Enhanced Blind Maximum Ratio Combining in Broadcasting Systems

Rana Ahmed (Institut für Nachrichtenübertragung, Universität Stuttgart), Ben Eitel (Sony Deutschland GmbH, European Technology Center (EuTEC)) and Joachim Speidel (Institut für Nachrichtenübertragung, Universität Stuttgart)

Abstract

We propose an enhanced blind maximum ratio combiner (BMRC) allowing for a transmit signal independent diversity combining in multi-antenna receivers. The underlying Multi-Channel Frequency Least Mean Squares (MCFLMS) algorithm comes with reasonable computational complexity and estimates the channel impulse response for each receive antenna iteratively by means of second order statistics. In literature, the MCFLMS algorithm is mainly applied to audio signals. In this work, we describe several enhancements of this algorithm to ensure its proper convergence with oversampled communication signals which are distorted by frequency-selective fast-fading channels. In addition, we provide BER simulation results for a 1x2 SIMO DVB-T2 system and show that our blind MRC can even outperform conventional pilot-based MRC at the receiver side.

1. Introduction

SIMO systems with coherent detection can deliver high channel capacity provided that an accurate knowledge of the channel state information (CSI) is available at the receiver. There exists a huge literature on the issue of receiver diversity combining, see for example [1]. Some approaches require only partial CSI knowledge, e.g. Equal Gain Combining (EGC), others expect full CSI knowledge, e.g. Maximum Ratio Combining (MRC). In case of spatially uncorrelated channels, the highest gain is obtained using MRC. In the absence of correlation among the antennas and assuming equally likely transmitted symbols, the total conditioned SNR per symbol, is given by [1]: $\Gamma_{total} = \sum_{i=1}^{M} \Gamma_i$, where Γ_i denotes the SNR of the i^{th} diversity branch and M is the number of receive antennas. Typically, CSI is acquired at the receiver side using Pilot Assisted Channel Estimation (PACE). Fig.1, depicts the conventional architecture to perform diversity combining. The sent signal s(n) goes through M different communication channels, where $h_i(n,m)$ refers to the m^{th} tap of the i^{th} channel at the n^{th} time instant, assuming a time varying channel. As shown, part of the demodulator circuit has to be duplicated to acquire the CSI for each receiver diversity branch which is needed to compute the combining filters c_1, c_2,…. c_M, which are then forwarded to the combiner block. The design of these blocks strongly depends on the communication signal structure e.g. the synchronization depends on the framing structure, the demodulation is applied differently for single-carrier or multicarrier signals, the pilot information is transmitted and thus extracted differently, and so on.

2. Blind Maximum Ratio Combining

In this work, we propose the use of a generic combiner, whose structure is shown in Fig.2. Based on the received signals and without prior knowledge of the sent signal structure, this combiner exploits the spatial diversity of the SIMO channel and combines the received signals into one signal to be forwarded to the SISO demodulator. The SI-SO demodulator removes the distortion introduced by both the channel and the time domain combiner using PACE. The advantage of this multi-antenna diversity receiver structure is its independency from the underlying transmit signal structure, making it applicable to a large variety of communication signals. A similar idea appeared in [2], where using an Eigenfilter approach the received signals were blindly combined. In that work, however, the communication channel was restricted to a flat fading SIMO channel corresponding to a one tap combiner. Instead, we assume a frequency selective fast fading SIMO channel making a multi-tap combiner mandatory. In order to acquire the CSI independently of the transmit signal structure, we propose using Blind Channel Identification (BCI) algorithms which exploit the differences between the received antenna signals to obtain sufficient CSI for MRC.

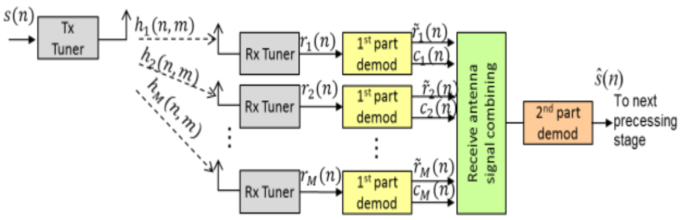

Figure 1 Standard SIMO receiver using MRC based on PACE

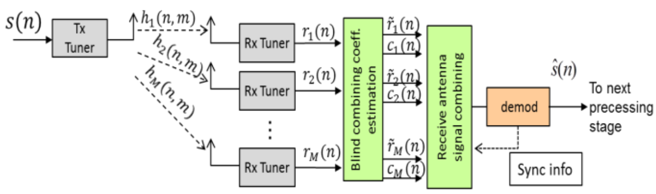

Figure 2 Blind maximum ratio combining

The combining itself is done by convolving the received signals with their respective channel matched filters in the time domain $c_i(n,m) = \hat{h}_i(n,m)$. In [3], the problem of jointly estimating the sent signal and the channel for an acoustic system was discussed. In that work, an iterative approach is considered, which includes two subsystems for array is also used for equalization. In that work, apriori information about the channel and the sent signal is assumed which is not the case in our work. In the choice of a suitable BCI algorithm, we considered the following points in our selection criteria:

1. Computational complexity
2. Speed of convergence
3. Ability to handle special traits in communication signals

3. Blind Channel Identification

There exists an extensive literature on the topic of BCI, see for example [4], [5]. However, these algorithms were mostly applied to acoustic signals in static channels. In contrast, fast convergence of the BCI has to be guranteed in order to track fast fading communication channels. Therefore, we select an algorithm which is based on second order statistics (SOS), as opposed to algorithms based on higher order statistics (HOS) [4], [5]. Although the latter possess better estimation accuracy, the former have the advantage of a faster convergence rate. The family of the SOS approaches includes the cross relations (CR) algorithm [6]. The idea behind the CR approach is straightforward: in the noise free case, given r_i is the received signal from antenna i, h_i is the communication channel between the transmitter and the i^{th} receiver and n is the time index, the received signal at antenna i, can be written as:

$$r_i(n) = s(n) * h_i(n) \quad (1)$$

Convolving $r_i(n)$ with $h_j(n)$and $r_j(n)$ with $h_i(n)$, yields

$$r_i(n) * h_j(n) = r_j(n) * h_i(n) \quad (2)$$

The cross relations problem statement is then to find the two sets of filter coefficients: h_i and h_j which satisfy (2). A very good summary of this family of algorithms can be found in [7]. Motivated by the desire to apply BCI to real life systems, thus requiring the algorithms to be both adaptive and computationally simple, an iterative implementation of the CR problem was developed in [8]–[12], namely the Multi-Channel Least Mean Squares (MCLMS) approach. In solving the iterative problem, the authors used the Least Mean Squares (LMS) approach and later Newton's algorithm to speed up the convergence. In [11], the authors derived an expression for an optimal step size blind multichannel LMS in the Wiener sense. In our work, we use the iterative version of the CR approach which is adapted to work in the frequency domain as in [9], [10]. We work with this particular adaptation of the CR algorithm because of the attractive reduction in computational complexity accompanied by frequency domain adaptive filtering [13]. The interested reader is referred to [10], page 4 for a complexity analysis of MCFLMS algorithm.

3.1 Outline of the iterative solution

We first put down the system model we shall use. We shall adopt the following matrix representation for describing the received signal at a single antenna i. $\boldsymbol{r}_i(n)$ is the received signal at antenna i, $\boldsymbol{H}_i(n)$ is the time domain Toeplitz channel matrix and $\boldsymbol{z}_i(n)$ is the added noise in the time domain.

$$\boldsymbol{r}_{i,N\times 1}(n) = \boldsymbol{H}_{i,N\times N+L}(n)\boldsymbol{s}_{N+L\times 1} + \boldsymbol{z}_i(n) \quad (3)$$

The received vector $\boldsymbol{r}_{i,N\times 1}(n)$ is defined as

$$\boldsymbol{r}_{i,N\times 1}(n) = [r_i(n) \quad \dots \quad r_i(n-N+1)]^T \quad (4)$$

We define the channel coefficients vector $\boldsymbol{h}_{i,N\times 1}(n)$ as

$$\boldsymbol{h}_{i,N\times 1}(n) = [h_i(n) \quad \dots \quad h_i(n-N+1)]^T \quad (5)$$

In (3), we use L to denote the FIR channel order and N denotes the observation window length, where N ≥ L+1. Inserting N = L+1 in (3) yields

$$\boldsymbol{r}_{i,N\times 1}(n) = \boldsymbol{H}_{i,N\times 2N-1}(n)\boldsymbol{s}_{2N-1\times 1} + \boldsymbol{z}_i(n) \quad (6)$$

The cross relations between two antennas in the noise free case, i and j, can now be put into this form

$$\boldsymbol{r}_i^T(n)\boldsymbol{h}_j(n) = \boldsymbol{r}_j^T\boldsymbol{h}_i(n) \quad (7)$$

Equation (7) is the basis for a cost function for the LMS algorithm. The cost function incorporates the cross relations between every pair of received antenna signals. The error signal e_{ij} for antennas i and j is defined as

$$e_{ij}(n) = \boldsymbol{r}_i^T(n)\boldsymbol{h}_j(n) - \boldsymbol{r}_j^T(n)\boldsymbol{h}_i(n) \quad (8)$$

The cost function can be defined as the summation of the squared cross relations errors among all M antennas:

$$J(n) = \sum_{i=1}^{M-1}\sum_{j=i+1}^{M}\left|\boldsymbol{e}_{ij}(n)\right|^2 \quad (9)$$

3.2 Multi-Channel Frequency LMS

In [9], [10], the authors describe the derivation and the main steps of the MCFLMS approach. We recall only the main update equation of the MCFLMS approach:

$$\hat{\tilde{\boldsymbol{h}}}_i(k) = \frac{\hat{\tilde{\boldsymbol{h}}}_i(k-1)-\mu\nabla\tilde{J}(k)}{||\hat{\tilde{\boldsymbol{h}}}_i(k-1)-\mu\nabla\tilde{J}(k)||}(10),$$

where μ is the step size parameter and $\hat{\tilde{\boldsymbol{h}}}_i(k)$ is frequency domain estimate of the i^{th} antenna at the k^{th} iteration of the algorithm. Note that MCFLMS operates in block-wise mode i.e. one iteration includes processing a block of N samples. $\nabla\tilde{J}(k) = \frac{\partial\tilde{J}(k)}{\partial\hat{\tilde{\boldsymbol{h}}}_i(k)}$, where $\tilde{J}(k)$ is the cost function of the MCFLMS in the frequency domain. The frequency domain gradient is computed as a function of the frequency domain CR error, $\tilde{e}_{ij}(k)$ as opposed to time domain CR error in (8). The diagonal matrices $\tilde{\boldsymbol{D}}_{r_j}(k)$ are computed from the FFT of the received signals as:

$$\hat{\tilde{\boldsymbol{h}}}_i(k) = \frac{\hat{\tilde{\boldsymbol{h}}}_i(k-1)-\mu\boldsymbol{W}_{N\times 2N}^{10}\sum_{j=1}^{M}\tilde{\boldsymbol{D}}^*{}_{r_j}(k)\boldsymbol{W}_{2N\times N}^{10}\tilde{e}_{ij}(k)}{||\hat{\tilde{\boldsymbol{h}}}_i(k-1)-\mu\boldsymbol{W}_{N\times 2N}^{10}\sum_{j=1}^{M}\tilde{\boldsymbol{D}}^*{}_{r_j}(k)\boldsymbol{W}_{2N\times N}^{10}\tilde{e}_{ij}(k)(k)||}(11),$$

where $\boldsymbol{W}_{N\times 2N}^{10}$ and $\boldsymbol{W}_{2N\times N}^{10}$ are defined in [9] and [10] as masks for the mathematical representation of the overlap save operation.

3.3 Enhanced MCFLMS

The problem statement of cross relations has an inherent ambiguity, which means the output blind channel estimates are scalar multiples of the actual channel impulse responses: $\hat{\tilde{\boldsymbol{h}}}_i(k) \approx \alpha\boldsymbol{h}_i(k) \ \ \forall i \in 1, \dots. M$. This is because multiplying both sides of (2) with a complex scalar factor still satisfies the equation. Hence a special metric is defined to measure the estimation accuracy, namely the Normalized Root Projection Mean Square Error (NRPM-

-SE). The NRPMSE is computed as follows [14]:

$$NRPMSE(k) = \left|\left| \boldsymbol{h}(k) - \frac{\hat{\boldsymbol{h}}^H(k)\, \boldsymbol{h}(k)}{\hat{\boldsymbol{h}}^H(k)\hat{\boldsymbol{h}}(k)}\, \hat{\boldsymbol{h}}(k) \right|\right| \quad (12)$$

where $\hat{\boldsymbol{h}}_{M(L+1)\times 1}(k) = [\hat{\boldsymbol{h}}_1^T(k) \quad \dots \quad \hat{\boldsymbol{h}}_M^T(k)]^T$

and $\hat{\boldsymbol{h}}_i(k) = IFFT(\hat{\tilde{\boldsymbol{h}}}_i(k))$

In the following, we present several modifications applied to the MCFLMS algorithm to enhance its tracking capability and adapt it to reliably estimate wireless channels based on communication signals. We demonstrate the effectiveness of these approaches using the NRPMSE. The subsequent simulation results were obtained using a Rayleigh fading TU6 channel, whose power delay profile is shown in Fig.3. The sent signal is a DVB-T2 signal, with an elementary period T = 7/ 64μsec, resulting in a TU6 channel of length 47 taps. However, in order to be able to use the FFT radix 2 we used a block size of 64 received samples for the MCFLMS. This implies an overestimation by 17 taps, knowledge of the actual channel length was however used at the end of each iteration to set the last 17 taps to zero. At the receiver side, we use M=2 antennas.

3.3.1Adaptive step size

In order to speed up the convergence rate of the MCFLMS we use the adaptive step size proposed in [11]. The idea is to utilize the fact that the gradient is orthogonal to the true channel impulse response in the noise free case. The adap tive step size is then computed as:

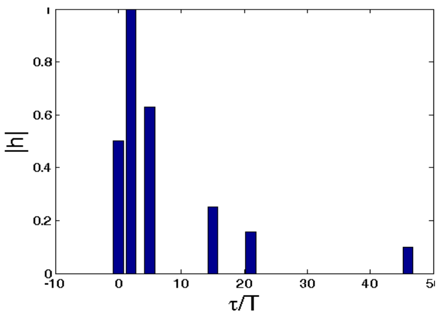

Figure 3 TU6 channel power delay profile

$$\mu = \frac{\hat{\boldsymbol{h}}^H(k)\nabla\tilde{J}(k)}{||\nabla\tilde{J}(k)||^2} \quad (13)$$

where $\nabla\tilde{J}(k) = [\nabla_1\tilde{J}^T(k) \quad \dots \quad \nabla_1\tilde{J}^T(k)]$

3.3.2 Adaptive Sparseness Control

In [15], [16], channel sparseness in the time domain is exploited to enhance the performance of the MCLMS approach. Since the sparseness is visible only in the time domain, we go back to the first definition of the cost function in (9).

3.3.2.1 Sparse Cross Relations

The sparseness of a channel h can be measured by the l_p norm $||h||_p^p$ where $0 < p < 1$. The idea is to minimize the l_p norm of the estimated channel. In [15],[16] the cross relations cost function is extended by adding the following sparseness constraint function (SC) function:

$$J^{SC}(k) = J(k) + \lambda||\boldsymbol{h}||_p^p \quad (14)$$

where the sparseness weighting factor $\lambda > 0$ controls the weight given to the SC related to the CR criteria. The gradient of the cost function in (14), can be found to be [15]

$$\boldsymbol{\nabla}_i J^{SC} = \boldsymbol{\nabla}_i J + \lambda\bar{\boldsymbol{h}}_i(k) \quad (15)$$

where

$$\bar{\boldsymbol{h}}_i(k) = p\ sign\left(\hat{\boldsymbol{h}}_i(k)\right)\left|\hat{\boldsymbol{h}}_i(k) + \epsilon\right|^{p-1}$$

The parameter $0 < \epsilon \ll 1$ helps to avoid divergence problems. We propose dividing the update steps into three parts:

a) MCFLMS update as in (1)
b) Update due to sparseness criteria (performed in the time domain via applying IFFT on the output of (11)), by adding the second term in (18) to the output from the MCFLMS. The final update equation is:

$$\hat{\boldsymbol{h}}_i(k) = IFFT\left(\hat{\tilde{\boldsymbol{h}}}_i(k)\right) + \lambda\bar{\boldsymbol{h}}_i \quad (16)$$

c) Apply FFT on the final estimate to be used in the next iteration k+1

$$\hat{\tilde{\boldsymbol{h}}}_i(k) = FFT\left(\hat{\boldsymbol{h}}_i(k)\right) \quad (17)$$

3.3.2.2 Adaptive Sparseness Weighting Factor

In this section, we look into optimizing the sparseness weight. In Fig.4, at very high SNR and low Doppler shift, we can see the trade-off between speed of convergence and steady state performance. In general, increasing λ results in in a faster convergence. However, as the algorithm converges, continuing to add the penalty function affects the steady state performance. Thus, once a steady state estimate is reached, the penalty function of the sparseness criteria should be given less weight. We therefore propose an adaptive sparseness weighting factor $\lambda(k)$. The idea is to set $\lambda(k)$ in relation to the change of the estimate every iteration. We choose to set

$$\lambda_{opt}(k) = \gamma||\mu(k)\boldsymbol{\nabla}J||, \quad (18)$$

where γ is a weighting factor, which should be set according to the channel conditions as shall be explained. In Fig.4, we can see how the proposed optimum weighting for the sparseness criterion achieves a much better steady state performance. As can be seen in Fig.5, at the beginning, the sparseness cost function is assigned with a high weighting value which decreases as the algorithm approaches a steady state performance. In Fig.6, we see the effect of using different values of λ, on the performance at different SNR and Doppler shifts. In general, we can conclude that there is a tendency for the optimum value of λ to increase as the Doppler shift increases (because then the convergence becomes of higher importance) and to decrease as the signal to noise ratio increases. In [16], the authors also indicate this tendency for the optimal λ to decrease as the SNR increases. From the plots, we can also observe that the Doppler shift affects the value of the optimum λ We therefore propose to set the optimum γ to be directly proportional to the AWGN variance and the Doppler shift.

3.3.3.3 Stability with partial spectrum excitation

In the proposed architecture, the blind combiner is placed before the SISO demodulator of a communication system. In order to keep this combiner independent of the transmit signal waveform (e.g. pulse shape, bandwidth), we have to assume a sampling frequency that fulfills the sampling theorem for all considered input signals. Consequently, the sampled receive signal that is forwarded to the input of the blind combiner may contain frequency bands which are not excited by the transmit signal, so-called null bands. This is especially true for the frequency band near half of the sampling rate which typically lacks of CSI and thus introduces an ambiguity into the problem of the cross relations. In fact, these null bands violate one of the so-called identifiability conditions [6], [17]: that the sampled receive signal must have full spectrum excitation. To demonstrate this problem, we refer to Figure 8, where a sent signal has only 50 percent of its spectrum excited with data information. We notice that, especially at low SNR the estimated channel tends to have high values in the non- excited regions, resulting in misconvergence behavior of the MCFLMS. Therefore, dealing with these

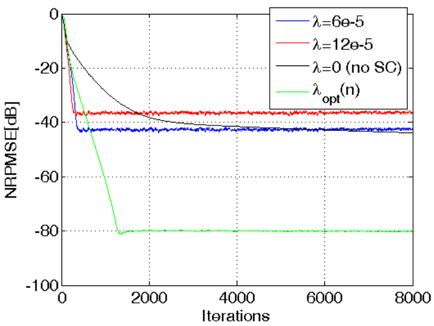

Figure 4 NRPMSE using fixed values of $\lambda(k)$ vs the proposed optimum λ with $\gamma = 6e-3$ at $f_D = 0.1$Hz and SNR=150dB

null bands is inevitable in our proposed architecture. Our solution to this problem, is to apply a weighting factor on the estimated channel in the out of band regions, once the ratio between the power in these regions to the power in the active regions exceeds a certain threshold. In Figure 8, we see the enhancement in NRPMSE brought by the control criteria. In this simulation, we used a threshold of 1 and a weighting factor which sets the power in the out of band region to half of the power in the active region.

4. Blind Maximum Ratio Combining

In this section, we present simulation results for a 1x2 DVB-T2 SIMO system. An OFDM signal is typically pro--cessed in the frequency domain i.e. after the FFT block. The frequency domain signals are maximum ratio com

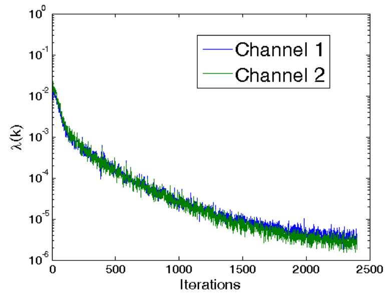

Figure 5 Values of $\lambda_{opt}(k)$ vs number of iterations with $\gamma = 6e-3$ at $f_D = 0.1Hz$ and SNR=150dB.

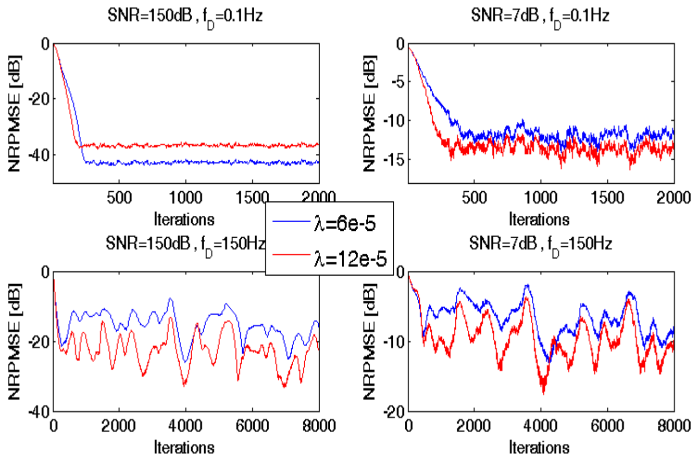

Figure 6 Effect of λ on the NRPMSE at different Doppler shifts and SNR

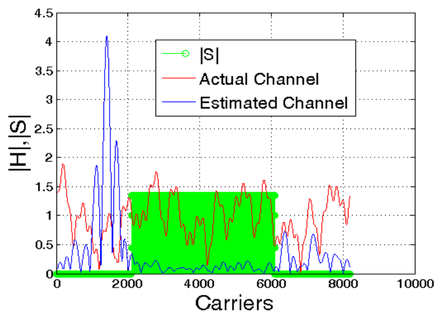

Figure 7 Spectrum of sent signal, true and estimated channel at SNR=5dB and $f_D = 0.1$ Hz

bined using the pilot assisted channel estimates of the corresoonding antennas. This approach is denoted by FDC (Frequency Domain Combining). Our approach, on the other hand, processes the received signals in the time domain regardless of the structure of the transmit signal, hence we denote it by BTDC (Blind Time Domain Combining). An 8k FFT is used with a guard interval of 2k samples. Out of the 8192 subcarriers, only 6817 carried data information and 16QAM modulation is used on the OFDM subcarriers with an LDPC coding rate of 0.5. The pilot pattern PP1 is used with $D_x = 3$ and $D_y = 4$ [18]. Pilot assisted channel estimation (PACE) is applied using linear interpolation in the frequency domain. Typically in static channels, 2D interpolation is applied which can give a very good performance. However, in mobile channels with high Doppler and especially with long FFT sizes (symbol time ∼1 ms) the temporal correlation doesn't

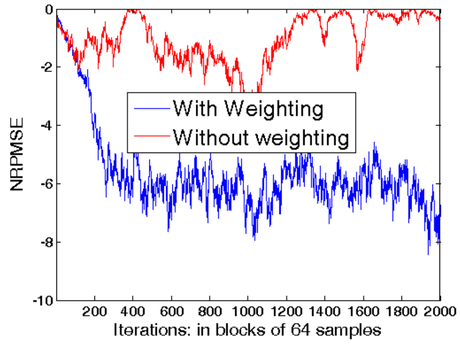

Figure 8 NRPMSE in the case weighting is used vs the case it is not used using $\lambda = 6e - 4$ at SNR=5dB and $f_D = 0.1Hz$

allow to utilize the scattered pilots in the time domain. Transmitting an OFDM symbol in a time-varying channel induces inter-carrier interference (ICI), which typically results in an error floor in the BER[19]. ICI can be mitigated by adding an ICI-canceler instead of the simple ZF equalizer. Furthermore, ICI also influences the quality of channel estimation. More sophisticated techniques for channel estimation which incorporates knowledge of the ICI could also be used. The conventional approach, denoted by FDC(hPACE), uses the PACE for frequency domain combining and equalization, whereas the proposed approach BTDC(hPACE) uses the PACE for equalization of the blindly combined signal only, as shown in Fig.2. In the synchronous mode of BTDC, denoted by BTDCSync(hPACE), every OFDM symbol is convolved with one matched filter obtained from the averaging of the MCFLMS estimates (for the corresponding antenna i) over the respective OFDM symbol time. The matched filter used at antenna i to combine the q^{th} OFDM symbol can be written as

$$c_i(q,m) = \frac{N}{N_{FFT}+N_{GI}} \sum_{k=(q-1)\left(\frac{N_{FFT}+N_{GI}}{N}\right)+1}^{q\left(\frac{N_{FFT}+N_{GI}}{N}\right)} \hat{h}_i^*(k,-m)$$

(19)

Where $\hat{h}_i^*(k,-m)$ is the m^{th} estimated tap of the i^{th} antenna captured during the k^{th} iteration of the algorithm, N_{FFT} and N_{GI} are the FFT size and the guard interval, respectively. This means that coarse-time synchronization to the OFDM transmitter is assumed. On the other hand, in the simulation denoted by BTDCAsync, synchronization to the transmitter is not assumed i.e. blocks of N = 64 samples within the received OFDM symbol are combined using the instantaneous estimates from the MCFLMS. As shown in Fig.9, using PACE and synchronization information, the proposed architecture performs even slightly better than the conventional solution. The main reason is the comparatively high frequency selectivity of the TU6 channel which doesn't allow for a very accurate frequency domain estimate of the channel using 1D frequency interpolation, especially with linear interpolation. Furthermore, the MCFLMS algorithm exploits all the received samples for its channel estimate and uses short blocks of data (N = 64 samples) in the time domain. Using perfect CSI, we can see the conventional approach denoted by FDC(h_{true}) equalization slightly outperformed the synchronous mode of the BTDC denoted by BTDC(h_{true}) which uses the MCFLMS estimate for combining and the perfect channel knowledge for equalization which uses the MCFLMS estimate for combining and the perfect channel knowledge for equalization. Asynchronous combining (i.e. block by block combining) leads to ICI, because of the time varying distortion introduced in the time domain combiner block on the OFDM symbol, and therefore a worse performance is achieved. As shown in Fig.9, a degradation in performance is observed in the asynchronous case (≈0.7dB and 1.1 dB SNR loss when using h_{PACE} and h_{true} for equalization respectively). However, the performance is still notably better compared to SISO. In addition, the ICI effect can be reduced by further smoothing the output of the MCFLMS to avoid abrupt changes in the blind channel estimate, which is used for time domain combining. We propose that the BTDC operates in the asynchronous mode until frame synchronization is achieved and fed back from the demodulator to the combiner block as shown in Fig.2. Because of the different architecture, the PACE block in the proposed architecture estimates an equivalent channel which can be written in the form:

$h_{eq}(k,m) = \alpha \sum_{i=1}^{M} h_i(k,m)\hat{h}_i^*(k,-m)$.

The equivalent channel is less frequency selective than the individual channels (nulls are typically eliminated by MRC), hence the equivalent channel can be better approximated by interpolation compared to SISO. In addition, the PACE takes as an input the output of the combiner block therefore it benefits from a higher SNR of the combined signal. This is shown in Fig.10, where the normalized MSE in CE is plotted in both cases for the conventional solution vs the BTDC solution. Fig.11 depicts the NRPMSE of the MCFLMS in dB vs time at a total SNR of 7dB.

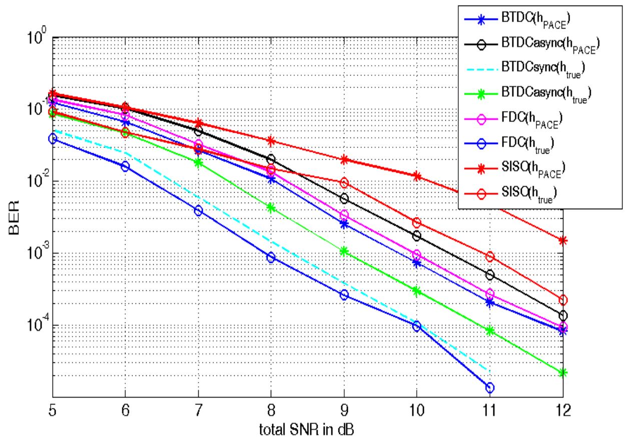

Figure 9 BER performance of the proposed architecture in a DVB-T2 system after the LDPC decoder, using the TU6 channel at $f_D = 50Hz$

4. Conclusion

In this work, we propose a communication receiver with a generic SIMO combiner. We suggest using blind channel

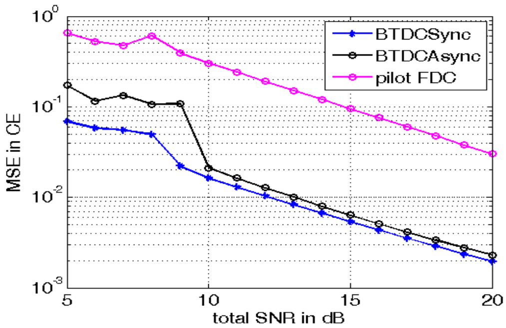

Figure 10 Normalized MSE in channel estimation using linear interpolation at $f_D = 50Hz$

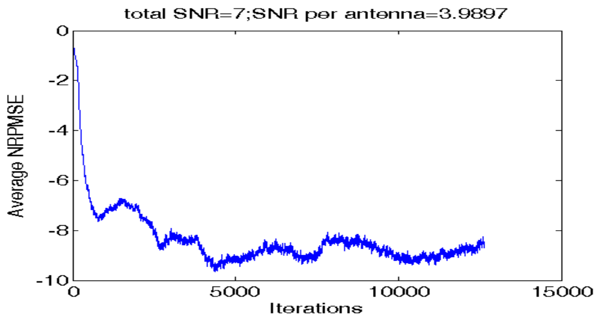

Figure 11 Normalized NRPMSE using 1x2 DVB-T2 system at $f_D = 50Hz$ and total SNR=7dB

estimation to acquire the amount of CSI that is required to perform MRC in the time domain. We restricted our work to SOS algorithms to ensure a high channel tracking capability for mobile channels and focused our investigation on an iterative algorithm based on frequency domain adaptive filtering as an attractive approach for real time implementation. Without explicit knowledge of the SNR and by relying on intermediate results of the MCFLMS algorithm, we computed low-complex adaptive step size and sparseness measures, which enhanced the convergence and channel tracking capability. Moreover, we applied a simple but effective stability criterion in order to ensure that the algorithm converges with oversampled communication signals. We presented results based on NRPMSE which illustrate the effectiveness of these measures. Finally, we presented coded BER results for a simulated DVB-T2 system, which highlights the competitiveness of BMRC compared to the conventional solution. The complexity of the proposed combiner exceeds the complexity of the conventional approach, however a sub-optimal solution which has less complexity is subject of current investigation.

5. References:

[1] M. K. Simon and M.-S. Alouini, Digital communication over fading channels, 2nd ed. Prentice Hall, 2005.
[2] H. Suzuki, Y. Sanada, and R. Hanai, “A blind diversity reception based on eigenfilter approach for mobile com munications,” Vehicular Technology Conference, 2000. IEEE VTS-Fall VTC 2000. 52nd, vol. 1, pp. 362–369, Sep. 2000
[3] D. Schmid and G. Enzner, “Robust subsystems for iterative multichannel blind system identification and equalization,” 2009
[4] S. Haykin, Blind deconvolution. Prentice Hall, 1994.
[5] ——, Unsupervised adaptive filtering: volume 2 Blind Deconvolution. Prentice Hall, 2000
[6] G. X. Hiu Liu and L. Tong, “A determinstic approach to blind identification of multi-channel fir systems,” ICASSP Proceedings of the Acoustics, Speech, and Signal Processing, vol. 4, 1994.
[7] L. TONG and S. PERREAU, “Multichannel blind identification:from subspace to maximum likelihood methods,” IEEE proceedings, vol. 86, no. 10, Oct. 1998.
[8] Y. A. Huang and J. Benesty, “Adaptive multi-channel least mean square and newton algorithms for blind channel estimation,” SIGNAL PROCESSING, vol. 82, pp. 1127–1138, 2002
[9] ——, “A class of frequeny-domain adaptive approaches to blind multichannel identification,” IEEE Transactions on signal processing,, vol. 51, no. 1, Jan. 2003.
[10] Y. A. Huang, J. Benesty, and J. Chen, “Adaptive blind identification of simo systems using channel cross-relation in the frequency domain,” ICASSP2003, 2003.
[11] N. D. Gaubitch and M. K. H. ans Patrick A. Naylor, “Generalized optimal step-size for blind multichannel lms system identification,” IEEE signal processing letters, no. 10, Oct. 2006.
[12] Y. A. Huang, J. Benesty, and J. Chen, “An exponentiated gradient adaptive algorithm for blind identification of sparse simo systems,” ICASSP2004, 2004.
[13] S. Haykin, Adaptive filter theory, 4th ed. Prentice Hall, 2008.
[14] D. R. Morgan, J. Benesty, and M. M. Sondhi, “On the evaluation of estimated impulse responses,” IEEE signal processing Letters, vol. 5, no. 7, Jul. 1998.
[15] A. A?ssa-El-Bey, K. Abed-Meraim, and C. Laot, “Adaptive blind estimation of sparse simo channels,” WOSSPA 2011: 7th International Workshop on Systems, Signal Processing and their Applications, May 2011.
[16] A. A?ssa-El-Bey and K. Abed-Meraim, “Blind simo channel identification using a sparsity criterion,” Signal Processing Advances in Wireless Communications, 2008.
[17] L. T. Ghaunghan Xu, Hiu Liu and T. Kaliath, “A least squares approach to blind channel identification,” IEEE Transactions on Signal Processing, vol. 43, no. 12, Dec. 1995.
[18] ETSI, “Etsi en 302 755 v1.1.1, frame structure channel coding and modulation for a second generation digital terrestrial television broadcasting system(dvb-t2),” Sep. 2009.
[19] Molisch, A.F.; Toeltsch, M..; Vermani, S..; , "Iterative Methods for Cancellation of Intercarrier Interference in OFDM Systems," *Vehicular Technology, IEEE Transactions on* , vol.56, no.4, pp.2158-2167, July 2007 doi: 10.1109/TVT.2007.897628