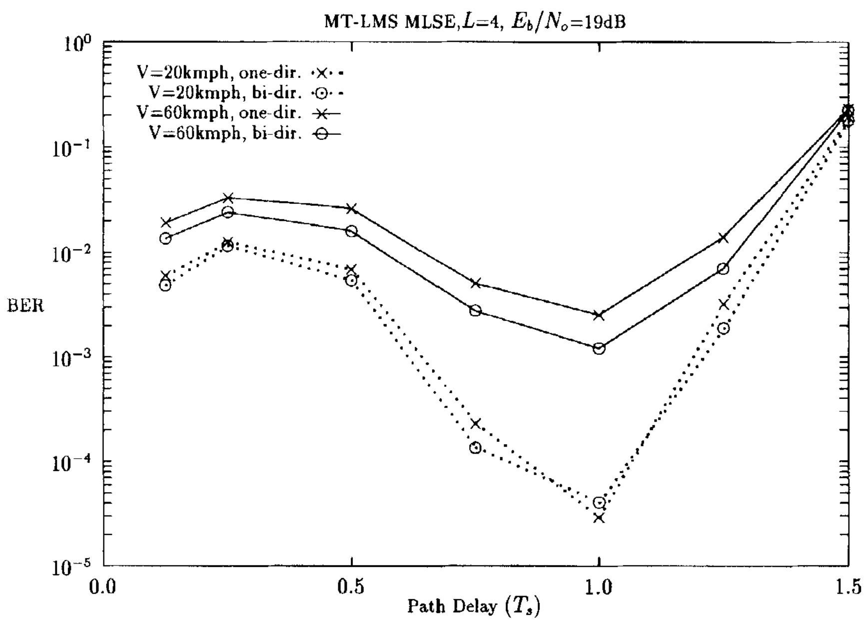


Figure 10. The BER performance of one-directional and bi-directional MLSE estimations

*⌊·⌋ is the floor function.

random bit streams which follow the IS-54 full-rate TDMA frame strucure. The bit streams are encoded by the $\pi/4$-DQPSK encoder and filtered by the SRRC filters. The sampling rate is chosen as eight samples per symbol and the impulse response of the SRRC filter is truncated to 10 symbols in duration, i.e., the tap length of the SRRC filter is 81. The complex baseband signals are then entered into the mobile radio channel which consists of the two-ray Rayleigh fading and the additive white Gaussian noise (AWGN).

At the receiver end, the faded signal is filtered by the SRRC filters to achieve Nyquist pulse shaping and sampled at twice the symbol rate for fractionally spaced DFE. A buffer size of $2 \times (162 + 14) + 1 = 353$ words is needed for one time slot, where the additional word is added for the symmetry of the bi-directional equalization. After the user slot is received, the FSDFE performs the bi-directional equalization with the MT-LMS algorithm. The multiple training number is chosen to be 20. The final decision symbol stream is output at the end of backward equalization according to the selecting rules. The bit error rate (BER) performance is averaged over three independent runs and each run goes to 500 frames (total 148,000 bits).

The block diagram of the MT-LMS bi-directional MLSE is shown in Figure 8. For the data buffering of the MT-LMS MLSE, A buffer size of 176 words is needed for one time slot with symbol rate sam-

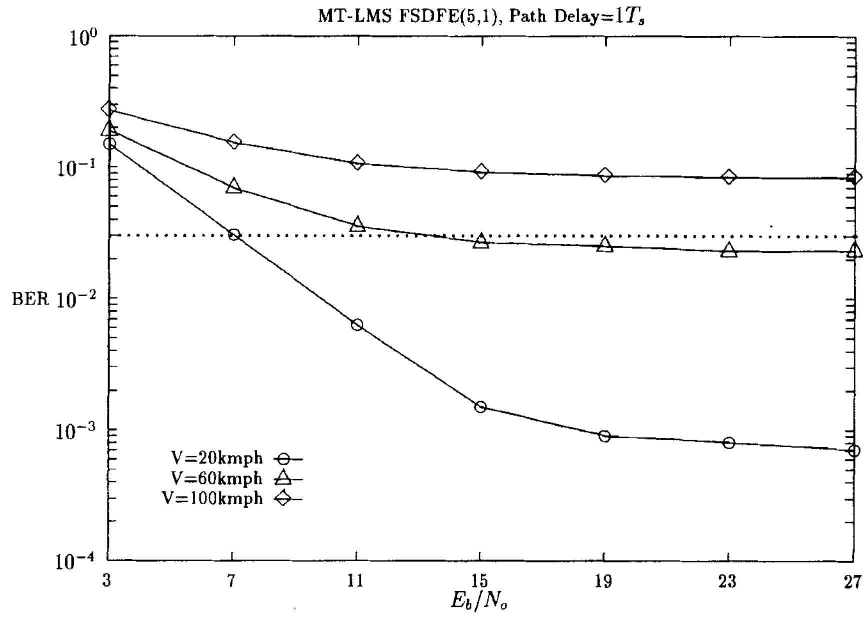


Figure 11. The BER performance vs. $E_b/N_o$ of FSDFE, path delay = $1\ T_s$

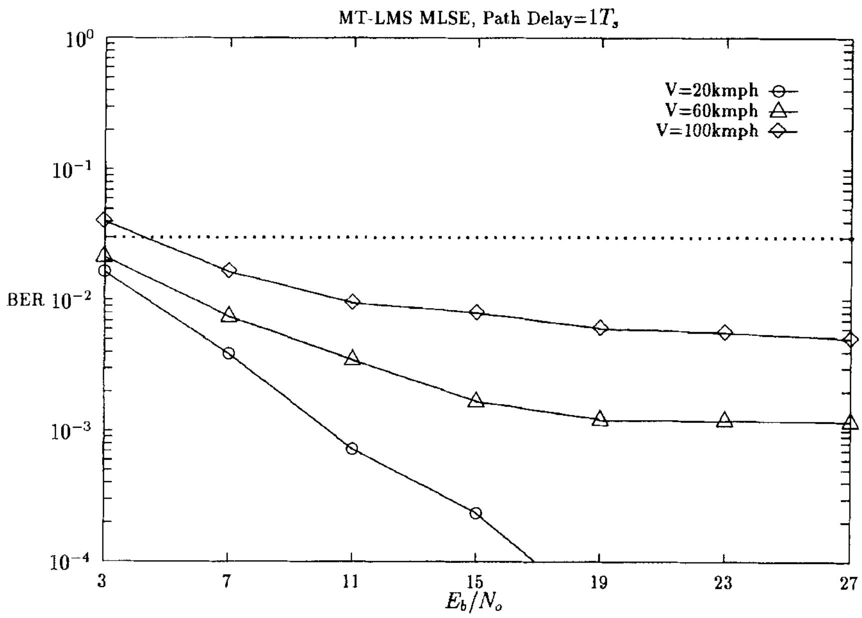


Figure 12. The BER performance vs. $E_b/N_o$ of MLSE, truncation length = 4

pling. The channel impulse response length is chosen as two taps which gives a control range of approximately one symbol period corresponding to the specified minimum control range for NADC. The error monitoring and data selecting rules are the same as FSDFE except the error signal $e_k$ is formed from the channel estimator and the error monitor threshold $T_E$ is empirically chosen again.

### 5.2. *Simulation results*

Figures 9 and 10 show the BER performance vs the path delay in the two-ray Rayleigh fading channel of one-directional and bi-directional equalization techniques for FSDFE and MLSE cases. We can see that the bi-directional technique gives better performance than the one-directional technique, especially for the FSDFE case. This is because MLSE is originally better than FSDFE (using the MT-LMS algorithm), so it takes little advantage from the bi-directional technique.

Figure 11 shows the BER performance vs $E_b/N_o$ of FSDFE when the path delay = 1 $T_s$. The BER performance degrades when the vehicle speed is higher and there exist error floors when the signal to noise ratio (SNR) is increasing. The BER is below 3 per cent when $E_b/N_o$ is greater than 14 dB and vehicle speed is equal to 60 kmph. Figure 12 shows the BER performance vs $E_b/N_o$ of MLSE when the path delay = 1 $T_s$.

Figure 13 shows the BER performance vs path delay of FSDFE when $E_b/N_o$ = 19 dB. The equalizer can achieve a BER below 3% when the vehicle speed is 100 kmph and the path delay is smaller than 0·25 $T_s$ or when the path delay is 1 $T_s$ and the vehicle speed is less than 60 kmph. It is noticed that when the vehicle speed is less than 40 kmph, the BER performance is better with the path delay up to 1 $T_s$. This is because the delay path signal provides a diversity gain for equalization. When the vehicle speed is high, the channel variation is too fast for the LMS algorithm to track, thus the diversity gain is not taken.

Figure 14 shows the BER performance vs. path delay when $E_b/N_o$ = 19 dB. The performance degrades with increasing delay up to 0·25 $T_s$ ~ 0·5 $T_s$ and then improves to one symbol interval. Above one symbol period the delay interval is larger than the equalizer control range, so the performance starts to degrade again. The performance gain at one symbol period is due to the diversity from independent fading of the two rays as described in the FSDFE case. From Figures 13 and 14, we can find that the MT-LMS algorithm is more useful for MLSE than FSDFE because the tracking capability of MT-LMS FSDFE is not as good as MT-LMS MLSE.

Figure 15 shows the BER comparison between the MLSE and FSDFE. The FSDFE outperforms the MLSE when the path delay is less than about 0·5 $T_s$ but is worse than MLSE when the path delay is greater than about 0·5 $T_s$. If the typical path delay is less than about 0·5 $T_s$ then the MT-LMS FSDFE is recommended for its hardware simplicity and insensitivity to the sampling phase.

## 6. CONCLUSION

In this paper, FSDFE and MLSE adaptive equalization methods were investigated and compared for the design of IS-54 NADC digital mobile receivers. MT-LMS adaptation algorithm and bi-directional equalization technique were adopted to improve the receiver performance for their relatively low complexity. The results show that both MT-LMS and bi-directional techniques are effective in improving

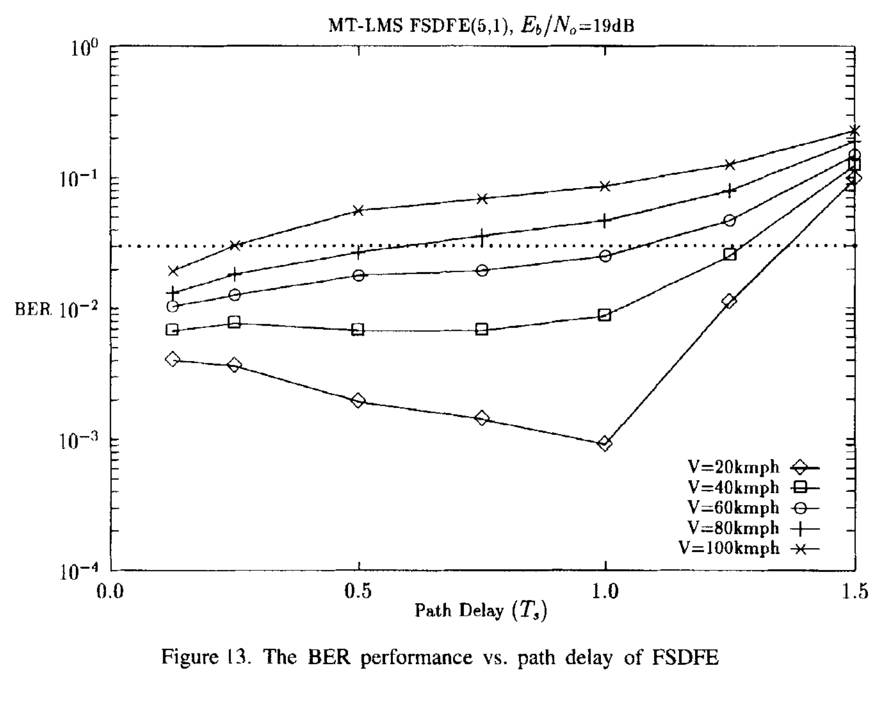


Figure 13. The BER performance vs. path delay of FSDFE

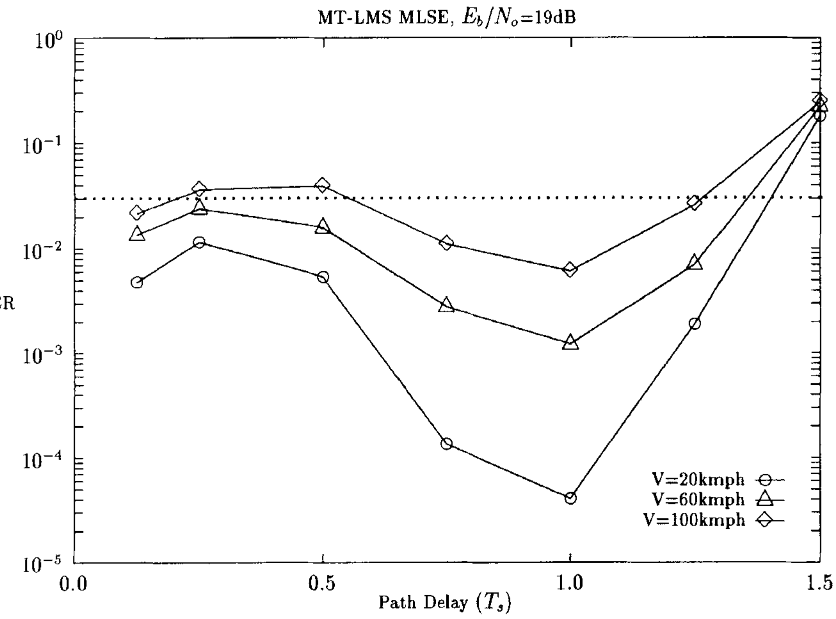


Figure 14. The BER performance vs. path delay, truncation length = 4

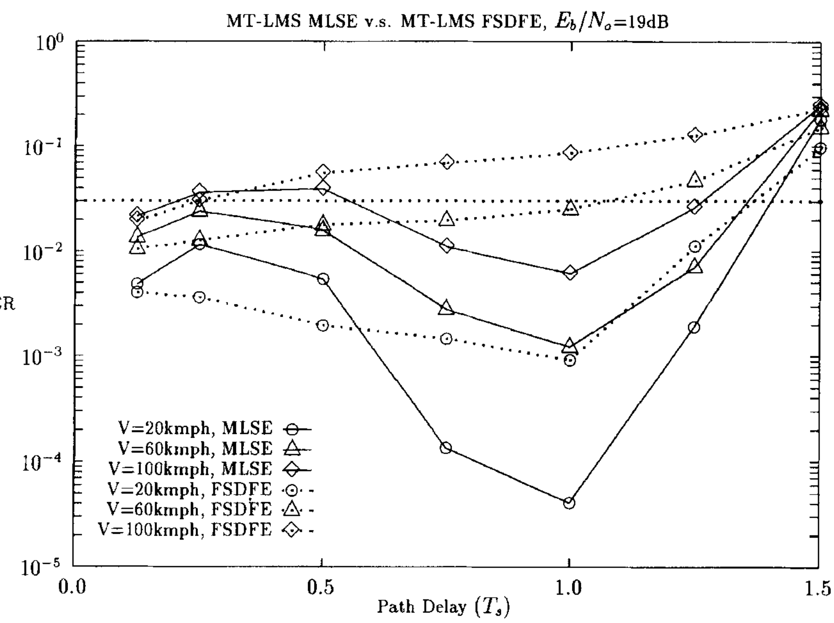


Figure 15. The BER performance comparison of FSDFE(5,1) and MLSE

the receiver performance. However, the MT-LMS algorithm is more useful for MLSE than FSDFE, whereas the bi-directional equalization technique improves FSDFE much more than MLSE. Furthermore, bi-directional MT-LMS MLSE slightly outperforms bi-directional MT-LMS FSDFE(5,1).


## ACKNOWLEDGEMENT

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He was a Visiting Scientist of IBM Research Division, Almaden Research Center in San Jose, California, in 1988–90. During the academic year of 1994–95, he visited Qualcomm Inc. in San Diego, California. He was involved in architecture and circuit designs of communications and signal processing applications, including storage channel, pattern recognition, and wireless communications.

Dr Shung's research interests include architecture and integrated circuits design for communications, signal processing and ATM switches, and computer-aided design for integrated circuits and field programmable gate arrays. He has published more than 40 technical papers in related areas.