LLR ENHANCEMENT MODEL FOR A TURBO EQUALIZER

Aruna Tripathy

Associate Professor, Department of Instrumentation and Electronics Engineering, College of Engineering and Technology, Bhubaneswar, India
aruna_igit@yahoo.com

ABSTRACT

The turbo equalizer (TEQ) is a baseband signal processor that combines the tasks of channel equalization and channel decoding in a closed loop by using turbo principles. The basic objective of a TEQ is to take care of interference in a communication system arising due to a host of reasons and correct the random errors caused by additive white Gaussian noise (AWGN) simultaneously. All the TEQs reported in literature can be broadly categorized into three types; the trellis based equalizers, the apriori aided minimum mean square error (MMSE) filters and the soft interference canceller (SIC) type of filters. Pivotal to the operation of all the TEQs is the flow of the extrinsic information between the equalizer and the channel decoder. The extrinsic information is the information about a given bit available by the use of knowledge about other bits in a transmitted data stream. Most often, the extrinsic information is modeled as a Gaussian random variable. However, a generic mathematical model capturing the operations of a TEQ seems to be missing in literature. It is with this motivation that we propose a suitable mathematical model for a TEQ under converging conditions. This is the log likelihood ratio (LLR) enhancement model that describes the evolution of the extrinsic information as observed at the equalizer output. The LLR becomes a monotonically increasing function of the signal to noise ratio (SNR) from the no apriori condition to the perfect apriori condition about the transmitted bits.

KEYWORDS: *Apriori, Extrinsic Information, LLR*

I. INTRODUCTION

The turbo equalizer (TEQ) [1-11] is a baseband signal processor that combines the tasks of equalization and channel decoding in a closed loop by using turbo principles. The equalizer takes care of intersymbol interference (ISI) that arises because of either a poor channel frequency response or the multipath nature of a mobile radio channel. The channel decoder corrects random errors that corrupt a given transmitted data stream caused by AWGN. Both the equalizer and the decoder generate LLR of each bit as present in a given transmitted data stream. The extrinsic information is derived from the LLR by subtracting the *apriori* information about a given bit. Literature on TEQs is mostly confined to finding low complexity architectures for the equalizer [12][14-19], application of TEQs to different channel types[21-28], improving the performance of the equalizer [29-30] and proposition of different performance measures [13][20] in order to study the convergence behavior of the TEQs. A generic model that captures the operations of a TEQ still seems to be missing in literature. It is with this view that we have attempted to describe the TEQ operation by developing a suitable mathematical model. For all three types of equalizer structures reported in literature, the LLR enhancement model establishes the monotonically increasing nature of the LLR under converging conditions. We discuss the problem in section 2 followed by LLR enhancement model in section 3. Numerical results presented in the section 4 establish the validity of such a model. Finally conclusions are drawn in section 5. $\boldsymbol{x}$ represents a vector of bits whereas the k-th element of this

ISSN: 2231 – 6604 Volume 3, Issue 1, pp: 54-62 ©IJESET

vector is denoted as x_k, ln(.) represents the natural logarithm.

II. PROBLEM FORMULATION

The equalizer processes the baud rate sampled samples that contain ISI and AWGN. The matched filter output samples are expressed as

$$z_k = \sum_{l=0}^{L-1} h_l x_{k-l} + w_k \tag{1}$$

where $w_k \sim N(0,\sigma_w^2)$, the length of the ISI channel being represented as a finite tapped delay line h_k is L, the x_k's are the coded interleaved bits as shown in Fig.1.

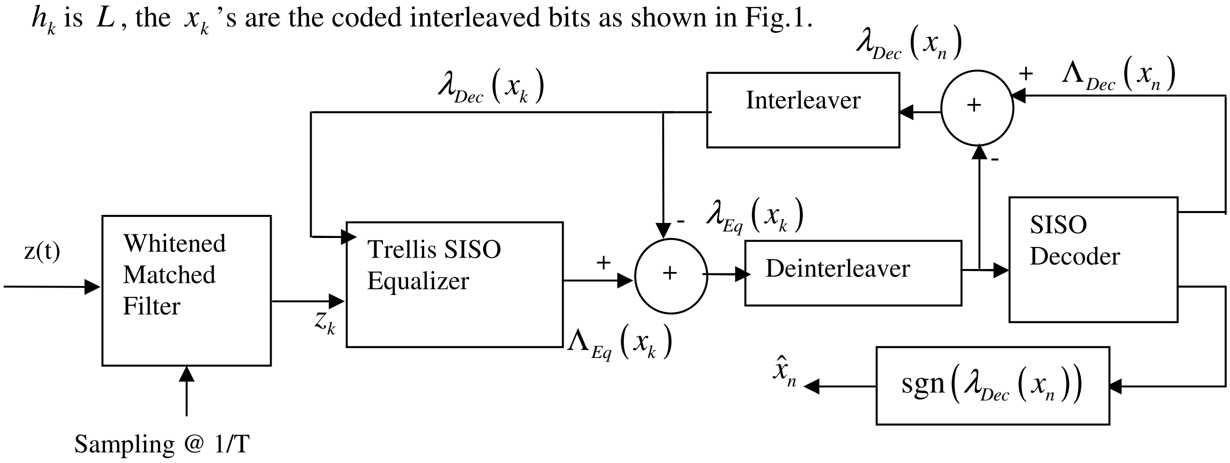


Fig 1. Block Schematic of the Binary Turbo Equalizer

The LLR of a bit x_k at the equalizer output is defined as a ratio of two conditional probabilities conditioned upon the observed interference contaminated noisy data vector as given below

$$\Lambda_{Eq}(x_k) = \log \frac{p(x_k = 1 \mid z_0 : z_{N-1})}{p(x_k = 1 \mid z_0 : z_{N-1})} \tag{2}$$

Where $z_0 : z_{N-1}$ is the N dimensional column vector of received samples z_k. For the filter based TEQ schemes, it is easier to find that, the equivalent operation is interference cancellation that approaches the true value of interference with respect to iterations provided the TEQ is operating above the threshold SNR [10]. For trellis based TEQs, the equivalent operation is not very apparent. Hence, an attempt is made here to provide the answer here.

III. THE LLR ENHANCEMENT MODEL

The equalizer works with the observed data vector $z_0 : z_{N-1}$ along with the soft input $\lambda_{Dec}(x_k)$ and generates soft outputs $\Lambda_{Eq}(x_k)$. It has two N dimensional vector inputs of WMF outputs z_k and the *apriori* information $L_a(x_k) = \lambda_{Dec}(x_k)$ of the interleaved coded symbols x_k appearing at the interleaver input. These two vectors are assumed to be statistically independent because of the presence of an interleaver (usually of sufficient length). The *apriori* information related to a given bit x_k is defined as

$$L_a(x_k) = \ln\left(\frac{p(x_k = 1)}{p(x_k = 1)}\right) \tag{3}$$

We derive a generic expression for the LLR of a binary sequence $\boldsymbol{x}$ in (4). For the system under consideration, the LLR in (2) is recast as

$$\Lambda_{Eq}(x_k) = \ln\frac{p(x_k=1|\boldsymbol{z})}{P(x_k=1|\boldsymbol{z})} = \ln\frac{\sum_{\boldsymbol{x}:x_k=1} p(\boldsymbol{x},\boldsymbol{z})}{\sum_{\boldsymbol{x}:x_k=0} p(\boldsymbol{x},\boldsymbol{z})} = \ln\frac{\sum_{\boldsymbol{x}:x_k=1} p(\boldsymbol{z}|\boldsymbol{x})p(\boldsymbol{x})}{\sum_{\boldsymbol{x}:x_k=0} p(\boldsymbol{z}|\boldsymbol{x})p(\boldsymbol{x})}$$

$$= \ln\frac{\sum_{\boldsymbol{x}:x_k=1} p(\boldsymbol{z}|\boldsymbol{x})\prod_{j=0}^{N-1} p(x_j)}{\sum_{\boldsymbol{x}:x_k=0} p(\boldsymbol{z}|\boldsymbol{x})\prod_{j=0}^{N-1} p(x_j)} = \ln\frac{\sum_{\boldsymbol{x}:x_k=1} p(\boldsymbol{z}|\boldsymbol{x})p(x_k=1)\prod_{j\neq k}^{N-1} p(x_j)}{\sum_{\boldsymbol{x}:x_k=0} p(\boldsymbol{z}|\boldsymbol{x})p(x_k=0)\prod_{j\neq k}^{N-1} p(x_j)} \quad (4)$$

The definition of the *apriori* information about x_k in (3) expresses (4) as

$$\Lambda_{Eq}(x_k) = L_a(x_k) + \lambda_{Eq}(x_k) \quad (5)$$

The product part in (4) is the desired extrinsic information that is obtained from the other bits in the transmitted data stream except the bit under consideration. The extrinsic information is obtained from (5) by certain algebraic manipulations in the following. The probability of the sequence $\boldsymbol{x}$ of length N in (6) has been written assuming statistical independence between all x_k's. The information gained about the bit x_k from other bits in the transmitted data stream is the extrinsic information by the equalizer is

$$\lambda_{Eq}(x_k) = \ln\frac{\sum_{\boldsymbol{x}:x_k=1} p(\boldsymbol{z}|\boldsymbol{x})\prod_{j\neq k}^{N-1} p(x_j)}{\sum_{\boldsymbol{x}:x_k=0} p(\boldsymbol{z}|\boldsymbol{x})\prod_{j\neq k}^{N-1} p(x_j)} \quad (6)$$

The iterative trellis algorithms update the *apriori* probability of x_k as

$$p(x_k=1) = \frac{e^{L_a(x_k)}}{1+e^{L_a(x_k)}} \quad (7)$$

and

$$p(x_k=0) = \frac{1}{1+e^{L_a(x_k)}} \quad (8)$$

For the no *apriori* information, where all bits are equiprobable, the probability of the binary sequence $\boldsymbol{x}$ becomes $p(\boldsymbol{x}) = \left(\frac{1}{2}\right)^N$, it is same for all sequences and hence, the LLR expressed by (5) reduces to

$$\Lambda_{Eq}(x_k) = \ln\frac{\sum_{\boldsymbol{x}:x_k=1} p(\boldsymbol{z}|\boldsymbol{x})}{\sum_{\boldsymbol{x}:x_k=0} p(\boldsymbol{z}|\boldsymbol{x})} \quad (9)$$

The conventional filter based equalizers work with (9) whereas the TEQ computes and works with (5). Thus, the TEQ is supposed to be a better performer than the conventional receivers in combating severe ISI. It is observed from (9) that, for a given WMF output vector and sequence, the LLR in (9) is a function of only the conditional probability as defined by the numerator or the denominator. For given ISI channel taps and noise variance, the two quantities are constant values that can change only if the nature of the channel changes or the noise power changes. This is analogous to the conventional soft output decision. For other *apriori* information as defined by (8), in a sequence of r number of 1's, the probability of the sequence $\boldsymbol{x}$ has been found to behave as

$$p(\boldsymbol{x}) = {}^{N}C_r \left(\frac{e^{L_a(x_k)}}{1+e^{L_a(x_k)}} \right)^r \left(\frac{1}{1+e^{L_a(x_k)}} \right)^{N-r} \quad \text{(10a)}$$

This is further simplified as

$$p(\boldsymbol{x}) = {}^{N}C_r \left(e^{L_a(x_k)} \right)^r . \frac{1}{\left(1+e^{L_a(x_k)}\right)^N} \quad \text{(10b)}$$

By substitution of (10b) in (9), the LLR for an all-zero codeword becomes

$$\Lambda_{Eq}(x_k) = \ln \frac{\sum_{\boldsymbol{x}:x_k=1} p(z|\boldsymbol{x})^N C_r \prod_{k=0}^{N-1} \left(e^{L_a(x_k)}\right)^r . \frac{1}{\left(1+e^{L_a(x_k)}\right)^N}}{\sum_{\boldsymbol{x}:x_k=0} p(z|\boldsymbol{x}) \prod_{k=0}^{N-1} \frac{1}{\left(1+e^{L_a(x_k)}\right)^N}} \quad \text{(11)}$$

For correct decision to take place, it should be ensured that,

$$\sum_{\boldsymbol{x}:x_k=1} p(z|\boldsymbol{x})^N C_r \prod_{k=0}^{N-1} \left(e^{L_a(x_k)}\right)^r < \sum_{\boldsymbol{x}:x_k=0} p(z|\boldsymbol{x}) \quad \text{(12)}$$

It is obvious that the converging condition of a TEQ is satisfied by (12) if it is true and represents the enhancement in the LLR of a given bit from its no *apriori* value. It is also apparent from (12) that, if an all-zero code word is transmitted, for very small values of SNR, there will be more number of 1's in the sequence $\boldsymbol{x}$ and the probability will be higher for 1's as per (12). This is equivalent to the equalizer making large number of errors at its output and this situation can not be improved further at the decoder output. The LLR enhancement becomes more demonstrative by (13) given below

$$\gamma_k(s_{k-1}, s_k) = \frac{1}{\sqrt{2\pi\sigma_w^2}} \exp\left(- \frac{\left(z_k - h_0 x_k - \sum_{l,l\neq 0} h_l x_{k-l} \right)}{2\sigma_w^2} \right). \frac{\exp(\lambda_{Dec}(x_k))^{x_k}}{1+\exp(\lambda_{Dec}(x_k))^{x_k}}, x_k = 0,1 \quad \text{(13)}$$

For very low values of SNR, the transition probability as defined in (13) attains a very small value and multiplication of small values of probability with and $p(\boldsymbol{x})$ is not expected to improve the situation of a small LLR. This is further equivalent to saying that, all sequences are equiprobable and the TEQ makes an erroneous decision. The effect of the *apriori* information on the sequence probability is such that, either (10a) or (10b) becomes higher for a given interference type and noise variance. Hence, for intermediate iterations, if the TEQ algorithm is converging, either the numerator or the denominator attains higher values and the LLR becomes a large value. The sequence probability $p(\boldsymbol{x})$ has a stronger effect on the extrinsic information for a given channel transition probability which may be observed from (11). This makes a clear distinction between the two probabilities of (13) and the equalizer produces more reliable information. The transition probability in (6) dominates the sequence probability for high values of SNR which aids the equalizer in making correct decisions. The LLR's about the information bits are used in the final iteration in order to take a final hard decision through a detection operation:

$$\hat{x}_k = \begin{cases} 1 \;\; if \;\; \Lambda_{Dec}(x_k) > 0 \\ 0 \;\; if \;\; \Lambda_{Dec}(x_k) < 0 \end{cases} \qquad (14)$$

For the *apriori* information aided MMSE filter based TEQ structures, the relationship between the equalizer LLR values and the MSE has been derived in [13]. The perfect *apriori* extrinsic information at the equalizer output is

$$\lambda_{Eq,pap}(x_k) = \frac{2}{\sigma_w^2}\left(E_h x_k + s^H w_k\right) \qquad (15)$$

where E_h is the energy trapped in the channel taps and s is a crosscorrelation matrix between x_k and z_k .For the no *apriori* case, the LLR at the equalizer output is

$$\lambda_{Eq,nap}(x_k) = \ln\frac{p(\hat{x}_k \mid x_k = 1)}{p(\hat{x}_k \mid x_k = 0)} = \frac{2\hat{x}_k \mu_k}{\rho_k^2} \qquad (16)$$

where μ_k and ρ_k^2 are the mean and the variance of the equalizer extrinsic information which is Gaussian distributed. For the convergence of the filter based TEQ algorithm, it is observed that

$$\lambda_{Eq,nap}(x_k) < \lambda_{Eq,iap}(x_k) < \lambda_{Eq,pap}(x_k) \qquad (17)$$

This implies that the LLR at the equalizer output increases from its no *apriori* value to the perfect value which establishes the validity of the LLR enhancement model for these kind of TEQ algorithms also. For the case, $\lambda_{Eq,nap}(x_k) \approx \lambda_{Eq,iap}(x_k) \approx \lambda_{Eq,pap}(x_k)$, the TEQ algorithm does not converge because no enhancement of LLR takes place. Therefore performance improvement with respect to iterations does not take place.

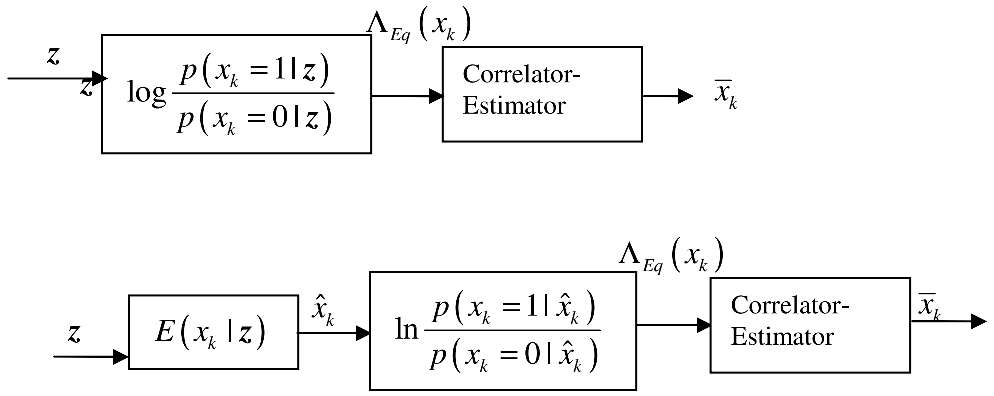


Fig.2 Analytical Models for the trellis based and the filter based TEQ schemes

In Fig.2, the upper figure corresponds to the trellis based TEQ and the lower figure is for the filter based TEQ. The former computes extrinsic information directly from the channel observations while the latter computes the same from the equalized samples; i.e. after the channel values are subject to filtering. As filtering removes some ISI, the mean of the soft output corresponding to the latter scheme has been found to be higher than that corresponding to the first scheme. Similarly, the variance of the second scheme has also been found to be lower than the first scheme. However, under asymptotic conditions, both schemes approach identical performance. The decoder has been modeled as a correlator-estimator in both the schemes.

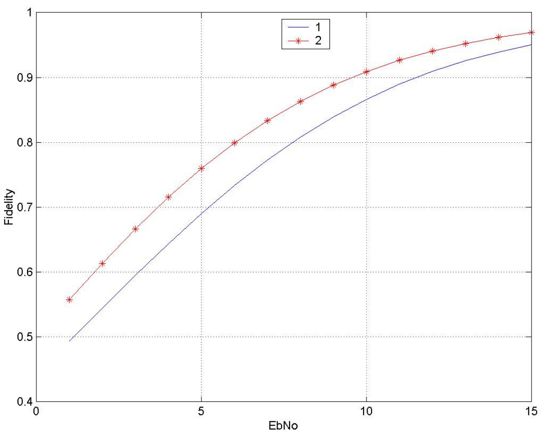
IV. NUMERICAL RESULTS

The simulations have been carried out in Matlab with a data block size of 1,00,000 with BPSK modulation. Recursive systematic convolutional coding of rate ½ has been the channel coding with a constraint length of 3. A random interleaver of size 20,0000 bits has been used in our experiment. Performance comparison of the TEQs have been presented for four channel models. These models include Proakis-B, Proakis-C, fast exponential decaying and slow exponential decaying model. The respective tap gains for these 4 channel models are given in Table 1. The soft output Viterbi algorithm (SOVA) has been used as the channel decoder. The MMSE filter used in this work has 3*L* number of taps.

Table 1. Tap gains of typical channel models

Channel No	Type of Channel	Tap gains
1	Proakis-B	0.407 0.815 0.407
2	Proakis-C	0.227 0.460 0.688 0.460 0.227
3	Slow Exponential Decaying	0.7840 0.5180 0.3422
4	Fast Exponential Decaying	0.8823 0.4241 0.2069

These channel taps are normalized so that, the sum of the squares of tap gains is equal to 1. Channels 1 and 2 represent the worst possible ISI whereas channel 3 produces interference that decays slowly and channel 4 is a transmitted bit stream friendly channel as is has a faster decay.

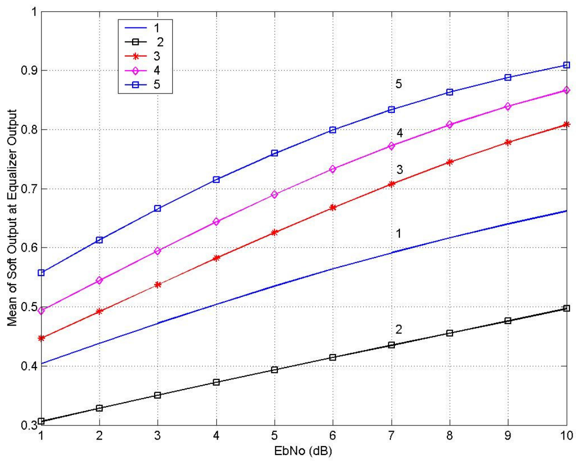


1: Fidelity of the linear MMSE equalizer for no apriori information for a typical good channel such as channel 3

2: Fidelity of the linear MMSE equalizer for perfect apriori information for a typical good channel such as channel 3

Fig. 3 Fidelity Comparison for the two extreme cases of *apriori* information as obtained for a typical good channel

The fidelity comparison corresponding to the no *apriori* and the perfect *apriori* information about the transmitted bits at the equalizer input is presented in Fig.3. Fig.3 clearly establishes the monotonically increasing nature of the LLR values as a function of the SNR for the filter based TEQ. We note that, for a typical good channel, the gap between fidelity corresponding to the no *apriori* case and perfect *apriori* case is not very significant. This is attributed to the fact that, the residual interference power after one round of combined equalization and decoding attains a small value quickly as compared to that for a similar numbered bad channel. The number of eigen values of the channel autocorrelation matrix that are less than the channel noise variance is small in this case.



1: No apriori fidelity for Proakis-B,

2: No apriori fidelity for Proakis-C,

3: No apriori fidelity for slow exponential decaying channel,

4: No apriori fidelity for fast exponential decaying channel,

5: Perfect apriori fidelity for all the channels

Fig. 4 Mean value of Soft Output at Equalizer for four different channels and the associated perfect *apriori* mean

The mean value of the extrinsic information at the equalizer output is indicative of its fidelity also. This is increasing nonlinearly for perfect *apriori* information as compared to the no *apriori* information. For reduced levels of ISI in the channel, for higher SNR, the perfect a priori and the no *apriori* mean values of the soft output of the equalizer gradually converge whereas at low SNR, this difference widens, however by a reduced margin as compared to high level of ISI case as shown in Fig.4. In a similar vein, the Proakis-C channel, the Proakis-B channel and a slow exponential decaying channel models are also tried in which the Proakis-C has the widest margin by which the perfect *apriori* receiver shows improvement, whereas for slowly decaying channel, it is in between Proakis-B and that of the fast decaying channel as shown also in Fig.4.

We note that, for a typical bad channel, the gap between fidelity corresponding to the no *a priori* case and perfect *a priori* case is quite significant. This is because of large residual interference and noise at the output of the equalizer at a given iteration for a bad channel for the non perfect *a priori* condition. It is for these channels that a TEQ is a much better performer than the conventional feed forward and the decision feedback equalizers. We further note that, for all the four channels specifying varying amounts of ISI, the perfect *apriori* information condition gives the TEQ the AWGN performance which means that all the interference suffered by a bit due to a harsh channel has been taken care of. This is shown by graph 5 in Fig.4.

The fidelity its ensemble average for a typical trellis based TEQ as computed from (6) is shown in Fig.5.

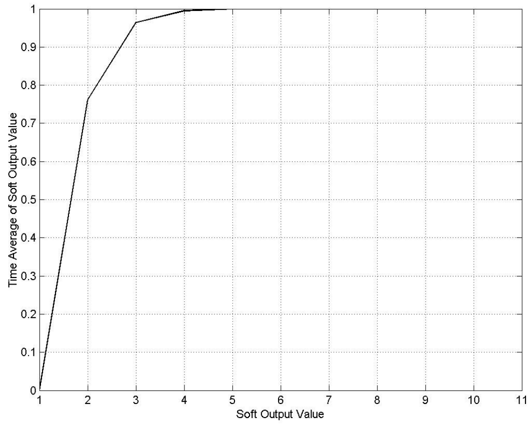


Fig.5 Plot of fidelity and its ensemble average for trellis based TEQs

The iteration wise time average of the equalizer soft output λ_{Eq} is plotted with respect to value of the soft output λ_{Eq} in Fig.5 which indicates that for higher values λ_{Eq}, the time average of the soft output asymptotically converges to 1. However, the average convergence, as shown in Fig.5 indicates that the average of m approaches unity value for iteration wise time average of λ_{Eq} approaching a value greater than or equal to 3. This in turn gives an interesting phenomenon of convergence that helps in error free decoding with fewer numbers of iterations in an average sense.

V. CONCLUSION

An LLR enhancement model is presented for both trellis and filter based TEQs that describes the evolution of the extrinsic information at the equalizer output. This is observed to be a monotonically increasing function from the case of no *apriori* information to the perfect *apriori* information. The objective of the TEQ is to operate the receiver over the range from no *apriori* to perfect *apriori* condition at a given SNR. However, this model is valid for converging TEQ operation. Under very low values of signal to noise ratio, this model may not be appropriate as the residual interference and noise in a bit after equalization may prevent it from approaching its true LLR value.

REFERENCES

[1] C.Douillard, A.Picart, P.Didier, M.Jezquel, C.Berrou and A.Glavieux,(1995) “Iterative correction of intersymbol interference: Turbo equalization,” Eur. Trans. Telecommun, pp 507-511
[2] C. Laot, A.Glavieux and J.Labat, (2001) “Turbo Equalization: Adaptive Equalization and Channel Decoding Jointly Optimized”, IEEE Journal on Selected Areas in Communications, vol.19, No.9, pp 1744-1752
[3] M.Tuchler, A.C.singer and R.Koetter, (2002) “Minimum Mean Squared Error Equalization Using *A Priori* Information”, IEEE Trans. on Signal Processing,vol.50,No.3, pp 673-683
[4] M.Tuchler, R.Koetter and A.C. Singer, (2002) “Turbo Equalization: Principles and New Results”, IEEE Trans. on Comm.,vol.50, No.5, pp 754-766
[5] Ralf Koetter, Andrew C. Singer and Michael Tuchler, (2004) “ Turbo Equalization: An iterative equalization and decoding technique for coded data transmission”, *IEEE Signal Processing Magazine*, pp 67-80,
[6] X.Wang and H.V.Poor, (1999) “Iterative (Turbo) Soft Interference Cancellation and Decoding for Coded CDMA”, IEEE Trans. on Comm., Vol.47, No.7, pp 1046-1061
[7] A.Paulraj, R.Nabar and D.Gore, (2003) “Introduction to Space-Time Wireless Communications”, Cambridge University Press
[8] D.Divsalar, S.Doliner and F.Pollara, (2001) “Iterative Turbo Decoder Analysis Based on Density Evolution”, IEEE Jou. on Selected Areas in Comm., Vol.19, No.5, pp 891-907
[9] Gerhard Bauch ,Volker Franz, (1998) “Comparison of Soft-In/Soft-Out Algorithms for Turbo-Detection,” *Proc.of ICT,1998*,Thessaloniki,Greece, pp 259-263

[10] N.Sellami, A.Roumy and I.Fijalkow, (2004) " On the analysis of the MAP equalizer performance within an iterative receiver," SPWAC 2004, Lisbon, Portugal

[11] S.J.Lee, A.C.Singer and N.R.Shanbag, (2003) " Analysis of Linear Turbo Equalizer via EXIT Chart", GLOBECOM, 2003, 1-5th Dec., San Francisco, California ,pp 2237-2242

[12] A.Tripathy, (2008) "Error Performance and Complexity Analysis of Low Complexity Turbo Equalization", Ph.D. Thesis, IIT, Kharagpur

[13] A.Tripathy, (2009) " On the Convergence of a Turbo Equalizer in terms of AMI", Int. J. on Recent Trends in Engineering, Issue 1, vol.3, pp.283-286

[14] H. C. Myburgh, Jan C. Olivier and A. J. Vanzyl (2012) "Reduced Complexity Turbo Equalization Using a Dynamic Baysian Network ", European Jou. on Advance in Signal Processing

[15] D.Ampeliotis and K.Berberidis, (2006) "Low Complexity Turbo Equalization for High Data Rate Wireless Communication", EURASIP Jou. On Wireless Communication and Networking, pp.1-12, vol. 12

[16] A.Dejonghe and L.Vandendorpe, (2002) "Turbo-equalization for multilevel modulation: an efficient low-complexity scheme, ICC '02, pp.1863-1867

[17] M. Koca and B. C.Levy, (2005)"Broadband Beamforming for Joint Interference Cancellation and Low-Complexity Turbo Equalization, "IEEE Globecom, pp.2161-2165

[18] K.Fang and G.Leus, (2007)" Low complexity Block Turbo Equalization for OFDM Systems in Time-Varying Channels", ICASSP 2007. pp. 445-448

[19] L. Liu and Li Ping, (2004) " An Extending Window MMSE Turbo Equalization Algorithm", IEEE Signal Processing Letters, vol.11, No.11, pp.891-894, Nov

[20] S.Ten Brink,(1999)" Convergence behavior of iteratively decoded parallel concatenated codes," *IEEE Trans. on Commun.*, vol.49, pp 1727-1737, Oct.

[21] A. Kundu, B. K. Sarkar and A. Chakarbarty, (2008) " Adaptive Turbo Equalizer Design for Multiuser Mobile Communication Channel", Progress in Electromagnetic research, vol 2, pp 13-30

[22] K. Shimezawa (2008) , " A Novel SC- MMSE Turbo Equalization for Multi-carrier Systems with Insufficient Cyclic Prefix", 19th PIMRC

[23] G.Bauch and A.F.Naguib, (1999)" MAP Equalization of Space-Time Coded Signals Over Frequency Selective Channels", IEEE WCNC 99, pp.261-265, Sep 1999

[24] L. M. Davis, I. B.Collings and P. Hoeher, (2001)"Joint MAP Equalization and Channel Estimation for Frequency-Selective and Frequency-Flat Fast-Fading Channels", IEEE Trans. on Comm., vol.49, No.12, pp.2106-2114, Dec

[25] C.Fragouli, N.Al-Dahir, S.N.Diggavi and W.Turin, (2002)" Prefiltered space-time M-BCJR equalizer for frequency selective channels", IEEE Trans. on Comm., vol.50, pp.742-753, May

[26] J. Li, K.R. Narayanan, E. Kurtas and C. N.Georghiades, (2002)"The Performance of High-Rate TPC/SPC Codes LDPC Codes Over Partial Response Channels, " IEEE Trans. on Comm., Vol.50, No.5, pp.723-734, May

[27] . N.D.Doan and R.M.A.P. Rajatheva, (2000) " Turbo Equalization for Non-binary Coded Modulation Schemes over Frequency Selective Fading Channels, Proc. of VTC00 Spring, Tokyo, Japan, vol.3, pp.2217-2221, May

[28] N. Kalantarova, S. S. Kozat and A. T. Erdogan, (2012), " Robust Turbo Equalization under Channel Uncertainties", IEEE Tran. on Signal Processing,

[29] M. Danish Nisav and W. Utschick, (2011) "Minimax Robust A-priori Information Aware Channel Equalization", IEEE Tran. on Signal Processing, vol. 59,pp 1734 -1745

[30] W. Jingian, (2012) "Improved BDFE using A-priori information for Turbo Equalization", IEEE Tran. on Wireless Comm. to be published

Aruna Tripathy obtained the B.E. in Electronics and Telecommunication from Sambalpur University, both M.Tech. and Ph.D. degrees from IIT, Kharagpur. At present, she is working as an Associate Professor in the Department of Instrumentation and Electronics Engineering in the College of Engineering and Technology, Bhubaneswar and is involved in UG and PG teaching and research. Her interests include iterative signal processing, MIMO systems, MC systems and low complexity algorithms.