The Piece-Wise Linear Microstatistic Multi-User Receiver

Dušan Kocur, Jana Čížová, Stanislav Marchevský

Abstract--**In this paper, the microstatistic multi-user detection receiver (MSF-MUD) will be introduced. The output of the MSF-MUD is taken as the sign of the multi-channel non-linear transformation of the output of a bank of matched filters (BMF). In the case of the MSF-MUD, this transformation is done by multi-channel conventional microstatistic filter (M-CMF). Because the M-CMF theory has not been available, a method of the time-invariant M-CMF design is developed in this paper, too.**

Index Terms--**microstatistic filter, multi-user detection receiver, non-linear single-stage receiver, CDMA.**

I. Introduction

Multi-user detection (MUD) refers to the process of demodulating one or more user data streams from a non-orthogonal multiplex [1]. Here, the great work has been done especially for the development of receivers using MUD principle (so called MUD receivers) for the transmission systems based on code-division multiple access principle (CDMA). The possibility of the development of optimum MUD receivers providing maximum likelihood sequence detection [2] was the motivation for that work. The key algorithmic structure of the optimum MUD receivers is that of the BMF followed by the Viterbi decision algorithm. The performance gains of the optimum receiver are achieved by centralized implementation, which involves a high degree of complexity. For practical systems, implementation complexity needs to be reduced to a reasonable level even if the performance is degraded from the optimum one. Following this idea, a number of sub-optimum receivers have been proposed (e.g. [2, 3]). The most of these replace Viterbi decision algorithm with a reduced complexity algorithm. Here, non-linear single-stage MUD receivers (NSS-MUD) represent an interesting group of the sub-optimum receivers. The NSS-MUD techniques include e.g. neural network receiver and Volterra filter receiver [4,5]. The output of the NSS-MUD is taken as the sign of the non-linear transformation of the output of the BMF. From the point of view of the signal processing theory, the non-linear transformation given by neural network or Volterra filter can be understood as multi-channel non-linear filtering. In spite of the fact, that the complexity of the NSS-MUD is smaller then that of the optimum receiver, the complexity of the NSS-MUD based on neural network or Volterra filter is still relatively high.

With regard to these facts, it should be useful to propose another multi-channel non-linear filter in order to replace Viterbi decision algorithm. It follows from the non-linear filter theory, that a conventional microstatistic filter (CMF) is a promising candidate for this application. The CMFs belong to a group of minimum mean-square non-linear estimators based on the estimation of a desired signal by using a linear combination of vector elements obtained by the threshold or radix-q decomposition of the input signal of the filter [6-9]. The CMF can be also interpreted as the piece-wise linear system. It has been shown in [8,9], that CMF can outperform Wiener or Volterra filters.

The disadvantage of the CMF is the fact, that the theory of the M-CMF has not been developed. In order to solve this problem, the basic theory of the M-CMF will be introduced in our paper. Firstly, the multi-channel CMF structure based on multi-channel Wiener filter (M-WF) will be described. Then, the design of the time-invariant M-CMF will be presented. By using the M-CMF, a new sub-optimum receiver called the MSF-MUD will be proposed. Its performance properties will be demonstrated by using computer experiments. The obtained results will indicate that the MSF-MUD can be considered to be a promising sub-optimum CDMA receiver.

II. The M-CMF structure

A block scheme of the M-CMF is given in the Fig.1. Here, M, $y^{(i)}(n)$ ($i\in I=\{1,2,\ldots,M\}$) and $\hat{d}^{(k)}(n)$ ($k\in I$) are the number of the input signals, the i-th input of the M-CMF and the k-th output signal of the M-CMF, respectively. It can be seen from this figure that the M-CMF consists of M threshold decomposers (TD) and the set of M multi-channel Wiener filters (M-WF).

The performance of the i-th TD (TD_i, $i\in I$) can be described by the expressions

$$\begin{aligned} D^{(i)}[y^{(i)}(n)] = [&y^{(i,L)}(n)\; y^{(i,L-1)}(n)\ldots \\ &\ldots y^{(i,1)}(n)\; y^{(i,-1)}(n)\ldots \\ &\ldots y^{(i,-L+1)}(n)\; y^{(i,-L)}(n)]^T \end{aligned} \quad (1)$$

In (1), $D^{(i)}[.]$ represents the decomposition operation of the signal $y^{(i)}(n)$ into a set of the $O=2L$ signals $y^{(i,j)}(n)$. The connection between $y^{(i)}(n)$ and $y^{(i,j)}(n)$ is given by $y^{(i,j)}(n)=D_j^{(i)}[y^{(i)}(n)]$ where $D_j^{(i)}[.]$ denotes the decomposition operation for the j-the level of the TD_i. In the case of the threshold decomposition, the threshold sample $y^{(i,j)}(n)$ is uniquely determined from $y^{(i)}(n)$ by

D. Kocur, J. Čížová, S. Marchevský are from the Department of Electronics and Multimedia Communications, Faculty of Electrical Engineering and Informatics, Technical University of Košice, Park Komenského 13, 041 20 Košice, Slovak Republic, (e-mail: Dusan.Kocur@tuke.sk,Jana.Cizova@tuke.sk,Stanislav.Marchevsky@tuke.sk).

$$y^{(i,j)}(n) = D_j^{(i)}[y^{(i)}(n)] = \begin{cases} 0 & for \;\; y^{(i)}(n) < l_{j-1}^{(i)} \\ y^{(i)}(n) - l_{j-1}^{(i)} & for \;\; l_{j-1}^{(i)} < y^{(i)}(n) \le l_j^{(i)} \\ l_j^{(i)} - l_{j-1}^{(i)} & for \;\; l_j^{(i)} < y^{(i)}(n) \end{cases} \quad (2)$$

for $y^{(i,j)}(n) \ge 0$, $l_L^{(i)} = \infty$, $i \in I$ and $j \in J = \{1,2,\ldots,L\}$. The threshold decomposition for negative values is given by

$$y^{(i,-j)}(n) = D_{-j}^{(i)}[y^{(i)}(n)] = \begin{cases} 0 & for \;\; y^{(i)}(n) > l_{-j+1}^{(i)} \\ y^{(i)}(n) - l_{-j+1}^{(i)} & for \;\; l_{-j+1}^{(i)} > y^{(i)}(n) \ge l_{-j}^{(i)} \\ l_{-j}^{(i)} - l_{-j+1}^{(i)} & for \;\; l_{-j}^{(i)} > y^{(i)}(n) \end{cases} \quad (3)$$

for $y^{(i,j)}(n) < 0$, $l_{-L}^{(i)} = -\infty$, $i \in I$ and $j \in J$.

The parameters $l_j^{(i)}$ and $l_{-j}^{(i)}$ (usually constant terms) are referred as the threshold values of the TD_i [6-9]. The threshold values of the TD_i are confined as $-\infty = l_{-L}^{(i)} < \ldots < l_{-1}^{(i)} < l_1^{(i)} < \ldots < l_L^{(i)} = \infty$.

The output signals of all TD are fed into the k-th M-WF ($M\text{-}WF_k$) for $k \in I$. The k-th output of the M-CMF $\hat{d}^{(k)}(n)$ is then given by the following set of expressions:

$$\hat{d}^{(k)}(n) = h_{(k,0)}(n) + \sum_{i=1}^{M} \hat{d}_k^{(i)}(n) \quad (4)$$

$$\hat{d}_k^{(i)}(n) = \sum_{j=-L}^{L} d_k^{(i,j)}(n) \quad (5)$$

$$\hat{d}_k^{(i,j)}(n) = \sum_{l=0}^{N} h_{(k,l)}^{(i,j)}(n) y^{(i,j)}(n-l) \quad (6)$$

The constant term $h_{(k,0)}(n)$ (expression (4)) is applied in the M-CMF structure in order to obtain an unbiased M-CMF output. The output of the M-WF fed by the outputs of the TD_i (signals $y^{(i,j)}(n)$ for $j \in S = \{-L, -L+1, \ldots, -2, -1, 1, 2, \ldots, L-1, L\}$ are given by $\hat{d}_k^{(i)}(n)$ (expression (5)). The sequence $h_{(k,l)}^{(i,j)}(n)$ represents the parameters of a single-channel Wiener filter fed by the signal $y^{(i,j)}(n)$ (expression (6)), which is the part of the $M\text{-}WF_k$.

III. THE OPTIMUM TIME-INVARIANT M-CMF DESIGN

The description of the M-CMF by (1) – (6) follows the M-CMF structure (Fig. 1) very clearly. However, these expressions are not very suitable for the derivation of the procedure of the optimum time-invariant M-CMF design. Therefore, we will derive a modified vector description of the M-CMF. It will be shown that this approach of the M-CMF description is very useful for the optimum M-CMF design.

Let us define the coefficient vector $\mathbf{H}_k^{(i,j)}(n)$ containing the coefficients $h_{(k,l)}^{(i,j)}(n)$ for $l \in P = \{0,1,\ldots,N\}$ and the vector $\mathbf{Y}^{(i,j)}(n)$ containing the input signal samples $y^{(i,j)}(n)$ as follows

$$\mathbf{H}_k^{(i,j)}(n) = \left[h_{(k,0)}^{(i,j)} \quad h_{(k,1)}^{(i,j)} \quad \ldots \quad h_{(k,N)}^{(i,j)} \right]^T \quad (7)$$

$$\mathbf{Y}^{(i,j)}(n) = \left[y^{(i,j)}(n) \quad y^{(i,j)}(n-1) \quad \ldots \quad y^{(i,j)}(n-N) \right]^T \quad (8)$$

By using (7) and (8), the expression (6) can be obtained in this form

$$\hat{d}_k^{(i,j)}(n) = \mathbf{H}_k^{(i,j)T}(n) \mathbf{Y}^{(i,j)}(n) \quad (9)$$

Now, let us define the block vector $\mathbf{H}_k^{(i)}(n)$ containing the vectors $\mathbf{H}_k^{(i,j)}(n)$ and the block vector $\mathbf{Y}^{(i)}(n)$ containing the vectors $\mathbf{Y}^{(i,j)}(n)$ as follows

$$\mathbf{H}_k^{(i)}(n) = \left[\mathbf{H}_k^{(i,L)T}(n) \ldots \mathbf{H}_k^{(i,1)T}(n) \; \mathbf{H}_k^{(i,-1)T}(n) \ldots \mathbf{H}_k^{(i,-L)T}(n) \right]^T \quad (10)$$

$$\mathbf{Y}^{(i)}(n) = \left[\mathbf{Y}^{(i,L)T}(n) \ldots \mathbf{Y}^{(i,1)T}(n) \; \mathbf{Y}^{(i,-1)T}(n) \ldots \mathbf{Y}^{(i,-L)T}(n) \right]^T \quad (11)$$

Then by using (10) and (11), the expression (5) can be obtained in this form

$$\hat{d}_k^{(i)}(n) = \mathbf{H}_k^{(i)}(n)^T \mathbf{Y}^{(i)}(n) \quad (12)$$

Finally, let us define the vector $\mathbf{H}_k(n)$ and the vector $\mathbf{Y}(n)$ as follows

$$\mathbf{H}_k(n) = \left[h_{(k,0)}(n) \; \mathbf{H}_k^{(1)T}(n) \; \mathbf{H}_k^{(2)T}(n) \ldots \mathbf{H}_k^{(M)T}(n) \right]^T \quad (13)$$

$$\mathbf{Y}(n) = \left[1 \; \mathbf{Y}^{(1)T}(n) \; \mathbf{Y}^{(2)T}(n) \ldots \mathbf{Y}^{(M)T}(n) \right]^T \quad (14)$$

Then by using (13) and (14), the k-th output of the M-CMF $\hat{d}_k(n)$ (expression (4)) is given by

$$\hat{d}^{(k)}(n) = \mathbf{H}_k^T(n) \mathbf{Y}(n) = \mathbf{Y}^T(n) \mathbf{H}_k(n) \quad (15)$$

It can be seen from this expression that the responses of the M-CMF are still linear functions with respect to the M-CMF coefficients although the M-CMF are non-linear filters.

Let us assume that the input signals of the M-CMF $y^{(i)}(n)$ and the desired signals $d^{(k)}(n)$ are stationary random processes ($i, k \in I$). Now, we want to find the optimum vectors $\mathbf{H}_k(n)$ ($k \in I$) of the M-CMF minimizing the mean-square error (MSE) $e_k(n) = d^{(k)}(n) - \hat{d}^{(k)}(n)$. Then the optimum M-CMF vectors are obtained as the solution that minimizes the cost functions

$$MSE(\mathbf{H}_k(n)) = E\left[e_k^2(n) \right] = E\left[\left(d^{(k)}(n) - \hat{d}^{(k)}(n) \right)^2 \right] \quad (16)$$

Here, $E[.]$ denotes the expectation operator. Substituting (15) into (16), the $MSE(\mathbf{H}_k(n))$ can be expressed in the form:

$$MSE(\mathbf{H}_k(n)) = E\left[d^{(k)^2}(n) \right] - 2\mathbf{H}_k^T(n) \mathbf{P}_k(n) + \mathbf{H}_k^T(n) \mathbf{R}(n) \mathbf{H}_k(n) \quad (17)$$

where

$$\mathbf{P}_k(n) = E\left[d^{(k)}(n) \mathbf{Y}(n) \right] \text{ for } k \in I \quad (18)$$

$$\mathbf{R}(n) = E\left[\mathbf{Y}^T(n) \mathbf{Y}(n) \right] \quad (19)$$

$\mathbf{P}_k(n)$ is the cross-correlation vector consisting of the samples of the cross-correlation function of the signals $d^{(k)}(n)$ and $y^{(i,j)}(n)$. The correlation matrix $\mathbf{R}(n)$ consists of the samples of the correlation function of the signals $y^{(i,j)}(n)$. It can be shown that under the condition of the

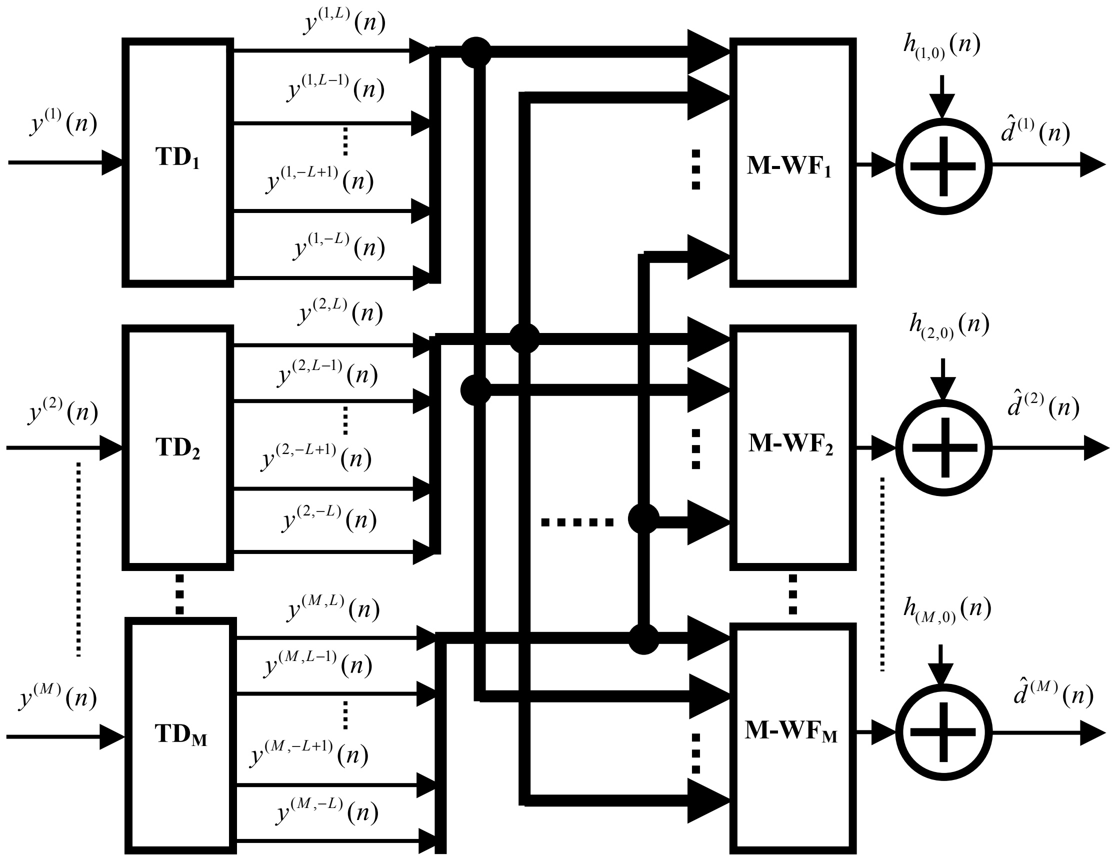

Fig. 1. The multi-channel conventional microstatistic filter (M-CMF)

constant threshold levels of the TD_k, $MSE(\mathbf{H}_k(n))$ has the only extreme represented by the global minimum. Then, taking into account that $\mathbf{R}(n)$ is positive definite, it can be found very easily from (17) that the $\mathbf{H}_k^{opt}(n)$ corresponding to the minimum of $MSE(\mathbf{H}_k(n))$ is given by

$$\mathbf{H}_k^{opt}(n) = \mathbf{R}^{-1}(n)\mathbf{P}_k(n) \quad \text{for} \quad k \in I \tag{20}$$

and

$$MSE(\mathbf{H}_k^{opt}(n)) = E\left[d^{(k)^2}(n)\right] - \mathbf{H}_k^{opt\,T}(n)\mathbf{P}_k(n) = \\ = E\left[d^{(k)^2}(n)\right] - \mathbf{H}_k^{opt\,T}(n)\mathbf{R}^{-1}(n)\mathbf{H}_k^{opt}(n) \tag{21}$$

IV. The piece-wise linear microstatistic multi-user detection receiver

It follows from (20) and [6-9], that the procedure of the time-invariant M-CMF design is similar to that of single-channel time-invariant CMF design. Therefore, it could be expected that the basic performance properties of these two kinds of filters will be also similar. The development of a new NSS-MUD receiver based on M-CMF was our motivation for the work done in the field of the M-CMF. With regard to that fact and taking into account the similarity between single- and multi-channel CMF, we will not demonstrate the simulation results concerning the M-CMF performance properties. Instead of that, our afford will be concentrated into the introduction of a new NSS-MUD receiver based on the M-CMF.

An optimum receiver applied in a CDMA transmission system can make decisions by selecting the transmitted sequence to minimize the sequence error probability. This decision type is called maximum likelihood sequence detection [2, 3, 10]. The maximum likelihood receiver for CDMA consists of the BMF (BMF receiver) followed by the Viterbi decision algorithm [2, 3, 10]. The performance gains of the optimum receiver are achieved by its centralized implementation, which involves a high degree of complexity. For practical systems, implementation complexity needs to be reduced to a reasonable level even if the performance is degraded from the optimum one. Following this idea, a number of sub-optimum receivers have been proposed. Most of these replace Viterbi decision algorithm with a reduced complexity algorithm. Some variations of receivers of that kind include e.g. decorrelating MUD receivers (D-MUD), linear minimum mean-square error MUD receivers (MMSE-MUD), NSS-MUD, etc. [2, 3, 10].

The theoretical analysis of a decision boundary in the CDMA receivers has shown that the optimum decision boundary is non-linear [2]. The optimum receiver approximates this non-linear boundary perfectly what is achieved at the expense of its high computational complexity. On the other hand, the NSS-MUD can approximate this non-linear boundary well and outperform linear receiver structures [4]. It has been our expectation, that the application of the M-CMF could be a possible solution for an effective approximation of the non-linear decision boundary.

The scheme of the MSF-MUD for the M -user base-band synchronous CDMA transmission system is given in the Fig. 2. The i -th matched filter (MF-i) of the BMF is matched to the i -th signature waveforms based on the i -th Gold sequence. The parameter T_B given in the Fig. 2

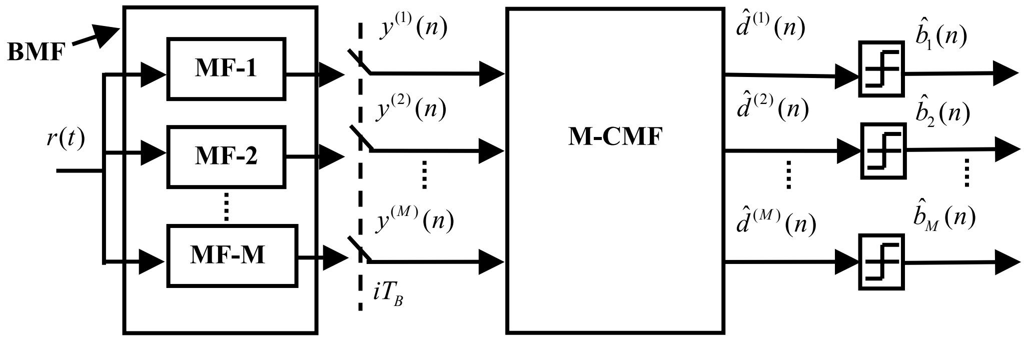

Fig. 2. The piece-wise linear microstatistic multi-user detection receiver (MSF-MUD)

represents the inverse of the data rate. It can be identified from the Fig. 2, that the MSF-MUD is obtained from the optimum receiver by replacing the Viterbi decision algorithm with the M-CMF. Then, the output of the MSF-MUD $\hat{\mathbf{b}}(n)=\left[\hat{b}_1(n) \quad \hat{b}_2(n) \quad \dots \quad \hat{b}_M(n)\right]^T$ is taken as the sign of the non-linear transformation of the output of the BMF $\mathbf{y}(n)=\left[y^{(1)}(n) \quad y^{(2)}(n) \quad \dots \quad y^{(M)}(n)\right]^T$ due to the M-CMF. Then, taking into account (15), the output of the MSF-MUD is given by

$$\hat{\mathbf{b}}(n)=sign\left(\mathbf{H}^T(n)\mathbf{Y}(n)\right) \quad (22)$$

where

$$\mathbf{H}(n)=\left[\mathbf{H}_1(n) \quad \mathbf{H}_2(n) \quad \dots \quad \mathbf{H}_M(n)\right] \quad (23)$$

and $\mathbf{Y}(n)$ and $\mathbf{H}_k(n)$ are defined by (1)-(3), (7), (8), (10), (11), (13) and (14).

The M-CMF belongs to the minimum MSE piece-wise linear estimator. With regard to that fact, and under consideration of the constant parameters of the threshold decomposers, the same approaches for the optimum MMSE-MUD design can be also applied for the optimum MSF-MUD design. Besides, it can be concluded that MMSE-MUDs represent a subset of the MSF-MUD class.

V. Computer Experiments

In order to demonstrate some performance properties of the MSF-MUD, three computer experiments were done. In these experiments, the base-band synchronous CDMA transmission system with two users ($M=2$) was simulated.

Here, we consider that the k-th user send information bits $b_k(n)$. As the spreading code, the Gold sequence with the period of seven chips was applied. The input signal to the receiver is given by the signal $r(t)$. It consists of the sum of antipodally modulated signature waveforms embedded in additive white Gaussian noise (AWGN). As the performance index of the simulated transmission system, bit error rate (BER) vs. information signal energy per bit to noise power spectral density (E_b/N_0) was used in our experiments.

As the receivers, the optimum receiver, BMF receiver, decorrelating MUD (D-MUD), minimum mean square error MUD (MMSE-MUD) and MSF-MUD were used. For the design of the optimum receiver, D-MUD and MMSE-MUD, the procedures described in [2, 10] were applied.

TABLE I

The review of the threshold values of $l_j^{(k)}$, $l_{-j}^{(k)}$ for the first experiment, where $k\in I$ and $j\in J$.

E_b/N_0	$l_{-2}^{(0)}$, $l_{-2}^{(2)}$	$l_{-1}^{(1)}$, $l_{-1}^{(2)}$	$l_{1}^{(1)}$, $l_{1}^{(2)}$	$l_{2}^{(0)}$, $l_{2}^{(2)}$
-10	$-\infty$	-3,3	3,3	∞
-8	$-\infty$	-2,14	2,14	∞
-6	$-\infty$	-3,04	3,04	∞
-4	$-\infty$	-2,18	2,18	∞
-2	$-\infty$	-3,35	3,35	∞
0	$-\infty$	-4,45	4,45	∞
2	$-\infty$	-4,81	4,81	∞
4	$-\infty$	-4,58	4,58	∞
6	$-\infty$	-4,78	4,78	∞
8	$-\infty$	-4,63	4,63	∞
10	$-\infty$	-2,65	2,65	∞
12	$-\infty$	-3	3	∞
14	$-\infty$	-3	3	∞
16	$-\infty$	-3	3	∞
18	$-\infty$	-3	3	∞
20	$-\infty$	-3	3	∞

TABLE II

The review of the threshold values of $l_j^{(k)}$, $l_{-j}^{(k)}$ for the second experiment, where $k\in I$ and $j\in J$.

E_b/N_0	$l_{-2}^{(0)}$, $l_{-2}^{(2)}$	$l_{-1}^{(1)}$, $l_{-1}^{(2)}$	$l_{1}^{(1)}$, $l_{1}^{(2)}$	$l_{2}^{(0)}$, $l_{2}^{(2)}$
-10	$-\infty$	-0,34	0,34	∞
-8	$-\infty$	-1,34	1,34	∞
-6	$-\infty$	-1,19	1,19	∞
-4	$-\infty$	-1,61	1,61	∞
-2	$-\infty$	-0,82	0,82	∞
0	$-\infty$	-0,36	0,36	∞
2	$-\infty$	-1,35	1,35	∞
4	$-\infty$	-1,86	1,86	∞
6	$-\infty$	-1	1	∞
8	$-\infty$	-1,07	1,07	∞
10	$-\infty$	-1,85	1,85	∞
12	$-\infty$	-1,1	1,1	∞
14	$-\infty$	-1,1	1,1	∞
16	$-\infty$	-1,1	1,1	∞
18	$-\infty$	-1,1	1,1	∞
20	$-\infty$	-1,1	1,1	∞

10000 information bits were transmitted through the AWGN channel. In all experiments, the MSF-MUD with $L=2$ and $N=0$ was used. The threshold values of the

TD_k ($k \in I$) were set experimentally in such a way as to minimize BER for particular values E_b/N_0. For the different values of E_b/N_0 the different threshold values were chosen. The review of the threshold values applied in the experiments is given in the Table I and Table II. Firstly, the matrices $\mathbf{R}(n)$ and $\mathbf{P}_k(n)$ for $k \in I$ have been estimated. Then, $\mathbf{H}(n)$ was computed by using $\mathbf{R}(n)$, $\mathbf{P}_k(n)$, (20) and (23). In order to obtain the output of the MSF-MUD, (22) was applied.

At the first experiment, the power of the signals at the input of the receiver produced by all users was the same. The results obtained in this case are given in the Fig. 3. It can be seen from this figure, that all receivers applied in our experiments can provide almost the same results.

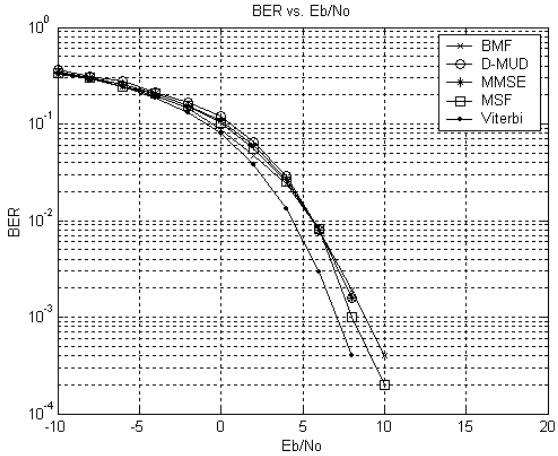

Fig. 3. BER vs. E_b/N_0 for the first user. The power of the signal at the input of the receiver produced by all users at the input of the receiver was the same.

In the second experiment, we would like to demonstrate the receiver performance properties under the condition, when the power of the signal at the input of the receiver produced by the first (desired) user was ten times smaller than that of the second user. The results of this experiment represented by the above mentioned performance index are given in the Fig. 4. The last experiment demonstrates a dependence on the near-far effect, of the individual types of the receivers. The power of the signal at the input of the receiver produced by the first (desired) user was changed from ten times smaller than that of the second user to the same magnitude as the magnitude of power of the second user. As we expected, the optimum receiver has provided the best results. On the other hand, it can be seen that the MSF-MUD outperforms clearly the linear MUD receivers. Therefore, the obtained results indicate that the MSF-MUD could be a promising sub-optimum CDMA receiver.

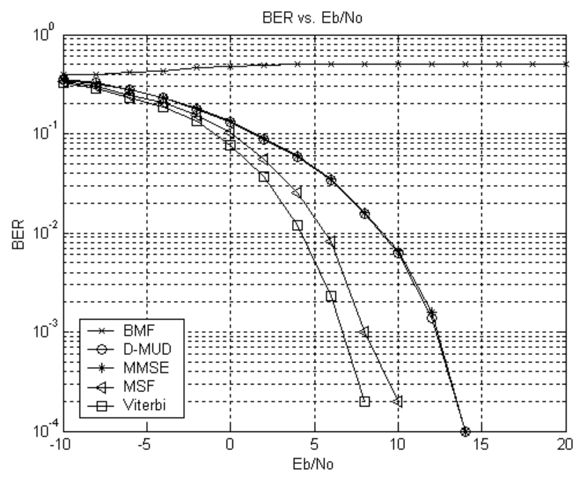

Fig. 4. BER vs. E_b/N_0 for the first user. The power of the signal at the input of the receiver produced by the first user was ten times smaller than that of the second user.

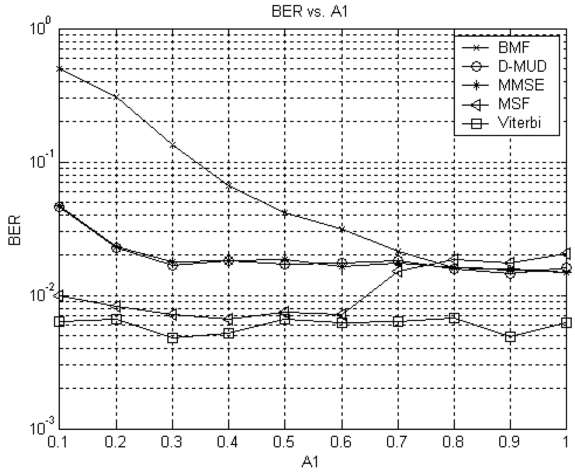

Fig. 5. BER vs. A_1 for the first user. The information signal energy per bit to noise power spectral density (E_b/N_0) was 5 dB.

CONCLUSIONS

In this paper, the new structure of the time-invariant M-CMF was introduced. Then, the procedure for the design of the optimum time-invariant M-CMF has been developed. By using the M-CMF, the MSF-MUD receiver structure has been proposed. The simple computer simulation has shown that the MSF-MUD could outperform the other tested linear MUD receivers. This result was achieved at the expense of the higher computational complexity of the MSF-MUD. Generally, the computational complexity of the MSF-MUD is $M(2L-1)$ times higher than that of the linear receivers. With regard to the computational complexity of the optimum or some suboptimum non-linear receivers [2-5] this computational complexity could be acceptable. Therefore, it can be concluded that the MSF-MUD could be a promising suboptimum CDMA receivers.

REFERENCES

[1] Poor, H. V.-Verdú, S: Probability of Error in MMSE Multi-user Detection. IEEE Transactions on Information Theory, Vol. IT-43, No.3, 1997, pp. 858-871

[2] S. Verdú: Multi-user Detection. Cambridge University Press, UK, 1998.

[3] Kocur, D.-Čížová, J.: Multi-user Detection Techniques for CDMA: A Review of Basic Principles. Acta Electrotechnica et Informatica, vol.3., No.1, 2003, pp. 28-35.

[4] Tanner,R.-Cruickhank, D.G.M.: RBF based Receivers for DS-CDMA with Reduced Complexity. Proceedings of IEEE ISSSTA '98, Volume 1/3, South Africa, 1998.

[5] Tanner,R.-Cruickhank, D.G.M.: Volterra based Receivers for DS-CDMA. The 8th IEEE International Symposium on Personal, Indoor

and Mobile Radio Communications PIMRC '97, vol.3, Helsinki, Finland, Sep. 1997, pp. 1166-1170.

[6] Arce, G.R.: Microstatistics in Signal Decomposition and the Optimal Filtering Problem. IEEE Trans. on Signal Processing, vol.40, No.11, 1992, s.2669-2682.

[7] Chen, S.-Arce, G.R.: Microstatistic LMS Filtering. IEEE Trans. on Signal Processing, vol.41., No.3, 1993, s.1021-1034.

[8] Kocur, D.-Drutarovský, M.-Marchevský, S.: Microstatistic Volterra Filters. Proceedings of the 40. Internationales Wissenschaftliches Kolloquium, Band 1. Ilmenau, Germany, September 1995, pp.376-381.

[9] Kocur, D.-Drutarovský, M.-Marchevský, S.: A New Class of Nonlinear Filters: Microstatistic Volterra Filters. Radioengineering, 1996, vol.5, No.1., pp.19-24.

[10] Glisic, S.-Vucetic, B.: Spread Spectrum CDMA Systems for Wireless Communication. Artech House, Inc., Noewood, 1997.

BIOGRAPHY

Dušan Kocur was born in 1961 in Košice, Slovakia. He received the Ing (MSc) and CSc (PhD) in radioelectronics from the Faculty of Electrical Engineering, Technical University of Košice, in 1985 and 1990. He is associate professor at the Department of Electronics and Multimedia Communications of his Alma Mater. His research interest are digital signal processing, especially in linear and nonlinear time – invariant and adaptive digital filters, higher order spectra, CDMA systems and psychoacoustics.

Jana Čížová graduated Ing. (MSc.) at the Department of Electronics and Multimedia Communications of the Faculty of Electrotechnics and Informatics at Technical University in Košice. Her scientific research is focusing on multi - user detection in DS – CDMA systems.

Stanislav Marchevský received the M.Sc. degree in electrical engineering at the Faculty of Electrical Engineering, Czech Technical University in Prague, in 1976 and Ph.D. degree in radioelectronics at the Technical University of Košice in 1985. From 2001 he is the full professor at the FEI TU in Košice. His research interest includes multimedia communications.