Enhanced Blind Maximum Ratio Combining Using Channel Tap Masking for Broadcasting Applications

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***Abstract*—In this work, we propose a new algorithm to exploit the communication channel sparseness via channel tap masking for blind channel identification using multi-channel frequency least mean squares algorithm (MCFLMS). The proposed technique has the advantage of significantly enhancing the tracking capability of MCFLMS and making it robust against channel order overestimation. In order to correctly assess the performance of MCFLMS in the context of blind maximum ratio combining (BMRC), we propose a new assessment criterion that is independent of inherent channel estimation ambiguities. We provide BER simulation results for a 1×2 SIMO DVB-T2 system which show the effectiveness of the tap masking on BMRC using MCFLMS, especially when synchronization information is not available in the BMRC block.**

I. Introduction

In [1], a BMRC receiver architecture is proposed which has the advantage of being transmit signal independent. Only limited information about the underlying system is required, therefore such a unit can be employed in almost any system. A comparison between the conventional diversity receiver and the BMRC architecture is shown in Fig. 1.

A conventional diversity receiver applies synchronization and channel state information (CSI) estimation separately for each antenna signal in a first standard-dependent demodulation part. In contrast, BMRC works without symbol synchronization and acquires the CSI through blind channel identification. In [1], MCFLMS is used for blind channel identification. The MCFLMS is a second-order statistics (SOS) iterative blind channel estimation method exploiting the cross-relations (CR) [2] between the antenna signals. Originally developed in [3], [4], MCFLMS has the advantage of a notable reduction in computational complexity due to the employment of frequency domain adaptive filtering [5].

In [6], [7], the sparseness of the communication channel is exploited to enhance the performance of the multi-channel least mean squares (MCLMS) approach. The estimated channel sparseness is measured using the l_1 norm, $||\hat{h}||_1^1$. A penalty function, $\lambda||\hat{h}||_1^1$, with weighting sparseness factor λ is added to the original cost function to force the algorithm to converge to the most sparse solution.

In our work, we propose a new algorithm to exploit the sparseness of a communication channel. A sparse communication channel consists typically of a few significant channel taps which are unequal to zero. The remaining taps are non-significant i.e. they have negligible contribution to the actual channel coefficient vector, but only appear in the estimated channel coefficient vector because of the noise. We detect and track the locations of the non-significant taps in the estimated time-domain channel coefficient vector. We then apply a mask on the whole estimated channel vector, where the non-significant taps are suppressed. Detection of those non-significant taps is done by means of tracking specific properties of each estimated channel tap in the time domain. This technique can be applied to blind and non-blind estimation algorithms and is not limited to sparse channels.

This paper is organized as follows: in Section II, we give a review of the blind channel identification (BCI) approaches which are based on SOS. We also derive the main steps of the MCFLMS. In Section III, we introduce the proposed scheme for channel tap masking and demonstrate its effectiveness. In Section IV, we present a new criterion to assess the performance of the MCFLMS algorithm when used for BMRC. In section V, we present BER simulation results for BMRC in a DVB-T2 system, where we show the effectiveness of the proposed channel tap masking approach when applied on top of MCFLMS. In Section VI, we draw the final conclusions of this work.

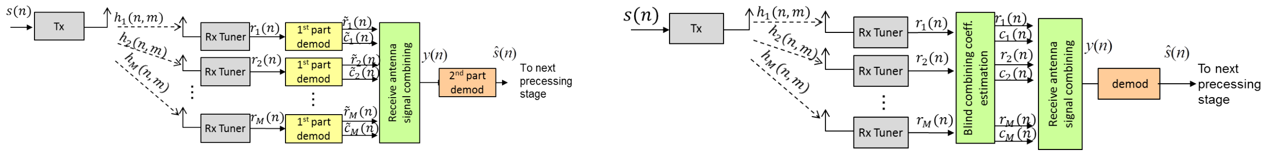
II. Blind Channel Identification

There exists an extensive literature for BCI, see for example [8], [9]. However, these algorithms were mostly applied to acoustic signals in static channels. In contrast, in this work we deal with fast fading communication channels where fast convergence of the BCI has to be guaranteed in order to track the channel successfully. Therefore, we select an algorithm which is based on SOS, as opposed to algorithms based on HOS [8], [9]. Although the HOS provides higher estimation accuracy, the SOS have the advantage of a faster convergence rate. The family of the SOS approaches includes the CR algorithm [2]. The idea behind the CR approach is straightforward: in the noise-free case, given r_i is the received signal at antenna i, h_i is the discrete time impulse response of 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:

$$r_i(n) = s(n) * h_i(n) \quad i = 1, ...M, \tag{1}$$

where M is the number of antennas at the receiver side. Convolving $r_i(n)$ with $h_j(n)$ and $r_j(n)$ with $h_i(n)$ yields

$$\begin{aligned} r_i(n) * h_j(n) &= s(n) * h_i(n) * h_j(n) \\ &= r_j(n) * h_i(n) \end{aligned} \tag{2}$$



(a) Conventional multi-antenna maximum ratio combining

(b) Blind multi-antenna maximum ratio combining

Fig. 1. Comparison between the receiver architecture of conventional multi-antenna system (left) and the proposed blind diversity receiver (right)

The CR problem statement is then to find the two sets of channel coefficients h_j and h_i, which satisfy (2). A very good summary of this family of algorithms can be found in [10]. 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 algorithm was developed in [11]–[13], namely the MCLMS approach. In solving the problem in an iterative manner, the authors use the Least Mean Squares (LMS) algorithm and later Newton's algorithm to speed up the convergence. In [12], the authors derive an expression for an optimal step size blind multi-channel 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 [3], [4]. We use this particular adaptation because of its attractive reduction in computational complexity accompanied by frequency domain adaptive filtering [5].

A. Outline of the iterative solution

In order to proceed with the outline of the iterative solution, we first put down the system model we shall use. The received signal vector $\boldsymbol{r}_i(n)$ at antenna i is defined as

$$\boldsymbol{r}_{i,N\times 1}(n) = \begin{bmatrix} r_i(n) & r_i(n-1) & \ldots & r_i(n-N+1) \end{bmatrix}^T. \tag{3}$$

We define $\boldsymbol{H}_i(n)$ as the time domain Toeplitz channel matrix and $\boldsymbol{z}_i(n)$ as the additive noise vector in the time domain. We use L to denote the number of channel taps in the impulse response. N denotes the observation window i.e. the number of samples considered per iteration where $N \geq L$. The received signal vector $\boldsymbol{r}_{i,N\times 1}(n)$ can then be written as

$$\boldsymbol{r}_{i,N\times 1}(n) = \boldsymbol{H}_{i,N\times N+L-1}(n)\boldsymbol{s}_{N+L-1\times 1}(n) + \boldsymbol{z}_i(n) \tag{4}$$

If we consider the multipath model depicted in (4) taking an observation interval $N = L$, (4) can be rewritten for a single antenna as

$$\boldsymbol{r}_{i,N\times 1}(n) = \boldsymbol{H}_{i,N\times 2N-1}(n)\boldsymbol{s}_{2N-1\times 1} + \boldsymbol{z}_i(n). \tag{5}$$

In the following we assume $N = L$.
We define the time domain channel coefficient vector $\boldsymbol{h}_i$ as

$$\boldsymbol{h}_{i,N\times 1}(n) = \begin{bmatrix} h_i(n,0) & h_i(n,1) & \ldots & h_i(n,N-1) \end{bmatrix}^T. \tag{6}$$

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

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

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

$$e_{ij}(n) = \boldsymbol{r}_i^T(n)\boldsymbol{h}_j(n) - \boldsymbol{r}_j^T(n)\boldsymbol{h}_i(n) \ \ \forall i \neq j. \tag{8}$$

The cost function can be defined as the summation of the squared CR error among all M antennas:

$$J(n) = \sum_{i=1}^{M-1}\sum_{j=i+1}^{M} |e_{ij}(n)|^2. \tag{9}$$

B. Multi-Channel Frequency Least Mean Squares (MCFLMS)

In [3], [4], the authors describe the derivation and the main steps of the MCFLMS approach. MCFLMS operates in block-wise mode i.e. one iteration includes processing a block of N samples. The frequency domain gradient, at the k^{th} iteration of the algorithm is computed as

$$\nabla_i \tilde{J}^k = \frac{\partial \tilde{J}^k}{\partial \tilde{\hat{\boldsymbol{h}}}_i^{k^*}} \tag{10}$$

where $\tilde{J}^k$ is the cost function of MCFLMS in the frequency domain. The frequency domain gradient is computed as a function of the frequency domain CR error $\tilde{\boldsymbol{e}}_{ji}^k$, as opposed to the time domain CR error in (8).

$$\tilde{\boldsymbol{e}}_{ji}^k = \tilde{\boldsymbol{W}}_{N\times 2N}^{10} \times \left[\tilde{\boldsymbol{D}}_{r_j}^k \tilde{\boldsymbol{W}}_{2N\times N}^{10} \tilde{\hat{\boldsymbol{h}}}_i^k - \tilde{\boldsymbol{D}}_{r_i}^k \tilde{\boldsymbol{W}}_{2N\times N}^{10} \tilde{\hat{\boldsymbol{h}}}_j^k\right], \tag{11}$$

where the main diagonal of the diagonal matrix $\tilde{\boldsymbol{D}}_{r_j}^k$ is composed of the FFT of the signals received on antenna j. $\tilde{\boldsymbol{W}}_{N\times 2N}^{10}$ and $\tilde{\boldsymbol{W}}_{2N\times N}^{01}$ are defined in [3], [4] as masks for the mathematical representation of the overlap save operation. They can be computed as follows:

$$\tilde{\boldsymbol{W}}_{N\times 2N}^{10} = \boldsymbol{F}_{N\times N}\boldsymbol{W}_{N\times 2N}^{10}\boldsymbol{F}_{2N\times 2N}^{-1}, \tag{12}$$

$$\tilde{\boldsymbol{W}}_{2N\times N}^{01} = \boldsymbol{F}_{2N\times 2N}\boldsymbol{W}_{2N\times N}^{01}\boldsymbol{F}_{N\times N}^{-1}, \tag{13}$$

where $\boldsymbol{W}_{N\times 2N}^{10}$ and $\boldsymbol{W}_{2N\times N}^{01}$ are time domain masks defined as

$$\boldsymbol{W}_{N\times 2N}^{10} = \begin{bmatrix} \boldsymbol{I}_{N\times N} & \boldsymbol{0}_{N\times N} \end{bmatrix} \tag{14}$$

$$\boldsymbol{W}_{2N\times N}^{01} = \begin{bmatrix} \boldsymbol{0}_{N\times N} \\ \boldsymbol{I}_{N\times N} \end{bmatrix}. \tag{15}$$

The update equation of the MCFLMS approach is then written as:

$$\begin{aligned} \tilde{\hat{\boldsymbol{h}}}_i^k &= \tilde{\hat{\boldsymbol{h}}}_i^{k-1} - \mu \nabla_i \tilde{J}^k \\ &= \tilde{\hat{\boldsymbol{h}}}_i^{k-1} - \mu \tilde{\boldsymbol{W}}_{N\times 2N}^{10} \sum_{j=1}^{M} \tilde{\boldsymbol{D}}_{r_j}^{k^*} \tilde{\boldsymbol{W}}_{2N\times N}^{01} \tilde{\boldsymbol{e}}_{ji}^k, \end{aligned} \tag{16}$$

where μ is the step size parameter and $\tilde{\hat{\boldsymbol{h}}}_i^k$ is the frequency domain estimate of the channel impulse response of the i^{th} antenna at the k^{th} iteration of the algorithm. The normalized update equation can then be written as

$$\tilde{\hat{\boldsymbol{h}}}_i^k = \frac{\tilde{\hat{\boldsymbol{h}}}_i^{k-1} - \mu \tilde{\boldsymbol{W}}_{N\times 2N}^{10} \sum_{j=1}^{M} \tilde{\boldsymbol{D}}_{r_j}^{k^*} \tilde{\boldsymbol{W}}_{2N\times N}^{01} \tilde{\boldsymbol{e}}_{ji}^k}{\sqrt{N} \left\| \tilde{\hat{\boldsymbol{h}}}^k \right\|}, \tag{17}$$

where $\tilde{\hat{\boldsymbol{h}}}_{MN\times 1}^k = \left[\begin{array}{cccc} \tilde{\hat{\boldsymbol{h}}}_1^{k^T} & \tilde{\hat{\boldsymbol{h}}}_2^{k^T} & \ldots & \tilde{\hat{\boldsymbol{h}}}_M^{k^T} \end{array} \right]^T$. In this work we consider using a simplified variable step size formula as explained in [12] for the noiseless case

$$\mu^k = \frac{\tilde{\hat{\boldsymbol{h}}}^{k-1^H} \nabla \tilde{\mathrm{J}}^{k-1}}{\left\| \nabla \tilde{J}^{k-1} \right\|^2}. \tag{18}$$

Moreover, we apply a sparseness penalty function according to [6], [7] to make use of the sparseness of the time domain communication channel to achieve a better performance. The sparseness of a channel h can be measured by the l_p norm $||h||_p^p$ where $0 < p \leq 1$. The idea is to minimize the l_p norm of the estimated channel. In [6], [7], the CR cost function is extended by adding the sparseness constraint with weight λ:

$$J^{SC}(k) = J(k) + \lambda \left\| \boldsymbol{h} \right\|_p^p. \tag{19}$$

The update equation can then be written as

$$\hat{\boldsymbol{h}}_i^k = IFFT\left(\tilde{\hat{\boldsymbol{h}}}_i^k \right) + \lambda \overline{\boldsymbol{h}}_i^k, \tag{20}$$

where

$$\overline{\boldsymbol{h}}_i^k = p \ \mathrm{sign}(IFFT\left(\tilde{\hat{\boldsymbol{h}}}_i^k \right)) \left(|IFFT\left(\tilde{\hat{\boldsymbol{h}}}_i^k \right)| + \epsilon \right)^{p-1}. \tag{21}$$

The parameter $0 < \epsilon << 1$ avoids division by zero. FFT is then applied on the final estimate to be used in the next iteration $k+1$. Our channel tap masking technique notably reduces the l_1 norm weight dependency on the signal to noise ratio (SNR) and Doppler frequency. In fact, λ can be set to a constant value over large SNR and Doppler frequency ranges, making our BMRC algorithm independent of these channel conditions. Therefore in this work, we use the l_1 norm with $p = 1$. We also use a fixed sparseness weighting factor $\lambda = 0.003$ to weight the sparseness penalty function according to [6], [7].

A well known criteria to assess the performance of the CR approach is the so-called normalized root projection mean square error (NRPMSE). The NRPMSE is computed as [14]

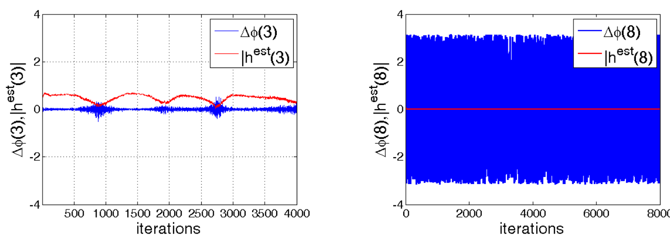
$$NRPMSE^k = \left\| \boldsymbol{h}^k - \frac{\hat{\boldsymbol{h}}^{k^H} \boldsymbol{h}^k}{\hat{\boldsymbol{h}}^{k^H} \hat{\boldsymbol{h}}^k} \hat{\boldsymbol{h}}^k \right\|, \tag{22}$$

where $\hat{\boldsymbol{h}}_{MN\times 1}^k = \left[\begin{array}{cccc} \hat{\boldsymbol{h}}_1^{k^T} & \hat{\boldsymbol{h}}_2^{k^T} & \ldots & \hat{\boldsymbol{h}}_M^{k^T} \end{array} \right]^T$, $\hat{\boldsymbol{h}}_i^k = IFFT(\tilde{\hat{\boldsymbol{h}}}_i^k)$ and $\boldsymbol{h}^k$ is the true stacked channel vector at the k^{th} iteration of the algorithm.

III. Channel Tap Masking

We verified the effectiveness of the proposed channel tap masking approach in a DVB-T2 system [15]. A DVB-T2 signal is received by a 1×2 SIMO system. An 8192 point FFT is used with a guard interval of 2048 samples. 6817 out of the 8192 frequency points carry information and 16QAM modulation is used on these subcarriers. We assume a frequency-selective Rayleigh fading channel, which follows the Jakes model, namely the Typical Urban 6 tap channel (TU6) as defined in [16]. At the given sampling rate of $9.14MHz$, this corresponds to a total channel length of 47 taps. We considered a Doppler frequency of $100Hz$. At an RF carrier frequency of $600MHz$, it corresponds to a user moving at a speed of 180km/h.

To demonstrate the proposed algorithm, we refer to Fig. 2, where the estimated magnitude and phase differences between every two successive iterations are plotted for a significant channel tap (left) and a non-significant channel tap (right). We



(a) Significant tap (b) Non-significant tap

Fig. 2. Phase variation and amplitude values of the estimated MCFLMS channel taps at SNR=$10dB$, $f_D = 100Hz$ and $N = 512$ samples

observe that the phase difference of a non-significant channel tap exhibits large non-monotonous changes compared to the variations recorded for a significant channel tap. Our approach is to monitor the average magnitude of these phase difference variations, and hence deduce which channel taps are significant and which are not. A channel tap mask is built based on comparing these values to a predetermined threshold. The masking operation, carried out in each MCFLMS iteration, is summarized in the following steps

1) At the k^{th} iteration of the algorithm, compute the phase difference, $\Delta\phi^k(m)$, for the m^{th} estimated tap of $\hat{\boldsymbol{h}}^k$ as
$$\Delta\phi^k(m) = \arg \hat{h}^k(m) - \arg \hat{h}^{k-1}(m), \tag{23}$$
where $\hat{h}^k(m) = \hat{h}(n_0 + kN, m)$.
2) Compute a time moving exponential average change value $\Delta\bar{\phi}^k(m)$ as
$$\Delta\bar{\phi}^k(m) = \xi \Delta\bar{\phi}^{k-1}(m) + (1-\xi)|\Delta\phi^k(m)|, \tag{24}$$
where ξ is the forgetting factor parameter of the averaging process.
3) Compare $\Delta\bar{\phi}^k(m)$ to a predetermined threshold κ_ϕ. If $\Delta\bar{\phi}^k(m) > \kappa_\phi$, the m^{th} estimated tap is set to zero. The resulting impulse response is used for the next iteration step.

The mask is calculated in every iteration. If a new echo appears, which previously was regarded as a non-significant

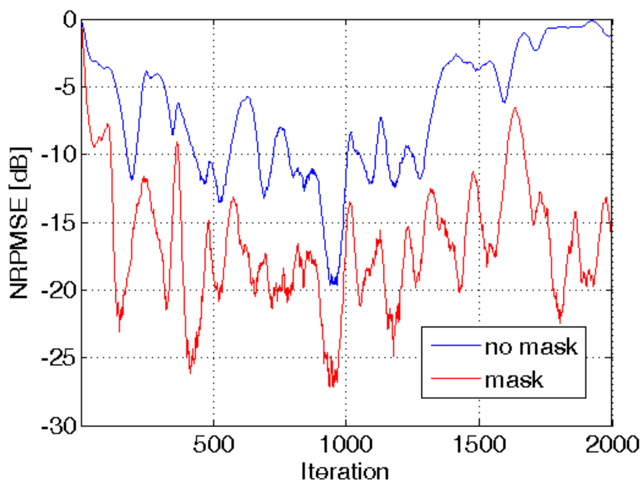


Fig. 3. NRPMSE of MCFLMS estimate with and without masking for a TU6 channel at SNR=$10dB$ and $f_D = 100Hz$

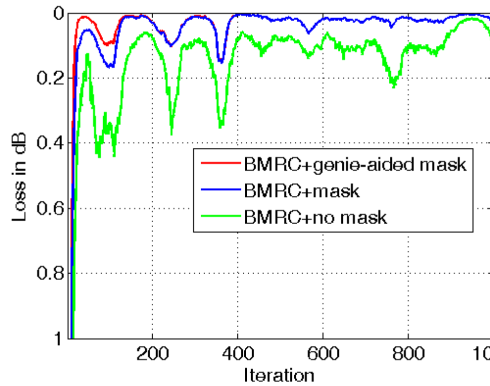


Fig. 4. SNR loss criteria computed at SNR= $10dB$ and $f_D = 100Hz$

channel tap, the algorithm is able to detect the new significant channel tap relying on the average phase difference.

In practical systems, the number of channel taps L is estimated. As explained in [17], channel order overestimation is a common challenge in the problem of BCI. In our work, we found that channel tap masking can enhance the estimation performance significantly in case of channel order overestimation. In Fig. 3, we compare the NRPMSE for the two cases with and without masking. The threshold parameter is set independent of the SNR to $\kappa_\phi = \frac{\pi}{4}$. In this work, we don't estimate L but we assume a case where L is overestimated. A receiver window size of $L = 512$ samples is used at the receiver side, which means the TU6 channel is overestimated by 465 taps. We can see that the masking approach can handle a very high degree of channel order overestimation.

IV. New performance assessment criterion

In the literature of BCI based on SOS, the NRPMSE criterion is widely used to assess the performance of the BCI algorithm, see for example [3], [4], [6]. As shown in (22), the NRPMSE measures the distance between the true channel and the estimated channel impulse responses scaled by the ambiguity factor. In our application, we care about how good the estimate is for the combining process. Equalization is done anyway in a subsequent SISO demodulator which typically relies on pilot information. In case of channel order overestimation, the NRPMSE can diverge, due to the additional ambiguity of a possible delay time that is common for all channel estimates $\hat{h}(n,l)$. On the other hand, a common delay of all channel estimates has no influence on the combining performance. For this purpose, we propose a new assessment criterion, that measures the average SNR loss of BMRC compared to perfect MRC. First, we define the output SNR after combining the received signals with $\hat{\boldsymbol{h}}^k$ according to MRC assuming AWGN with zero mean and same variance for all receive antennas. For convenience, we compute the output SNR in the frequency domain

$$\Gamma\left(\hat{\tilde{\boldsymbol{h}}}^k\right) = \sum_{u=1}^{N_{active}} \frac{|\sum_{i=1}^{M} \tilde{h}^k(u)\hat{\tilde{h}}^{k^*}(u)|^2}{\sum_{i=1}^{M} |\hat{\tilde{h}}^k(u)|^2} \tag{25}$$

The output SNR loss can then be computed as

$$\begin{aligned}\Gamma_{loss}\left(\hat{\tilde{\boldsymbol{h}}}^k\right) &= \frac{\Gamma\left(\tilde{\boldsymbol{h}}^k\right)}{\Gamma\left(\hat{\tilde{\boldsymbol{h}}}^k\right)} \\ &= \frac{\sum_{u=1}^{N_{active}} \frac{|\sum_{i=1}^{M} \tilde{h}^k(u)\tilde{h}^{k^*}(u)|^2}{\sum_{i=1}^{M} |\tilde{h}^k(u)|^2}}{\sum_{u=1}^{N_{active}} \frac{|\sum_{i=1}^{M} \tilde{h}^k(u)\hat{\tilde{h}}^{k^*}(u)|^2}{\sum_{i=1}^{M} |\hat{\tilde{h}}^k(u)|^2}},\end{aligned} \tag{26}$$

where $\hat{\tilde{h}}^k(u)$ is the u^{th} frequency bin of the estimated channel at the k^{th} iteration.

Fig. 4 depicts the SNR loss for MCFLMS without masking, with masking and with genie-aided masking at an SNR of $10dB$ and a Doppler frequency of $100Hz$. In the genie aided case, the positions of the significant taps are assumed to be known and the non-significant taps are suppressed after each iteration. As shown in Fig. 4, about $0.2dB$ performance gain is achieved using the masking operation. We also notice a negligible degradation in performance compared to the genie aided case where the tap locations are assumed to be known. This in turn proves that tracking the difference in phase information is a reliable method for identifying the non-significant taps.

V. Bit Error Ratio Results

In this section, we present BER results for a 1×2 DVB-T2 SIMO system, which are based on the simulation parameters mentioned in section III. We compare the case of conventional frequency domain combining (FDC) with perfect CSI at the receiver side against the cases of BMRC with and without channel tap masking. The FDC architecture is shown in Fig. 1a. The 1^{st} demodulator part includes an FFT block to convert the received signals to the frequency domain.

BMRC, (Fig. 1b), is realized by convolving the received signals with their respective channel matched filters in the

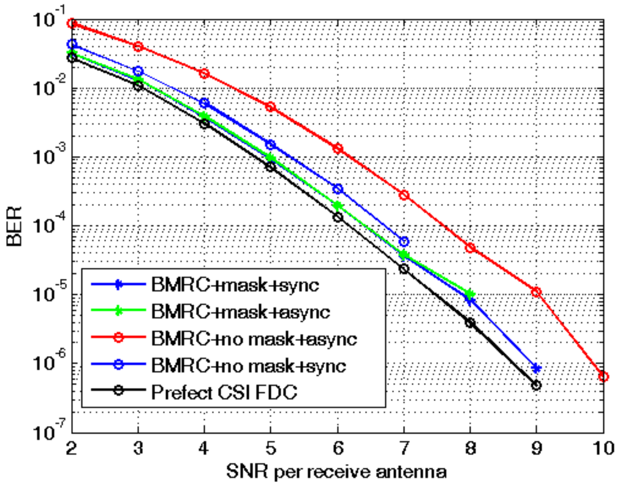


Fig. 5. BER performance for a TU6 channel and $f_D = 100Hz$

time domain $c_i(n,m) = \hat{h}_i^*(n,-m)$. In the synchronous mode of BMRC, every OFDM symbol is convolved with one matched filter obtained from the arithmetic mean of the MCFLMS estimates (for the corresponding antenna i) over the respective OFDM symbol time. This implies that coarse time synchronization to the OFDM symbol is available.

On the other hand, in the asynchronous mode of BMRC, synchronization to the OFDM symbols is not assumed. Instead, blocks of $N = 512$ received samples are combined using the instantaneous estimates from the MCFLMS. As mentioned earlier, this corresponds to a channel order overestimation by 465 taps. Fig. 5 depicts the BER performance of BMRC with/without masking and with/without synchronization. For all cases, perfect channel state information (CSI) is assumed to be available for zero forcing (ZF) equalization of the combined signal.

In Fig. 5, we can see a notable degradation in performance when synchronization information is not available at the receiver side and the masking is switched off. This is because combining different parts of the OFDM symbol with different matched filter coefficients induces inter-carrier interference (ICI) in the combined signal $\boldsymbol{y}^k$.

We can see the BER improvement brought by applying the masking to the estimated channel taps. More than $1dB$ SNR gain can be achieved in the asynchronous case with tap masking as it effectively suppresses estimation noise hence yielding less ICI on the combined signal [1]. By applying the masking operation on the estimated channel coefficients, the gap between the synchronous and the asynchronous receiver is almost eliminated. We also observe that only $0.2dB$ performance loss is obtained relative to the case of FDC with perfect CSI knowledge.

VI. Conclusion

In this work, we proposed a new method to enhance the performance of MCFLMS using channel tap masking. The new method can be applied to blind and non-blind estimation algorithms. It makes use of the sparse nature of wireless communication channels, which are characterized by a long impulse response in which only a few dominant taps and the remaining are almost zero. Using channel tap masking, the MCFLMS has shown a more robust performance especially in the case of channel order overestimation. In addition, we proposed a new criterion to evaluate the performance of MCFLMS applied for BMRC. We presented BER results which show the effectiveness of the new algorithm when combined with MCFLMS and used for BMRC in a DVB-T2 system. An improvement was observed especially in the case when synchronization information is not available at the combiner block of the receiver.

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