FACTA UNIVERSITATIS
Series: **Electronics and Energetics** Vol. 31, N° 4, December 2018, pp. 599-612
https://doi.org/10.2298/FUEE1804599K

A BLIND DECISION FEEDBACK EQUALIZER WITH EFFICIENT STRUCTURE-CRITERION SWITCHING CONTROL

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Abstract. *This paper considers and proposes an innovated method of structure-criterion switching control for the self-optimized blind decision feedback equalizer (DFE) scheme which operates by switching between adaptation modes according to the mean square error (MSE) convergence state. The new switching control shortens the blind acquisition period time of the DFE and, consequently, speeds up its effective convergence rate. The switching control is based on the variable switching threshold which combines the commonly used MSE estimate of the DFE's output and a posteriori error of the all-pole whitener performing front-end amplitude equalization during the blind operation mode. The efficiency of the DFE switching control is verified by simulations of single-carrier system transmitting QAM signals over multipath channels.*

Key words: *Blind equalization, decision feedback equalizer, maximum joint entropy, operation mode switching control.*

1. INTRODUCTION

In this paper, we have addressed the new method for the convergence rate increasing of the Decision Feedback Equalizer (DFE) scheme which is based on the improvement of the equalizer's operation mode switching control. With respect to the earlier version [1], presented at the 5th IcETRAN2017 conference, this paper includes a new set of case studies followed by the most recent simulation results.

The convergence rate of the blind equalization is, besides its complexity, an issue of the utmost importance from the perspective of its usage in today communication systems continually striving for the increased data throughput and frequency efficiency [2]. Because of that, the frequency efficiency advantages, achieved by removing a training sequence from the system [3], [4], have to be followed by an adequate equalization convergence rate if we want to preserve the benefits of the blind equalization.

To reconstruct an unknown source signal, blind equalizers use the higher-order statistics of channel outputs as well as some knowledge of the given signal statistic. In

Received February 12, 2018; received in revised form April 24, 2018
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*The earlier version of this paper was presented at the 5th International Conference IcETRAN2017, Kladovo, Serbia, June 5-8, 2017. [1]

such environment the resulting symbol-by-symbol based blind algorithms are typically characterized by the relative low convergence rate and high residual mean square error (MSE) [3], [4] compared to the conventional pilot-trained equalizers employing the second-order statistic based algorithms [5]. As a way to mitigate these drawbacks two-steps adaptation strategy is commonly used dividing blind equalization task between blind and decision-directed operation modes [4], [6]. At the initial (blind) operation mode, the equalizer adjusts its adaptive parameters to open “eye diagram” enough and then, depending on convergence state, switches adaptation to the decision-directed (DD) operation mode that should guarantee both the successful proceeding of the convergence process and the maximal reduction of the output MSE. In such scenario, blind equalizers must be provided by an algorithm estimating some measure of convergence state or signal quality as well as an appropriate performance threshold to decide operation mode switching. This task, as well as blind equalization alone, is not so easy because it depends on unknown system parameters, such as a source signal and channel characteristic.

The operation mode switching control based on the online MSE estimation of the equalizer’s output and its comparison with in advance selected threshold level is an often used method because of its simplicity [6]. On the other hand, this scheme strongly depends on both the applied MSE estimation efficiency and the heuristically selected threshold level according to the given signal statistic and the assumed channel characteristics. An alternative but more complex approach is to join an equalizer’s operation mode switching control with its blind adaptation algorithm aiming at the soft switching scheme [7], [8] which eliminates the above mentioned difficulties and possibly improves equalization performance. In [7], the noise-predictive Decision Feedback Equalizer (DFE) smoothly transforms the equalization process between its two extreme stages: blind linear and DD steady state. For that purpose, the equalizer employs the soft decision device defined by the linear convex function combining identity function (linear) and hard decision (nonlinear) device. In [8], using a similar convex mixing rule, the soft switching blind equalization is considered more generally in the context of linear blind equalization. This soft-switching scheme combines the outputs of two linear equalizers working in parallel: one adapted blindly and the other adapted using the DD-LMS algorithm minimizing MSE. Both schemes aggregate the equalizer’s adaptation algorithm and the operation mode control function into one adaptation task not needing a switching threshold.

In this paper we have considered the blind DFE, called Soft-DFE [9], using the operation mode switching control scheme based on both the on-line estimation of MSE and the variable switching threshold [1], [10]. The purpose of using the variable threshold instead of a fixed one includes several goals such as relaxing the issue of MSE threshold level selection and speeding up the equalizer’s effective convergence rate all with minimal computation complexity rate. Besides, these goals have been concerned with keeping the error propagation phenomenon [11] - a major drawback of blind DFE equalization - under the control guaranteeing high values of equalization successfulness.

The paper is organized as follows. Section 2 describes the Soft-DFE structure-criterion optimization scheme. In Section 3 the insufficiency of the existing switching control is addressed and then the innovated control that combines the variable threshold with online MSE estimation is introduced. In Section 4 the efficiency of the threshold variable switching control is verified by simulations.

2. SOFT-DFE: BACKGROUND AND PROBLEM DEFINITION

2.1. Structure-criterion optimization

A simplified based-band model of a single-carrier QAM (quadrature amplitude modulated) system with the Soft-DFE is presented in Fig. 1 where the in-phase and quadrature components of complex-valued symbols $\{a_n\}$, generated in time intervals of T seconds, are independent identically distributed real zero-mean variables with a finite variance and sub-Gaussian distribution, the time-invariant channel pulse response $\{h_n\}$ represents combined effects of the transmitter filter, channel impulse response and anti-alias filter at the receiver side and the noise is a zero-mean white Gaussian process independent of the source data. The signal $x(t)$ at the input of the equalizer's feedforward part given by the fractionally-spaced equalizer (FSE) is sampled at the rate 2/T and its odd and even samples $x(t_0 + nT - iT/2) = x_{n,i}$, $i = 1,2$, are alternatively shifted to the delay lines of the corresponding FIR filters presented by coefficient vectors $\mathbf{c}_i$.

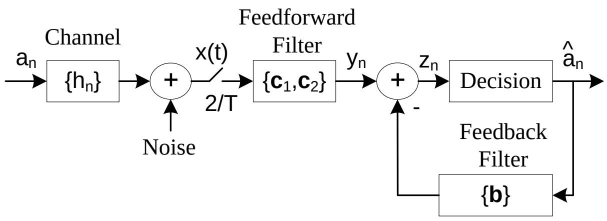


Fig. 1 Simplified model of transmission system with DFE (Soft-DFE)

The operation of Soft-DFE is based on the principles of the Self-Optimized DFE scheme [6] which, in order to eliminate the error propagation effects, optimizes both the structure and the cost criteria according to its convergence state. Specifically, the Soft-DFE optimizes both the filter structure including four FIR filters, two in FFF (feedforward) and two in FBF (feedback) part, and the combination of three cost criteria: Joint Entropy Maximization (JEM) [12], Constant Modulus [13] and minimum MSE (MMSE) [5]. Also, besides blind and tracking operation modes, which are commonly performed by blind equalizers, the new soft-transition mode has been introduced into the Soft-DFE scheme in order to mitigate the error propagation effects caused by a rapid structure-criterion switching from the blind to decision-directed adaptation mode. At the beginning of the blind mode, the Soft-DFE transforms its structure into the cascade of four linear signal transformers - the gain control (*GC*), whitener (*WT)*, blind equalizer (*TE*) and phase rotator (*PR*) - operating independently of each other except of the *GC*-*WT* pair, Fig. 2a. Effectively, in the blind mode the Soft-DFE acts as a T/2-FSE linear equalizer [14] dividing the equalization task between the whitener of the received signal and the *TE* equalizer where the *WT*-JEM and the *TE*-CM, respectively, performs the channel amplitude and phase equalization. In the next soft-transition mode the Soft-DFE proceeds to adapt filters combining the MMSE and JEM criteria, Fig. 2b. Finally, in the tracking mode, the Soft-DFE continues to converge to the MMSE steady-state using the DD-LMS algorithm.

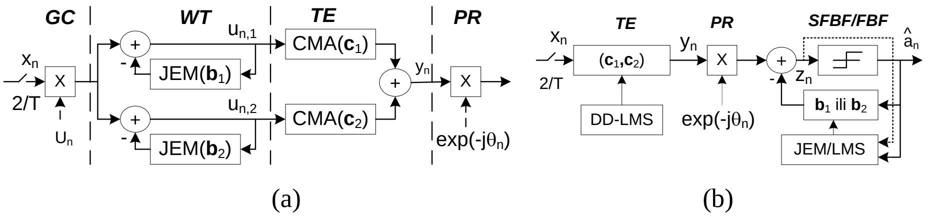


Fig. 2 Soft-DFE structure-criterion transformation:
(a) blind mode and (b) soft-transition mode (*SFBF* with JEM, dotted line) and tracking mode (*FBF* with DD-LMS, solid lines)

The phase rotator *PR* is realized as a modified variant of the decision-directed phase-locked loop [15] that, using the reduced signal constellation based only on the symbols with the largest energy [16], aims to evade catastrophic effects being caused by the carrier phase estimation exploiting an insufficiently open signals; this is particularly critical for high-order signal constellations such as 64-QAM and higher.

2.2. Algorithms

In this subsection, the adaptation algorithms used by the Soft-DFE are revisited in the order following the operation mode switching.

Gain control. The gain control *GC* is realized as a single-coefficient equalizer [6] which has a task to recover the power of the source signal. The *GC* operation is enhanced by the whitener's outputs $u_{n,i}$, $i=1,2$, and given by the recursion

$$G_{i,n+1} = G_{i,n} - \mu_G[|u_{i,n}|^2 - \sigma_a^2]\,,\; g_{i,n+1} = \sqrt{|G_{i,n+1}|} \tag{1}$$

where μ_G is the adaptation step size and σ_a^2 is the variance of source symbols $\{a_n\}$.

JEM whitening algorithm. The whitener *WT* of the received signal is realized as all-pole filter (equalizer) to compensate for the channel amplitude distortion, i.e., recover the second order statistic of the given source signal by using the entropy-based JEM cost [12]. The corresponding stochastic-gradient JEM whitening algorithm (JEM-VL) [16] is given by

$$u_{i,n} = x_{i,n} - \mathbf{b}_{i,n}^T \mathbf{u}_{i,n}\,,\; i=1,2 \tag{2}$$

$$\mathbf{b}_{i,n+1} = \mathbf{b}_{i,n} - \gamma_n \mathbf{b}_{i,n} - \mu_{BB} u_{i,n}(1-\beta_W |u_{i,n}|^2)\mathbf{u}_{i,n}^* \tag{3}$$

where $\mathbf{u}_{i,n} = [u_{i,n,1},...,u_{i,n,N}]^T$ and $\mathbf{b}_{i,n} = [b_{i,n,1},...,b_{i,n,N}]^T$ are, respectively, whitener's regression and coefficient vectors, $\gamma_n \geq 0$ is the time-variable leaky factor, β_W is the free parameter representing the slope of the employed neuron function, μ_{BB} is a step-size, N is the span of the whitener delay line given in T periods and the superscripts T and * signify, respectively, the transpose and conjugation. The specific of the JEM-VL algorithm, besides the slope β_W controlling its entropic capability, is its variable leaky factor γ_n . Acting in opposition to the entropy-gradient term, the leaky term $\gamma_n b_n$ controls the magnitudes of whitener coefficients avoiding superfluous coefficients to degrade the equalizer convergence process. The undesirable influence of superfluous coefficients is particularly exposed at the time of equalizer switching from the blind to decision-directed operation mode.

The adaptation of the leaky γ_n is based on the analysis of the whitener's a posteriori errors and the heuristic punish/award rule [17] which decides when and how much to increase or decrease the leaky factor. Accordingly, the leaky adaptation rule in JEM-VL comprises the following three operations: the calculation of a posteriori errors with ($\gamma > 0$) and without ($\gamma = 0$) coefficient leakage, decisions when and decisions how much to increase or decrease leaky. The a posteriori error $\tilde{e}_n^{VL}$ estimate for $\gamma > 0$ in JEM-VL is given by

$$\tilde{u}_n = x_n - \mathbf{b}_{n+1}^T \mathbf{u}_n \tag{4}$$

$$\tilde{e}_n^{VL} = \tilde{u}_n (1 - \beta_W |\tilde{u}_n|^2) \tag{5}$$

and the corresponding a posteriori error $\tilde{e}_n^{W}$ estimate for $\gamma_n = 0$ in (3) (corresponds to the original whitening algorithm JEM-W [9]) is given by

$$\mathbf{b}_{n+1} = \mathbf{b}_n - \mu_{BB} u_n (1 - \beta_W |u_n|^2) \mathbf{u}^* \tag{6}$$

$$\tilde{u}_n = x_n - \mathbf{b}_{n+1}^T \mathbf{u}_n \tag{7}$$

$$\tilde{e}_n^{W} = \tilde{u}_n (1 - \beta_W |\tilde{u}_n|^2) \tag{8}$$

It should be noted that the a posteriori errors, given in (5) and in (8), are obtained using the same current value of the whitener input $\boldsymbol{x}_n$; in the above recursions the indexing $i = 1, 2$ is omitted for simplicity.

In the next step, based on the comparison of the achieved a posteriori errors, the "if-else" relation

$$\begin{aligned} &\text{If } \left|\tilde{e}_n^{VL}\right| > \left|\tilde{e}_n^{W}\right| \text{ then} \\ &\qquad \text{set } m_{n+1} = \max(m_n - l_d, 0) \\ &\text{else} \\ &\qquad \text{set } m_{n+1} = \min(m_n + l_u, M) \\ &\text{end if} \end{aligned} \tag{9}$$

decides when to decrease or to increase the leaky factor and, finally, the quantized function

$$\gamma_n = f(m_n) = \gamma_{\max}(m_n / M) \tag{10}$$

estimates how much to decrease or to increase the leaky factor employing parameters $(m_0, l_d, l_u, M) \in \mathbb{Z}$, $\gamma_{\max} \in \mathbb{R}$ and $m_n = 0, \ldots, M$ is an independent variable.

CMA algorithm. The constant modulus algorithm (CMA) is realized in its commonly used variant for dispersion function of order p=2 [13]

$$y'_{i,n} = \mathbf{c}_{i,n}^T \mathbf{u}_{i,n}\,,\;\; y_n = \sum_{i=1}^{2} y'_{i,n} \tag{11}$$

$$\mathbf{c}_{i,n+1} = \mathbf{c}_{i,n} - \mu_{FB} y'_{i,n}\left(\left|y'_{i,n}\right|^2 - R_C\right)\mathbf{u}_{i,n}^*\,,\;\; R_C = \frac{E\{|a_n|^4\}}{E\{|a_n|^2\}} \tag{12}$$

where $\mathbf{c}_{i,n} = [c_{i,0},..., c_{i,M-1}]^T$ is the coefficient vector of FFF, μ_{FB} is an adaptation step-size and the constant R_C is the kurtosis of the source signal which represents the source probability density function (PDF) distance measure from normality [18]. Assuming the amplitude equalization is done efficiently by the *GC-WT* pair, the T/2-FSE-CMA has the task to equalize for a channel phase distortion by retrieving the kurtosis statistic of the source signal [19].

Soft JEM algorithm*.** The performing of the Soft-DFE in the soft-transition mode is characterized by the ***SFBF equalizer behaviour operating between the original soft FBF equalizer maximizing the joint entropy of the neuron outputs [9] and a hard DD FBF equalizer suffering from incorrect decisions $\hat{a}_n$. The operation of the *SFBF* is described by the following relations

$$y_n = \mathbf{c}_n^T \mathbf{u}_n \exp(-j\hat{\theta}_n) \tag{13}$$

$$z_n = y_n - \mathbf{b}_{n-1}^T \hat{\mathbf{a}}_n \tag{14}$$

$$\mathbf{b}_{n+1} = \mathbf{b}_n - \mu_{BS} z_n \cdot \left[1 - \beta_D |z_n|^2\right] \cdot \hat{\mathbf{a}}_n^* \tag{15}$$

where $\hat{\theta}_n$ is a carrier phase estimate, $\hat{\mathbf{a}}_n = [\hat{a}_{n-1},...,\hat{a}_{n-N}]^T$ is the vector of previously detected symbols, μ_{BS} is a step size and β_D is the neuron slope which is determined by the given source statistic [20].

Tracking mode. In the tracking mode, the Soft-DFE approaches to the MMSE steady-state and continues to follow slow-time channel variations using DD-LMS algorithms in its both FFF and FBF parts optimizing jointly the MMSE criterion given by

$$J_{MMSE}(\mathbf{c}_n, \mathbf{b}_n, \hat{\theta}_n) = E\left\{|z_n - \hat{a}_n|^2\right\} \tag{16}$$

It should be noted that despite the Soft-DFE strives to reach a global MMSE solution, the local solutions cannot be avoided at all because the Soft-DFE's final convergence state depends on the local $J_{JEM}(\mathbf{b})$ and $J_{CM}(\mathbf{c})$ criteria.

3. SWITCHING CONTROL WITH VARIABLE THRESHOLD

The Soft-DFE controls the convergence state using the *MSE* monitor which estimates online the output MSE and, according to the a priori selected MSE threshold levels (TL), switches the structure and adaptation criterion through three operation modes. To switch from the blind to soft-transition mode and from the soft-transition to tracking mode, the monitor, respectively, compares the estimated MSE with TL1 and TL2 thresholds. Also, to switch the *PR* operation between a reduced and full signal constellation, the MSE is compared with threshold TL3. Since the latter indicates the signal constellation opening, it is also utilized as a measure of equalization successfulness, given by the equalization success index (ESI), which is defined by the ratio of the number of successful equalizations and the total number of Monte Carlo runs. Thus, the Soft-DFE controls its convergence process completely by MSE thresholds satisfying the relation TL1>TL2>TL3.

3.1. MSE switching control

The online estimation of the MSE in the blind mode is given by the relation

$$MSE_{B,n} = \lambda \cdot MSE_{B,n-1} + (1-\lambda)\left(|y_n| - \sqrt{R_C}\right)^2 \tag{17}$$

where the forgetting factor $\lambda > 0$ regulates a quality of estimation process, and typically takes values little less than 1.0. The same MSE estimation principle is also used during the next soft-transition and tracking modes provided that the error $\left(|z_n - \hat{a}_n|\right)$ is substituted for the error $\left(|y_n| - \sqrt{R_C}\right)$ in (17).

The quality of $MSE_{B,n}$ estimate obtained by (17) suffers from several weaknesses. Firstly, the $MSE_{B,n}$ is a crude estimate of the MSE for all non-constant modulus QAM signals (except for 4-QAM) because the term $\left(|y_n| - \sqrt{R_C}\right)$ on the right-hand side of (17) is not a real error but a dispersion measure of the modulus of symbol estimates with respect to the constant $\sqrt{R_C}$. Secondly, the $MSE_{B,n}$ estimate aggregates the MSE affected by the cascaded *GC*-*WT*-*TE* (see Fig. 2a) with the dominate influence of the *TE*-CMA algorithm which is based on the fourth-order statistic represented by the constant R_C (12). In other words, the estimate $MSE_{B,n}$ relays mostly on the outlier sensitive kurtosis statistic [18] neglecting the second-order statistic being reconstructed by the *WT*-JEM.

To illustrate the Soft-DFE convergence behaviour controlled by the $MSE_{B,n}$ estimator, we have presented in Fig. 3 the results of the convergence tests carried out for three different heuristically selected thresholds $\mathrm{MSE_{TF}} = \mathrm{TL1}$ using system in Fig. 1 with 64-QAM signal and Mp-E channel; see channel amplitude in Fig. 5 in the next section. If we suppose the optimal mean square error $MSE_{B,opt}$ is achievable during the blind mode if the equalizer's coefficients reached the optimal setup then the three typical equalization scenarios are possible: 1) for $\mathrm{MSE_{TF}} \approx MSE_{B,opt}$ the equalizer successfully switches operation from the blind to the DD operation mode, 2) for $\mathrm{MSE_{TF}} < MSE_{B,opt}$ the equalizer stays longer in the blind mode than in the case 1) or, possibly, it will never reach the soft-transition mode and the equalization will be ended in failure and, finally, 3) for $\mathrm{MSE_{TF}} > MSE_{B,opt}$ the equalizer switches operation to the DD mode faster than in the case 1) but, the MMSE steady-state performance is not guaranteed, and even some pathological states are possible. As can be seen from the presented convergence curves the threshold TL1=8.02 dB is selected to be the best threshold.

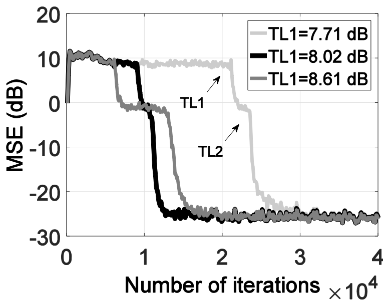


Fig. 3 MSE convergence curves obtained for three different fixed thresholds TL1; Soft-DFE single run test for 64-QAM signal and Mp-E channel

3.2. Variable threshold

In order to compensate for insufficiency of the $MSE_{B,n}$ estimation given by (17), we have combined a fixed threshold $\mathrm{MSE}_{\mathrm{TL}}$, generally different from the threshold $\mathrm{MSE}_{\mathrm{TF}}$, with the whitener's a posteriori errors $\tilde{e}^{VL}_{i,n+1}$ introducing in such a way the variable threshold $\mathrm{MSE}_{\mathrm{TLV}}$ [10]

$$\mathrm{MSE}_{\mathrm{TLV}} = \mathrm{MSE}_{\mathrm{TL}} - S\left(\left|e^{VL}_{1,n+1}\right| + \left|e^{VL}_{2,n+1}\right|\right) \tag{18}$$

which includes two terms, the fixed threshold $\mathrm{MSE}_{\mathrm{TL}}$ and the variable term $S\left(\left|e^{VL}_{1,n+1}\right| + \left|e^{VL}_{2,n+1}\right|\right)$ where S is a small positive scale factor.

It is worth noting that the scaling factor S should be selected through the analysis of the ratio between the sum of a posteriori errors and the $\mathrm{MSE}_{\mathrm{TL}}$ threshold. The first verifications of the variable threshold model have proved its efficiency for the S values scaling down a posteriori term to a level comparable with the $\mathrm{MSE}_{\mathrm{TL}}$ term. The full exploration of the variable threshold usage and its limitations need to be a subject of further study.

The above innovation of the blind mode threshold comes from the fact that a posteriori errors of the *WT*-JEM carry up-to-date information on the second-order statistics missing to the $MSE_{B,n}$ (17). A posteriori errors of the JEM-VL algorithm are functions of *WT*-JEM outputs which are almost free from ISI disturbance (outliers) coming from channel amplitude characteristics. As it is mentioned in the previous section JEM-VL provides efficient compensation for frequency-selective channels.

Practically, by introducing the whitener's a posteriori errors as a variable threshold term we have created the switching control that directly reflects the recovery of both the second-order and four-order statistics of the applied source data. Using the variable threshold, the switching control responds as follows: for a lower a posteriori error the $\mathrm{MSE}_{\mathrm{TLV}}$ becomes higher, which shortens the blind equalization time and, hence, speeds up the equalizer convergence rate, and reverse, for a higher a posteriori error the $\mathrm{MSE}_{\mathrm{TLV}}$ becomes lower which lengthens the blind acquisition time and slows the equalizer convergence. Effectively, from the perspective of the MSE estimation quality, the $\mathrm{MSE}_{\mathrm{TLV}}$ becomes more robust against the dispersion of magnitudes $|y_n|$ of symbol estimates.

To avoid the false equalizer switching through the operation modes, which could be caused by the non-stationarity of the MSE data, the Soft-DFE switching control implementation is based on the multiple checking of the threshold level passage. According to the switching rule presented in Fig. 4, the equalizer is allowed to switch from the blind to the soft-transition mode if and only if the $MSE_{B,n}$ satisfies $MSE_{B,n} < \mathrm{MSE}_{\mathrm{TLV}}$ during the K equalizer's update iterations where K is an integer larger than 1. The same switching rule is valid for the Soft-DFE switching from the soft-transition to the tracking operation mode but it is less critical than the former from the perspective of convergence rate.

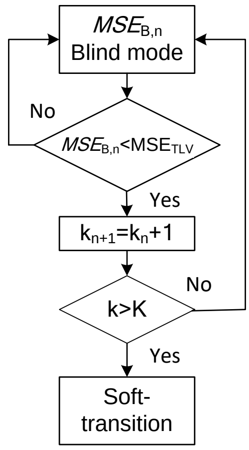


Fig. 4 Soft-DFE rule switching from blind to soft-transition mode

4. SIMULATION RESULTS

The efficiency of the innovated structure-criterion switching control and its impact on the equalizer's convergence rate is verified by the software simulator of the QAM system presented in Fig. 1. The simulations are carried out using 16- and 64-QAM signals and the multi-path channel adding the white Gaussian noise determined by the signal-to-noise ratio (SNR). The selection of Soft-DFE dimensions and parameters is done aiming at the best compromise between the convergence rate achievements and the equalization successfulness defined by ESI. The frequency selective Mp-(A, C, E) channels, whose normalized amplitude characteristics are presented in Fig. 5, are design in a way to gradually increase ISI severity from Mp-A to Mp-E.

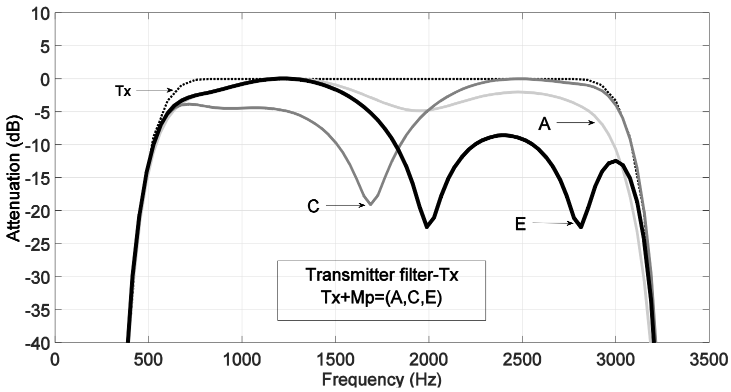


Fig. 5 Normalized attenuation characteristics of Mp-(A, C, E) channels

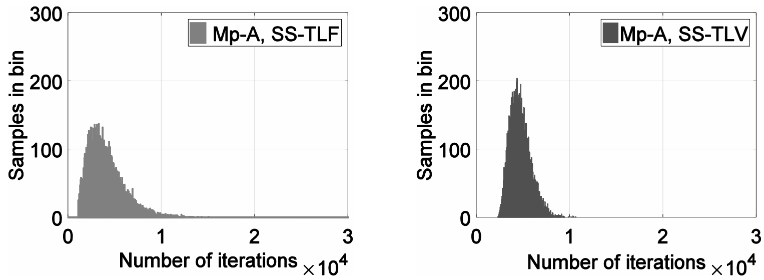
The Soft-DFE parameters are given as follows. The filter tapped-delay line span, in T intervals, for FBF is 5 for both QAM signals and for FFF is 23 and 24, respectively, for 16- and 64-QAM signals. The FBF is initialized for all zero coefficient-values while the initialization of the FFF is realized by two strategies: 1) double-spike initialization (DS) with two central reference tapes $c_{1,r} = c_{2,r} = 0.707$ and 2) single-spike initialization (SS) with a single central reference tape $c_{1,r} = 1.0$. The adaptation steps for the GC, JEM, CMA and LMS algorithms are selected in a way to optimize their efficiency through the corresponding operation modes. It is of particular importance for GC, JEM and CMA algorithms which divide the blind equalization task into several simpler subtasks. For example, the *GS* uses two adaptation steps $\mu_G = \{2^{-11}, 2^{-20}\}$ for both signals. The first step, applied at the early beginning of the blind mode, is much larger than the second one aiming to prevent the WT and TE equalizers from taking over the gain control function. The adaptation steps of JEM, CMA and LMS algorithms are selected in order to produce the best response of the FBF and FFF filters through three operation modes. Depending on the 16- and 64-QAM signals, they are selected as follows: 1) for FBF $\{\mu_{BB,16} = 2^{-19},\ \mu_{BB,64} = 2^{-22}\}$, $\{\mu_{BS,16} = 2^{-18}, \mu_{BS,64} = 2^{-21}\}$, $\{\mu_{BT,16} = 2^{-14}, \mu_{BT,64} = 2^{-13}\}$ and 3) for FFF $\{\mu_{FB,16} = 2^{-16}, \mu_{FB,64} = 2^{-21}\}$, $\{\mu_{FS,16} = 2^{-15}, \mu_{FS,64} = 2^{-20}\}$, $\{\mu_{FT,16} = 2^{-13}, \mu_{FT,64} = 2^{-16}\}$; the second subscripts of adaptation steps, B, S and T, respectively signify blind, soft-transition and tracking modes. The leaky parameters are given by $\{m_0 = 40, l_d = 5, l_u = 40, M = 400, \gamma_{\max} = 2^{-11}\}$ for both signals. The selection of neuron slopes $\{\beta_W, \beta_D\}$ is done according to the considerations given in [16], [20]. The slope β_D, which depends mostly on the given signal constellation , takes values 12 and 1.95, respectively, for 16- and 64-QAM constellations. On the other hand, the slope β_W, together with the threshold parameters S and K, is used as a tool to optimize an initial convergence rate of the equalizer, see TABLE 1.

The comparison of the Soft-DFE performance achieved by the fixed (TLF) and variable (TLV) switching controls are given in the terms of the PDF histograms of the blind acquisition period time, MSE convergence and equalization successfulness ESI. The comparison tests are carried out for SS and DS equalizer initialization methods, (16,64)-QAM signals and switching control parameters $\{MSE_{TF}/MSE_{TL}, S, K\}$ as given in Table 1. The motivation to test the switching control for two initialization methods comes from the fact that the success and speed of convergence of FSE-CMA equalization are strongly affected by the coefficient initialization [14]. The presented PDH histograms and ESI tests are obtained for 10000 and MSE convergence curves for 200 independent Monte Carlo runs.

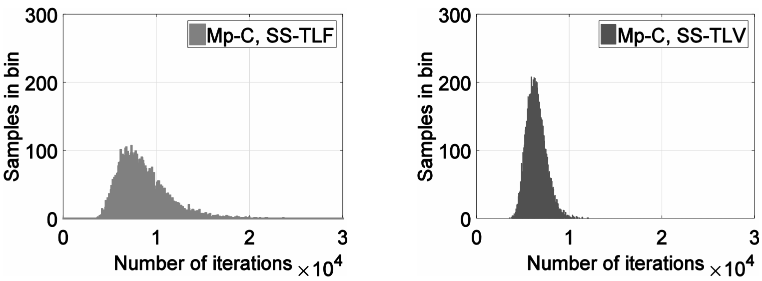
Table 1 System setups: switching control parameters

QAM/Soft-DFE	MSE_{TF}/MSE_{TL}	β_W	K	S
16QAM-TLF	1.30 dB	7.5	95	0
16QAM-TLV	2.30 dB	9	105	0.00145
64QAM-TLF	8.02 dB	2.4	95	0
64QAM-TLV	8.61 dB	2.8	105	0.00165

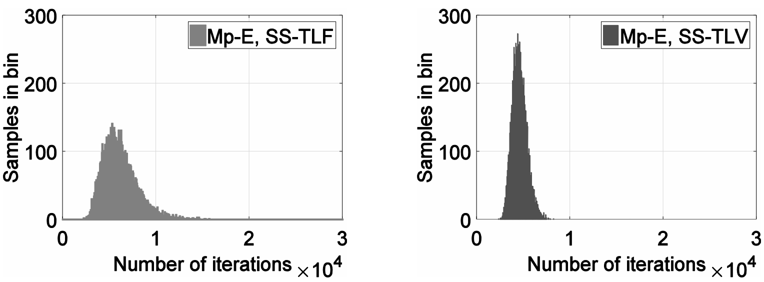
Fig. 6 presents the PDF histograms of the blind acquisition period time obtained with TLF and TLV switching controls for the 64-QAM signal. The histogram obtained by TLF control demonstrates a positive skewness caused by FSE-CMA kurtosis outliers in contrast to the histograms obtained by TVL control which are much more symmetrical; the latter is obviously affected by a posteriori variable threshold term in (18). The more quantitative measure of the switching control impact on the blind acquisition time is provided by Mean and standard deviation (SD) statistic presented in Table 2 for (16,64)-



(a) Channel Mp-A



(b) Channel Mp-C



(c) Channel Mp-E

Fig. 6 PDF histograms of blind acquisition period time for TLF and TLV thresholds and SS initialization: 64-QAM, SNR=30 dB, a) Mp-A, b) Mp-C, c) Mp-E

Table 2 Blind mode statistic, [T]: (16, 64)-QAM, SS

Mean, STD/Channel	Mp-A	Mp-C	Mp-E
	16-QAM		
Mean: TLF	3146	4264	3317
STD: TLF	759	1314	843
Mean: TLV	2778	2957	2684
STD: TLV	232	301	173
	64-QAM		
Mean: TLF	4776	8431	6103
STD: TLF	1893	2507	1795
Mean: TLV	4691	6422	4585
STD: TLV	1142	1049	793

QAM signals and SS initialization method. The presented results emphasize an important decrease of Mean and SD in the case of the TLV control. For example, for the TLV control and 64-QAM signal, Mean and SD values are, respectively, 18% and 51.8% smaller (averaged over all channels) with respect to the TLF control.

The impact of the operation mode switching control on the equalizer convergence rate is presented in Figures 7 and 8. In Fig. 7, the convergence curves obtained for TLF and TLV controls and SS and DS initializations in the case of the 16-QAM signal are given. As can be seen, the convergence rates achieved by the TLV control are significantly higher than by the TLF for both SS and DS initialization provided that the residual MSE is not sacrificed and, also, the best results are reached for SS-TLV combination. The similar results are achieved for the 64-QAM signal, Fig. 8. In this case, for the sake of the figure clarity, only the convergence curves obtained by the TLV control and for SS and DS initializations are presented. It is worth noting that the equalizer converges faster by TLV control because the

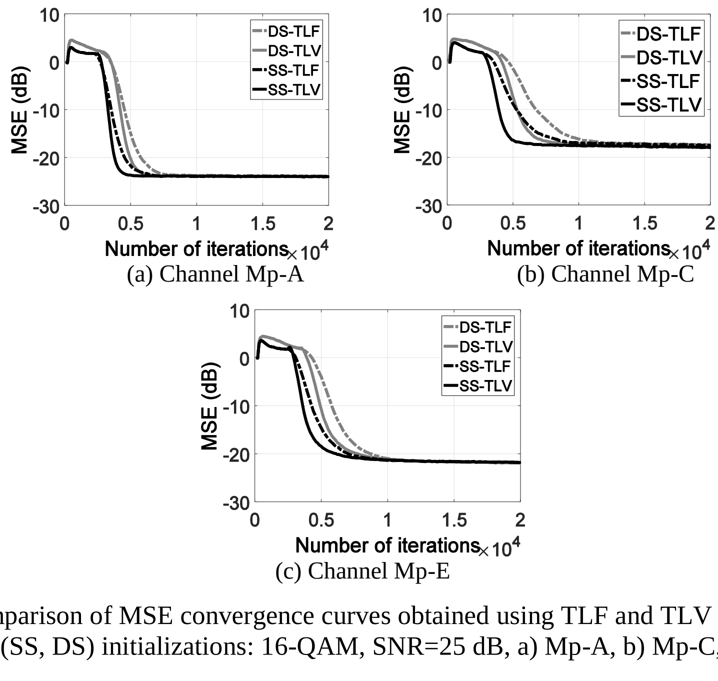


Fig. 7 Comparison of MSE convergence curves obtained using TLF and TLV controls and (SS, DS) initializations: 16-QAM, SNR=25 dB, a) Mp-A, b) Mp-C, c) Mp-E

blind mode time has been made shorter as a result of the improved switching control. Also, these results have proved an efficiency of the *GC-WT* amplitude equalizer that has been insufficiently visible unless the TLV control has been applied.

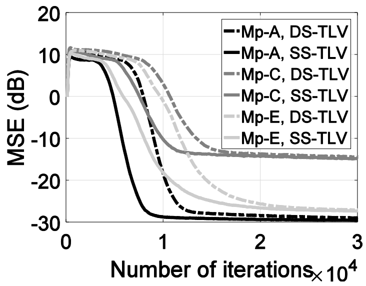


Fig. 8 Comparison of MSE convergence curves obtained using TLV control and (SS, DS) initializations: 64-QAM, SNR=30 dB, Mp-(A,C,E)

The results of ESI tests are given in Table 3. The purpose of these tests is to prove that the new TLV control does not degrade the equalization successfulness; the results for both the TLF and the TLF methods are practically same for parameters selected in Table 1. It is of an essential importance because we have used different control switching parameters (β_W , S, K) aiming to achieve the best convergence performance by both methods and, at the same time, to preserve the equalization efficiency.

Table 3 Equalization Success Index [%]

ESI/Channel	Mp-A	Mp-C	Mp-E
	16-QAM		
SS-TF	99.99	99.80	100
SS-TV	99.99	99.75	100
DS-TF	99.97	99.91	99.16
DS-TV	100	99.87	98.94
	64-QAM		
SS-TLF	100	99.68	98.83
SS-TLV	100	99.80	98.64
DS-TLF	100	99.69	98.65
DS-TLV	100	99.84	98.03

CONCLUSIONS

Our goal in this paper was to increase the convergence rate of the blind Soft-DFE equalizer by improving its operation mode switching control. The performing of the online MSE estimator monitoring the equalizer's convergence state is enhanced by the innovated switching control that combines the fixed value threshold term with the a posteriori error of the all-pole amplitude equalizer coefficient updates. In this innovation the robust second-order statistic of a posteriori errors is employed to compensate for the undesirable effects of the outlier sensitive kurtosis statistic of FSE-CMA outputs. It is verified by different simulation setups that the simple MSE estimation method combined with the variable up-to-date threshold information significantly reduces the blind mode operation time and, hence, greatly improves the effective equalizer convergence rate.

Acknowledgement: *The paper is a part of the research done within the project TR 32037, 2011-2018, The Ministry of education, science and technological development of the Republic of Serbia. The authors thank to the anonymous reviewers for their valuable suggestions and comments.*

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