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Blind DFE with Parametric Entropy-Based Feedback

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1. Introduction
The key drawback of blind decision equalization is *error propagation phenomena*.

The classical decision feedback equalizer structure includes feedforward filter (FFF) and feedback filter (FBF) with a nonlinear (hard) decision device.
2. The basic model of blind self-optimized DFE (SO-DFE). This scheme optimizes both the structure and the criterion with the aim to “skip” the error propagation effects, [Labat et al., 1998].

In blind mode SO-DFE transforms its self into the linear equalizer cascaded structure to initialize a convergence process and then, when eye diagram is open enough, transforms itself back into classical nonlinear scheme. 

$W$ is all-pole linear recursive equalizer (whitener) and $T$ is FIR equalizer.
The improved version of the SO-DFE scheme, named (Soft-DFE) [Krštić, 2009], performs equalization through three operation modes: (a) blind acquisition, (b) soft transition and (c) tracking.
The basic model of entropy-based soft feedback filter (SFBF) applied to the Soft-DFE acting as a single neuron unit of Bell-Sejnowski type.

\[
J_E(b) = E \left\{ \ln \left| \frac{\partial r_n}{\partial z_n} \right| \right\}
\]

The cost function maximizing the joint Shennon’s entropy (JEM) of SFBF outputs.

\[
g(z_n, \beta) = r_n = z_n \left( 1 + \beta |z_n|^2 \right)
\]

The parametric complex-valued nonlinear (activation) function.
SFBF is herustically transformed into two adaptive equalizer structures with JEM type algorithms corresponding to the self-optimized DFE scheme.

\[
JEM - W1: \quad b_{i,n+1,j} = b_{i,n,j} - \mu_W u_{i,n} \left(1 - \beta_W |u_{i,n}|^2\right) u_{i,n-j}^*
\]

\[
JEM - W2: \quad b_{i,n+1,j} = (1 - \gamma_W)b_{i,n,j} - \mu_W u_{i,n} \left(1 - \beta_W |u_{i,n}|^2\right) u_{i,n-j}^*
\]

\[
JEM - D: \quad b_{n+1,j} = b_{n,j} - \mu_D z_n \left(1 - \beta_D |z_n|^2\right) \hat{a}_{n-j}^*, \quad j = 1, \ldots, N.
\]

**SFBF-W** in blind acquisition mode

**SFBF-D** in soft transition mode
The Beta-W selection by means of the kurtosis statistics of estimated data symbols at the output of FSE-CMA.

\[ kurt = \frac{1}{2} \sum_{i=1}^{2} kurt_i, \quad kurt_i = \frac{kurt(y_{i,n})}{kurt(a_n)} = \left[ \frac{\|c_i\|_4}{\|c_i\|_2} \right]^4, \quad \|c_i\|_q = \left[ \sum_{k=0}^{L-1} |c_{i,k}|^q \right]^{1/q} \]

Kurtosis statistics of m-QAM signal.

Kurtosis statistics at the output of FSE-CMA.
3.1 Optimal Beta-W parameters for 16- and 32-QAM.

\[ \beta_{W,16} = (1.0 - 2.0), \beta_{W,32} = (1.0 - 1.4) \]
Optimal Beta-D parameters for 16- and 32-QAM. The Beta-D is selected to minimize symbol error rate (SER) in soft transition mode.

\[ \beta_{D,16} \approx 12.0, \quad \beta_{D,32} \approx 10.0 \]
3.2 Optimal Gamma and Beta parameters for 64-QAM.

\[ \{\gamma_w = 2^{-14}, \beta_w \approx 0.3\}, \{\gamma_w = 2^{-13}, \beta_w \approx 0.5\}, \{\gamma_w = 2^{-12}, \beta_w \approx 0.8\} \]
Optimal Beta-D parameter for 64-QAM constellation. The Beta-D is selected to minimize mean-square error transition time (MSE-TT) in soft transition mode.

Optimal Beta-D is estimated in the range of (1.75-2.25).

Attenuation response of multipath channels Mp-(A,B,C,D,E).
The 64-QAM signal in the phase of passing threshold levels: (a) MTL-1, (b) MTL-2 and (c) MTL-3. Presented signals are observed during the periods of time of 1000 symbol intervals.

Simulation setting: channel Mp-C, SNR=30 dB, Beta-W=1.0, Gamma=2E(-12), Beta-D=2.0

(a) $M_{TL1}=7.9$ dB  (b) $M_{TL2}=-2.2$ dB  (c) $M_{TL3}=-7.9$ dB
The MSE convergence characteristics of Soft-DFE with 64-QAM and Mp channels with SNR=30 dB for Gamma=2E(-13) and Beta-D=2; the curves are averaged over 100 Monte Carlo runs.
6. Conclusions

In this paper the optimization method for the parametric recursive part of the blind Soft-DFE is presented. It is proved via simulations that the parameters of the selected complex-valued nonlinearity can be optimally adjusted for the given signal in the system with a large scale of severe ISI channels.

- The efficiency of the presented method is verified with 16-, 32- and 64-QAM signals.
- The slope Beta of mapping surface of the neuron $SFBF$ decreases by increasing the complexity of signal, i.e., the variance of ISI at the input of Soft-DFE.