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INTERFERENCE SUPPRESSION IN DSSS SYSTEM BY QUADRATURE DEMODULATION NEURAL NETWORK

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Abstract. In this paper a DSSS receiver with the quadrature demodulation and neural network is presented. Extended Kalman algorithm is used for the network coefficients adaptation. Results, given as BER, show that the neural network receiver performs better in the presence of the strong broadband interference.

1. Introduction

Fast development of modern personal mobile communication systems (PCS) brought into focus the problem of coexistence of these systems with the existing broadband communication systems that use the same frequency band. This problem is usually resolved by employing the direct–sequence spread–spectrum (DSSS) concept in PCS design and implementation. Interference suppression in DSSS systems is obtained primarily by increasing the processing gain. In many practical situations, however, this gain can be insufficient for achieving the desired communication quality, as DSSS system generally operate with small transmitted power level. In such case some additional methods of interference suppression has to be implemented in DSSS receiver.

Among the different methods of strong interference suppression in DSSS receiver, use of the adaptive transversal filters (ATF), [1], is the most common. It is shown that by using this filter the strong narrowband interference can be sufficiently suppressed. It is also shown, however, that the efficiency of ATF decrease with the increasing of the interference bandwidth relative to DSSS bandwidth, and with the introduction of interference carrier frequency offset to DSSS carrier frequency.

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In this paper the efficiency of the nonlinear approach to the broadband interference suppression in DSSS receiver is addressed. The device used for the interference suppression in the quadrature demodulation receiver is the two–layer neural network (NN) [2]. The results, presented as the bit error rate at the receiver output, show that the receiver that contains the neural network generally achieve the better broadband interference suppression than the receiver equipped with ATF.

Paper contains five sections. After the introduction, in the Sec.2 block diagram of the proposed receiver is given and input signals are defined. Sec.3 contains the description of the extended Kalman algorithm, implemented in the NN coefficients adaptation process. It is shown thatthis algorithm gives the better NN convergence than the classical backpropagation algorithm. In Sec.4 the results regarding the bit error rate (BER) are given. Proposed receiver is compared in performance to the receiver containing the two sided complex adaptive transversal filter (ATF). Finally, the last section contains some concluding remarks.

2. Receiver description

Block diagram of the proposed BPSK receiver containing the neural network is presented at the Fig.1.

The receiver contains the in–phase and quadrature branch. In each branch the coherent demodulation, integrating and sampling on the chip period is performed, forming the two discrete signals $x_c(n)$ and $x_s(n)$. These signals are fed to two delay lines, whose taps are connected to the NN inputs. NN output is despreaded, after which the data bit detection is made.

Neural network implemented in the receiver contains two layers. First layer node detail is presented at Fig.2. Each node in this layer forms the linear combination of the delay line outputs and a constant, which is fed to the nonlinearity, [2],

$$f(.) = th(.). \tag{1}$$

There are N nodes in the hidden layer, and they are marked as S at Fig.1.

Second, output layer contains one node that forms the linear combination of the hidden layer outputs.

Signal at the receiver input consists of three components. First one is the desired BPSK signal, defined by,

$$u(t) = Ud(t)PN(t)\cos(\omega_0 t), \tag{2}$$

where U and ω_0 are the BPSK carrier and angular frequency respectively.

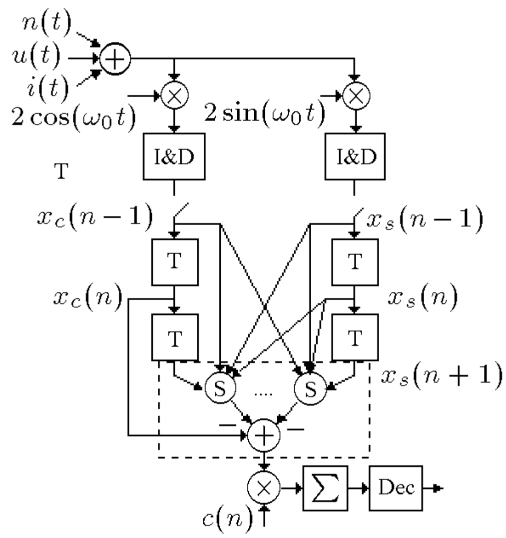

Figure 1. Block diagram of the proposed DSSS receiver. I&D–integrate and dump circuit, T–delay, (S)–neural network node, c(n)–local PN sequence, Dec-decision circuit.

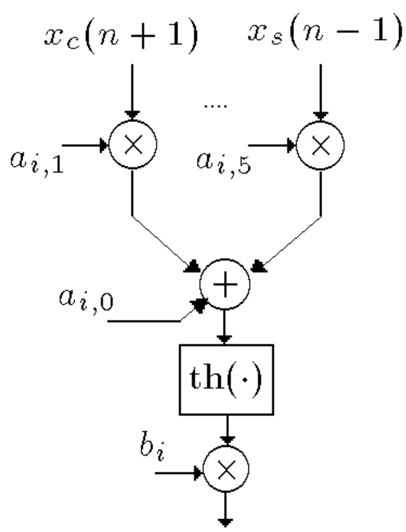

Figure 2. Detail of the neural network node s

Desired signal input power is P_u, and its effective bandwidth is B_u. Message signal $d(t)$ is given by,

$$d(t) = \sum_i d_i \Pi(t - iT_b), \qquad d_i \in \{-1, 1\}, \qquad \Pi(t) = \begin{cases} 1, & |t| \le \dfrac{T_b}{2}, \\ 0, & |t| > \dfrac{T_b}{2}. \end{cases} \tag{3}$$

where T is the desired signal bit duration. Pseudonoise sequence sequence $PN(t)$ is given by,

$$PN(t) = \sum_i d_i \Pi_c(t - iT), \quad d_i \in \{-1, 1\}, \quad \Pi_c(t) = \begin{cases} 1, & |t| \le \dfrac{T}{2}, \\ 0, & |t| > \dfrac{T}{2}. \end{cases} \tag{4}$$

Second input signal component is the interference $i(n)$, modelled as the broadband BPSK signal,

$$i(t) = U_s d_s(t) \cos[(\omega_0 + 2\pi f_\Omega)t + \varphi], \tag{5}$$

where U_s and f_Ω stand for the interference amplitude and carrier frequency offset to the BPSK carrier, and φ is the initial phase. Interference message $d_s(t)$ is given by,

$$d_s(t) = \sum_i d_i \Pi_s(t - iT_s), \quad d_i \in \{-1, 1\}, \quad \Pi_s(t) = \begin{cases} 1, & |t| \le \dfrac{T_s}{2}, \\ 0, & |t| > \dfrac{T_s}{2}. \end{cases} . \tag{6}$$

where T_s stands for the interference bit duration. Interference power at the receiver input is P_s, and its effective bandwidth is B_s.

Third component of the received signal is the additive white gaussian noise (AWGN), represented by the model,

$$n(t) = n_c(t) \cos(\omega_0 t) + n_s \sin(\omega_0 t). \tag{7}$$

In–phase and quadrature noise components are mutually independent. One–sided noise power spectral density at the receiver input is η.

All three received signal components are mutually independent and wide sense stationary.

3. Extended Kalman algorithm

Standard algorithm used for the NN coefficients adaptation is the back-propagation algorithm, [3]. This algorithm, however, is marked by the slow convergence, which can result in the unacceptable duration of the NN training before any significant interference suppression can be obtained.

For this reason, in this paper the modification of the extended Kalman (EK) algorithm, [4], is implemented. In each adaptation step the input–output neural network function is linearized in the vicinity of the instantaneous values of the coefficients, and the single iteration of the standard Kalman algorithm is implemented in this linear model. Single algorithm iteration corresponds to the one signal sampling period.

Receiver containing the in–phase and quadrature branches can be analysed by introducing the complex signal notation. NN components. By introducing,

$$\begin{aligned} x(n-1) &= x_c(n-1) + jx_s(n-1), \\ x(n) &= 1 + jx_s(n), \\ x(n+1) &= x_c(n+1) + jx_s(n+1) \end{aligned} \tag{8}$$

Signal at the NN output (Fig.1) is given by,

$$y(n) = x_c(n) - \sum_{i=1}^{N} b_i th \left[\mathrm{Re} \left\{ \sum_{j=-1}^{1} a_{i,j} x(n+j) \right\} \right], \tag{9}$$

where $a_{i,j}$ is the complex first layer coefficient, b_i is the real second layer coefficient, and N is the number of the hidden layer nodes.

EK algorithm, obtained by the eq.9 linearisation, is defined by;

- state vector

$$w(n) = [b_1, \ldots, b_N, a_{1,-1}, \ldots, a_{1,1}, \ldots, a_{N-1}, \ldots, a_{N,1}]. \tag{10}$$

- measurement vector:

$$\begin{aligned} C(n) = \Bigg[& th \left(\mathrm{Re} \left\{ \sum_{j=-1}^{1} a_{1,j} x(n+j) \right\} \right), \ldots, \\ & \frac{b_1 x^*(n-1)}{ch^2 \left(\mathrm{Re} \left\{ \sum_{j=-1}^{1} a_{1,j} x(n+j) \right\} \right)}, \ldots, \\ & \frac{b_N x^*(n+1)}{ch^2 \left(\mathrm{Re} \left\{ \sum_{j=-1}^{1} a_{1,j} x(n+j) \right\} \right)} \Bigg] \end{aligned} \tag{11}$$

- EK algorithm:

$$\begin{aligned} g(n) &= K(n-1)C(n)[C^T(n)K(n-1)C(n)+0.01]^{-1}; \\ y(n) &= u_d(n) - \sum_{i=1}^{N} b_i th\left(a_{i,0} + \sum_{j=-1}^{1} a_{i,j+2}x(n+j)\right); \\ w(n) &= w(n-1) + g(n)y(n); \\ K(n) &= K(n-1) - g(n)w^T(n)K(n-1) \end{aligned} \tag{12}$$

- initial state: $K(0) = I$, $w(0)$=random values.

Implementation of the EK algorithm imposes the important question regarding the algorithm convergence compared to the backpropagation algorithm used under the same conditions.

In order to test the EK convergence in the proposed receiver, the simulation model of the receiver presented in Fig.1(a) is developed. Simulation model is developed in C language, and the number of simulation runs is performed on the PC 486/100 computer. For the sake of comparison, the receiver model containing the classical adaptive two-sided transversal filter (ATF), [5], instead of NN is developed. ATF is adapted by the standard Kalman algorithm, [4,5].

Average signal power at the NN output as a function of the number of algorithm iterations is presented at Fig.3. Presented diagrams are obtained by ensemble-averaging 50 independent computer simulations with the different initial NN coefficient values, randomly chosen.

Interference carrier offset $f_\Omega = 0.06$. Effective interference bandwidth is 59% of the signal bandwidth. NM has $N = 4$ nodes in the hidden layer. signal/interference ratio (SIR) equals -6dB, signal/noise ratio (SNR) equals 18dB.

Fig. 3 presents the performance of the different receivers in the presence of the strong interference. Receiver containing the NN adapted with the backpropagation algorithm has the slowest convergence and has the strongest residual interference at the output. Receiver with the ATF and Kalman akgorithm converges very fast, and has the weaker residual interference at the output. Finally, NN with the EK algorithm obtains the moderate convergence speed, but has the best interference suppresion at the output. It should be noted, however, that the single iteration of the extended Kalman algorithm is much more computationally complex than the single backpropagation algorithm iteration.

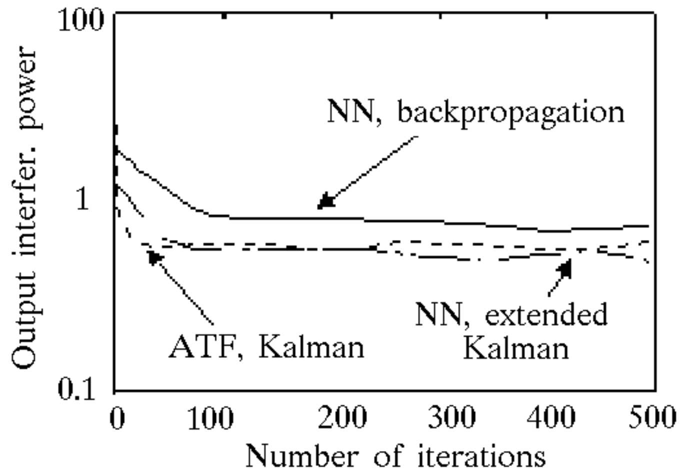

Figure 3. Normalised interference power at the NN output as function of the adaptive algorithm iteration number. SIR=−6dB, SNR=18dB, $B_u/B_s = 0.59$, $f_\Omega = 0.065$.

4. Results

After the NN in the analysed receiver converges to the steady state, the measure of its performance in the analysed receiver is the bit error rate (BER), defined as,

$$P_e = \frac{1}{2} erfc\left(\frac{E\{s\}}{\sqrt{2\mathrm{var}\{s\}}}\right), \tag{13}$$

where s is the sample at the decision circuit input, Fig.1. It is supposed that this sample has the Gaussian distribution. Processing gain is $G = 7$.

NN receiver is compared in performance to the receiver containing the quadrature demodulation adaptive transversal filter (ATF). It should be noted than the receiver containing the ATF is much simpler in its structure, and this structural simplicity can in some applications outweigh the better BER results obtained by the NN receiver.

Fig.4 presents the BER as a function of the input signal/interference ratio (SIR). Receivers containing NN with EK and ATF with classical Kalman algorithm are considered. ATF is of the second order. NN has $N = 4$ nodes in the hidden layer. Input signal/noise ratio (SNR) equals 18dB. Results are obtained by the computer simulation, and it is considered that the stationary state in the receiver has been reached after 1000 adaptation algorithm iterations.

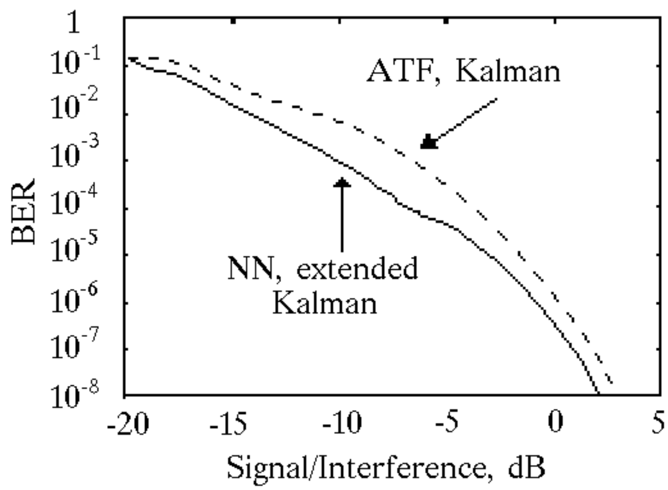

Figure 4. BER as a function of the input SIR.
$B_u/B_s = 0.21$, SNR=18dB, $f_\Omega = 0.065$.

It can be seen from Fig. 4 that the SINR improvement obtained by the NN is better than the one obtained by the ATF, almost by an order of magnitude for input SIR between the -10dB and 0dB.

At Fig. 5 BER as a function of the interference bandwidth, normalised to the DSSS signal bandwidth is presented. Input SIR=-6dB, SNR=18dB, $f_\Omega = 0.065$.

It can be seen from the Fig. 5 that the broadband interference is less efficiently suppressed in the receiver. The NN, however, can again obtain the BER by the order of magnitude better than the ATF filter adapted by the Kalman algorithm.

Fig.6. presents the BER as a function of the interference carrier offset f_Ω, relative to the bit duration T. Relative interference bandwidth is $B_u/B_s = 0.37$. All other parameters have the same values as those used on the Fig.3.

It can be seen from Fig.6 that the obtained broadband interference suppression is generally better in the receiver containing NN than in the receiver containing ATF. NN receiver performs better than ATF for smaller interference offsets, which is the case of greater practical importance. Interference suppression is increasing with the increase of the frequency offset.

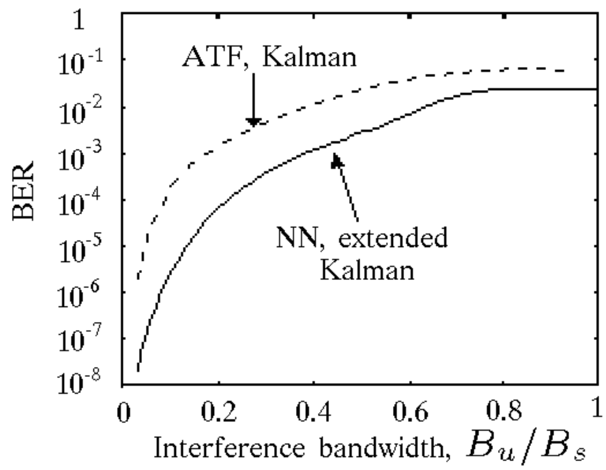

Figure 5. BER as a function of the normalised interference bandwidth, B_u/B_s for the NN and ATF receivers. input SIR=–6dB, SNR=18dB, $f_\Omega = 0.065$.

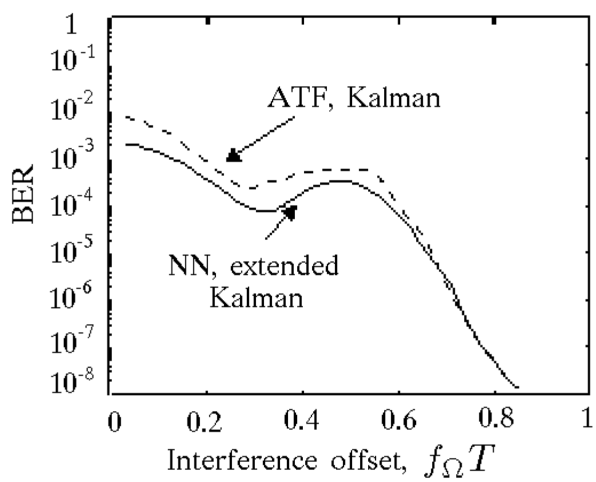

Figure 6. BER as a function of the normalised interference offset, $f_\Omega T$ for the NN and ATF receivers. Input SIR=5dB, SNR=15dB, $B_u/B_s = 0.6$.

5. Conclusion

In this paper the DSS receiver containing the quadrature demodulator and the neural network is analysed in the presence of the strong broadband interference. Interference is modelled as the broadband cochannel BPSK signal with the carrier frequency offset to the desired signal. The extended Kalman algorithm is implemented for the network adaptation. Proposed receiver performance is compared to the DSSS quadrature receiver containing the two–sided transversal filter.

Results cover the algorithm convergence analysis and the bit error rate. Based on the results, it can be concluded that the extended Kalman algorithm can be efficiently used for the neural network adaptation and that the good results in the broadband interference suppression can be obtained. The extended Kalman algorithm is, however, computationally demanding algorithm, and the neural network is the structure with the complexity that is much greater than the adaptive transversal filter.

REFERENCES

1. L. Milstein: *Interference Rejection Techniques in Spread–Spectrum Communications.* Proc. of the IEEE, Vol.76, No 6, pp.657–671, June 1988.
2. Z.S. Dobrosavljević, M.L. Dukić: *Potiskivanje širokopojasne smetnje u sistemu sa PSDS primenom neuralne mrež.* XL Konferencija ETRANa, jun 1996.
3. R. Hecht–Nielsen: *Neurocomputing.* Addison–Wesley, Reading, 1990.
4. J. Candy: *Signal Processing – the Model–Based Approach.* McGraw–Hill, New York, 1986.
5. S. Haykin: *Adaptive Signal Processing.* Prentice–Hall, New Jersey, 1986.