Geometric Approach of Blind Channel Estimation

Agbeti Bricos Ahossi[1], Ahmed Dooguy Kora[2(✉)], and Roger Marcelin Faye[1]

[1] Ecole Supérieure Polytechnique, Université Cheikh Anta Diop, Dakar, Senegal
[2] Ecole Supérieure Multinationale des Télécommunications, 10 000 Dakar, Senegal
ahmed.kora@esmt.sn

Abstract. This paper introduces a geometric approach of channel estimation (GACE). It is a blind channel estimation method for multiple input multiple output systems. GACE is based on a two-step geometric approach of source separation (GASS) that outperforms the existing ones. It is an approximated maximum likelihood estimation method which proceeds by the determination of the polyhedral edges tilts representing the matrix parameters. It operates by identifying matrix parameters using a geometric consideration depending on the probabilistic hypothesis of the sources. The simplicity of this method is based on a cloud observation, which is used to determine the edge of parallelogram describing the matrix channel parameters. In this paper, the case of real channel parameters and complex data sources for higher modulation order are performed. The simulation results show the efficiency of the proposed approach.

Keywords: Channel estimation · Blind · Geometric approach
Sources separation · MIMO

1 Introduction

The huge demand of bandwidth despite the progress of signal processing is still challenging the spectral channel efficiency. One potential solution is the blind channel estimation which becomes an opportunity for new investigations. It is the reason why in recent years, many researchers in signal processing have focused on the problem of blind sources separation approaches [1–10]. This is due to voracity in data rate of applications and bandwidth cost of actual methods to ensure the restitution of the transmitted sequence. Moreover, with increasing variety of applications requiring high data rate, wireless communication systems become more and more complex at the physical layer. Efficient method could considerably increase the data rate. Blind sources separation (BSS) consists in retrieving a vector of n independent sources signals noted, determined from a vector of m observations. The term blind assumes that there is no prior information on the n sources and on the mixture system. According to the value of n and m, we can deduce:

- under-determination problem if $m < n$, less observations points than sources number;
- over-determination problem if $m > n$, more observations points than sources number;
- determination problem if $m = n$, as observations points equals to sources number.

C. M. F. Kebe et al. (Eds.): InterSol 2017/CNRIA 2017, LNICST 204, pp. 234–244, 2018.
https://doi.org/10.1007/978-3-319-72965-7_22

Different methods including subspace [9, 11], receiver diversity [12, 13], precoding and geometric approach [1, 14–17] have been investigated. Our interest in simple and accurate approach of channel estimation without any prior information on the transmitted data has led to reinvestigate on the pure geometrical method of blind source separation which was first introduced by Puntonet et al. in [1] which pointed out the disadvantage of previous source separation approach due to its complex algebraic calculations. Puntonet has noted that an alternative approach could consist of estimating, by geometric method, these channel parameters. This has the advantage to be simpler compared to the others. The existing geometric approach of sources separations has been abandoned because of its poor performance. In addition to this, it has just considered the case of real parameters of the sources and the channels. MIMO systems channel estimation for complex channel with better performance has been investigated in this paper. The proposed method operates by identifying matrix parameters from geometric consideration depending on the probabilistic hypothesis of the source. It is an approximated maximum likelihood estimation method which proceeds by determining the polyhedral edges tilts representing the matrix parameters. The simplicity of this method is based on the cloud observation which is used to determine the edge of parallelogram which describes the matrix channel parameter.

The rest of this paper is organized as follows. In Sect. 2, a summary of related works considering the simple case study of real channel and real source has been presented. Section 3 depicts the new geometric approach of source separation for 2×2 systems (GASS2), which is more efficient compared to the existing one. Section 4 tackles the geometric approach of channel estimation (GACE) in the case of real channel parameters coupled with higher modulation. A conclusion ends this work.

2 Related Works

Let's consider an access system where a given user terminal equipped with a system of n sources or transmitting antennas which send data to a common base station using also m receiving antennas (Fig. 1). To simplify our work, the case of two sources and two receivers, (2×2), is studied. It could be generalized to higher MIMO systems. The data sent are supposed real. The number of possible combinations of symbols to be transmitted according to the number of antennas result in a cloud of p groups symbols. The

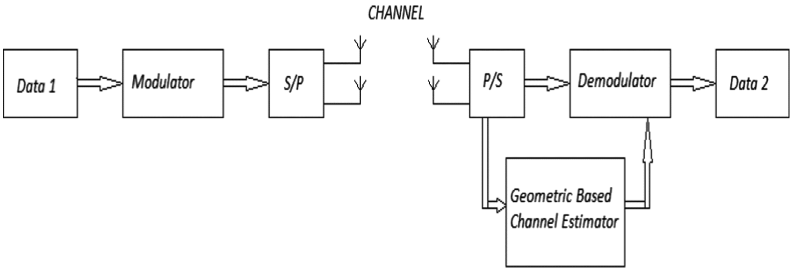

Fig. 1. Transmission system

modulated data is sent without any training sequences. The received data depend on the channel conditions. Once the data is received at the destination, it is processed in order to estimate firstly the channel parameters.

The data are received after it had undergone channel mixture. In Fig. 1, the signal processing at the receiver side is divided in successive groups of n data blocs which are a mixture of signals from different antennas. At this stage, the communication channel state information between a given transmit antenna and a receiving antenna is unknown and the transmitted sequences are also a priori completely unknown by the receiver. In the case of coherent detection, the channel parameters need to be estimated and these are used to recover the symbols sequences sent by each transmitting antenna. The main related work is the one of Puntonet et al. [14–16]. The problem of blind source separation and blind channel estimation lead to a restitution of a message transmitted without knowledge on the sources and the channels properties. The system could be separated into three components which are: the transmitting part including the sources, the channel and the receiving part.

It has been noticed in [14–16] the complex calculations as disadvantage of algebraic approach. An alternative approach has been to investigate on geometric technique to estimate the channel parameters. The main advantage is that it is simpler. The data are transmitted simultaneously by all the transmit antennas. The received signal at the destination by each antenna branch i at a given time t is affected by the channel conditions at this moment and it could be expressed as follows:

$$\forall i \in \{1, \cdots, m\} \;\; \mathrm{y_i} = \sum_{j=1}^{n} h_{ij} x_j + W_i \tag{1}$$

where y_{i} is the signal at the ith receiving antenna from the n transmits antennas;

- $h_{\mathrm{i,j}}$ is the channel parameter between the source j and the ith receiving antenna;
- x_{j} is the data emitted by the jth transmit antenna;
- n is the number of transmit antennas;
- W_{i} is an additive hite Gaussian noise (AWGN) with zero mean and variance σ^2 at the receiving branch i.

Receiving antennas generate m mixtures of n sources.

Then, as in [14–16], the system studied could be rewritten at the cost of constant algebraic factors as:

$$\begin{cases} y_1 = x_1 + a x_2 \\ y_2 = b x_1 + x_2 \end{cases} \tag{2}$$

where

- y_1 and y_2 are the received samples by antennas 1 and 2 respectively,
- a and b are the unknown channel parameters to be determined based on geometric approach,
- x_1 and x_2 are data sent by transmitting antennas 1 and 2 respectively,
- the condition of Puntonet is assumed to be satisfied for:

$$H = \begin{pmatrix} 1 & a \\ b & 1 \end{pmatrix}$$

The approach presented in [14–16] to estimate a and b consists in translating to the origin the highest point determined with the highest norm from the cloud of points described by the parameters (y_1, y_2).

Puntonet and Ali Mansour have presented the previous geometric algorithm in two steps. The first step consists in translating the cloud using the maximum norm and a second step consists in estimating the edge slope on the limiting parallelogram of cloud. Actually, their approach presents an instability while processing the first step. The limitation of this old method relays in the translated cloud while inappropriate norm is founded at the first iteration. It sometimes requires over two, three or four iterations to get satisfactory results. More disconcerting, the max used instead of the min translates the cloud in the first or third dial. This prevaricates the edge calculation using the translated cloud. These might be probably the main reason why this method is abandoned.

3 GASS2 Algorithm

In this section, a geometric approach of source separation for 2×2 systems denoted GASS2 is presented. It is an improved algorithm compared to the existing ones.

A geometric approach of source separation for 2×2 were discussed in [17] but it is refined in this paper as follows:

- First step, computation of the cloud to get the minima of each axis by (min (y_1), min (y_2)) that means translating the values of each antenna to origin by using the minimum of the value received on the antennas,
- Second step consists to estimate the slope of the limiting parallelogram using the (min(y_i (n)/y_j(n)) for i, j Є{1,2} and $i \neq j$.

An evaluation test on 1000 samples has been performed in Fig. 2. A cloud weight with 8 as size of source alphabet is considered. The results clearly show that GASS2 has outperformed the old geometric approach reducing drastically the RMSE which were order of 10^{-1} to order of 10^{-16}.

The new way the second step is implemented gives better results in comparison with the one of Puntonet and Ali Mansour in [15, 16] where the edge were computed with the new origin. Better result is obtained while the edge has been computed from the max point of axis for all points having this coordinate superior to this max.

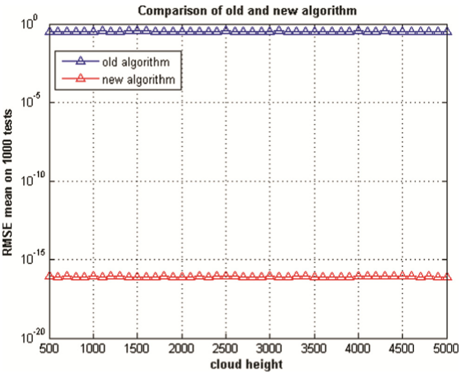

Fig. 2. GASS2 performance compared to previous geometric algorithm

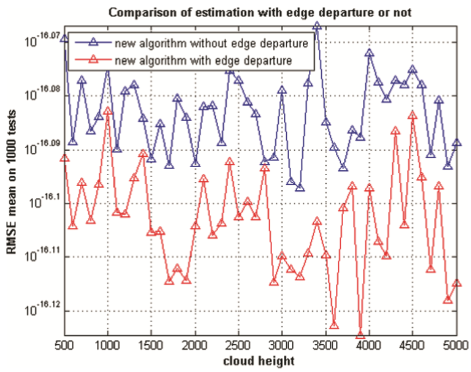

Fig. 3. Two sub cases of GASS2

With Fig. 3, it is easy to show that both ways to implement the second step of GASS2 present the same order (10^{-16}) of performance but the implementation with the edge calculation departure estimation is slightly more efficient to the implementation without estimating edge departure calculation. It is then interesting to deduce that for all height of cloud, the algorithm with edge departure calculation is always more efficient than the algorithm without edge departure calculation for any cloud height as shown on the following picture where the brown color represents the part of parallelogram with missing data in the observation space. In red marked, we have the departure for the edge calculation (Fig. 4).

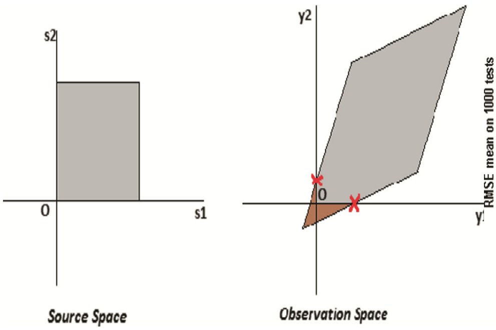

Fig. 4. Departure calculation problem (Color figure online)

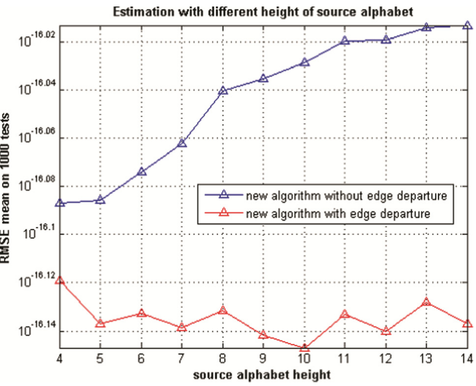

Fig. 5. GASS2 and alphabet height

The simulations have been done with a 5000 cloud weight in order to have more representative cloud. The following three tests compare each time GASS2 algorithm without edge departure calculation to edge departure calculation.

In Fig. 5, we compare both way for different size of source alphabet. It can be seen that the case with edge departure present better performance when the source alphabet size increase and on the other side, the performance without edge departure slightly degrades around 10^{-16}.

One can conclude from Fig. 5 that it shows edge departure calculation algorithm as more accurate because it is not badly affected by the size of the alphabet.

Figure 6 depicts the case of different gaps between consecutives elements of source alphabet for the same size with 8 as source alphabet size. The results show that the RMSE have the same behavior when the gap increase but edge departure algorithm is still more accurate.

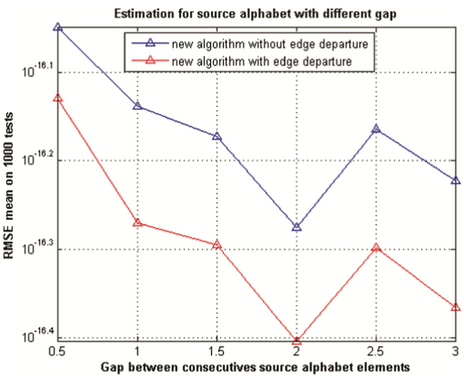

Fig. 6. GASS2 for gap between consecutives source alphabet

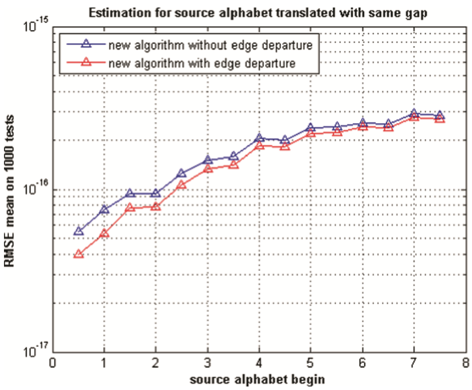

Fig. 7. GASS2 for alphabet first element with source alphabet size up to 8 and gap 2

The results in Fig. 7 is the investigation outputs of alphabets with the same set size and the same consecutive symbol deviation but different beginnings set. The mapping constellation size decreases when higher values of consecutive symbols are chosen. Figure 7 shows a decreasing performance while increasing the level of the first source alphabet. The same shape in both cases with better performance for departure calculation is depicted.

Figure 8 confirms the accuracy of GASS2 for any combination of channel parameters (a, b). It can be seen that the channel estimation still give the same order of RMSE around 10^{-16}.

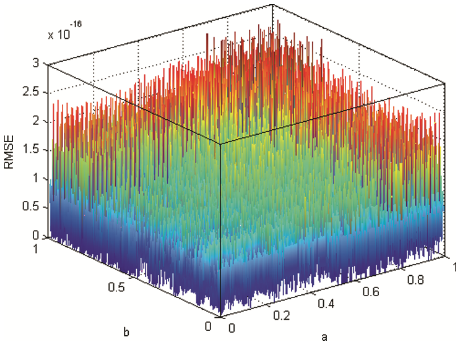

Fig. 8. GASS2 performance with mesh 0.005 for source alphabet size 8

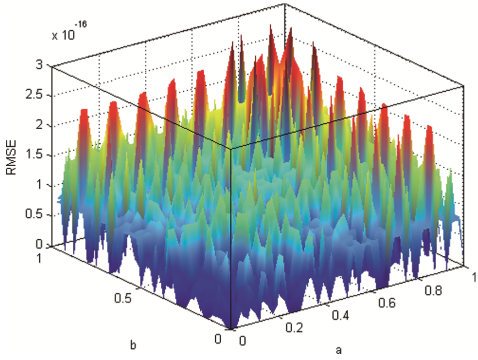

Fig. 9. GASS2 performance with mesh 0.025 for source alphabet size 8

For practical reasons, we adopt a meshing step 0.025 to view channel parameters restitution topology as shown in Fig. 9 because it is easier to appreciate and compare a topology at this meshing level. This mesh allows us to compare easily different topologies in their presentation and view. The topologies are presented with an interpolation option. Compared to the finer meshing in Fig. 8, the interpolation between RMSE points is not acceptable but this can give a different overview on topology according to the selected meshing and the source alphabet.

9.93%, 8.12% and 8.54% are respectively the percentage for the perfect estimated combinations for the precision 0.025, 0.005 and 0.001 depending on the parameters tested (source alphabet size, deviation between consecutives words, source alphabet beginning) as showed in the previous pictures (Table 1).

Table 1. Combination for a perfect estimation and different channel precision meshing for source alphabet size 8.

Mesh (Channel parameters precision)	All combination estimated	Combination estimated perfectly
0.025	1681	167
0.005	40401	3281
0.001	1002001	85631

The two previous topologies obtained have shown that, for some combination of *a* and *b*, the RMSE of the parameters estimation is equal to zero and that means the estimation is perfect and provides the right channel parameters and a general order of 10^{-16} compared the old algorithm where we have less performances in the order of $10^{-1,5}$ in general.

This new algorithm presented is improved according to the two ways to implement the second step in the noisy conditions on the channel propagation where it has been considered increasing SNR (Signal Noise Ratio) per step of 10 dB in order to appreciate the resistance to noise.

Figure 10 depicts the bad impact of noise. In its first plot, it has been noticed the same performances as previously presented for both ways to estimate the slope (without and with edge departure calculation) on 20 series of 1000 tests, the second plot and third plot show that if only one of both receivers is affected by the noise, the performance increases with the SNR but in the fourth plot, it can be noticed the actual limitations of geometric approaches have not improved anymore even for SNR greater than 40 dB.

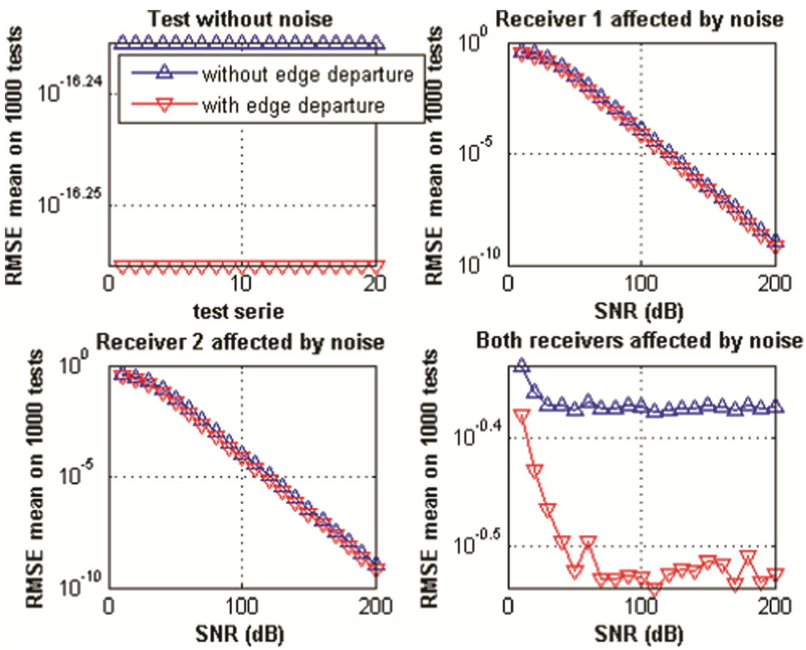

Fig. 10. RMSEs in noisy condition

4 Geometric Approach of Channel Estimation (GACE2)

The estimation of a and b where performed before in [17] with the improved algorithm of the geometric approach by translation to the origin of the lowest point determined with the minima on each axe from the cloud of points described by the parameters (y_1, y_2) as:

$$(\min(y1), \min(y2)) \tag{3}$$

$$y = Hc + W \tag{4}$$

where $x = c$ and W are complex variables. PSK or QAM symbols are considered but the channel is supposed real. Expression (4) could be rewritten as:

$$y = H(\Re(c) + j\Im(c)) + W \tag{5}$$

In the case of noiseless model

$$y = H(\Re(c)) + jH(\Im(c)) = \Re(y) + j\Im(y) \tag{6}$$

where the considered system presents imaginary and real parts as follows:

$$\begin{cases} \Re(y) = H\Re(c) \\ \Im(y) = H\Im(c) \end{cases} \tag{7}$$

For a 2 × 2 MIMO system, we get:

$$\begin{cases} \begin{pmatrix} \Re(y_1) \\ \Re(y_2) \end{pmatrix} = \begin{pmatrix} 1 & a \\ b & 1 \end{pmatrix} \begin{pmatrix} \Re(c_1) \\ \Re(c_2) \end{pmatrix} \\ \begin{pmatrix} \Im(y_1) \\ \Im(y_2) \end{pmatrix} = \begin{pmatrix} 1 & a \\ b & 1 \end{pmatrix} \begin{pmatrix} \Im(c_1) \\ \Im(c_2) \end{pmatrix} \end{cases} \tag{8}$$

From the complex cloud of points, we can extract two sub-clouds, one for the real part and the other for the imaginary part. Then the coefficients a and b can be derived from the ratio of real part of y_2 over real part of y_1 and the ratio of imaginary part of y_2 over imaginary part of y_1. In theory, it is possible to return the same coefficients by the two extracted clouds when the constellation presents for real and imaginary parts the same configuration and the same representativeness. We have experienced slightly

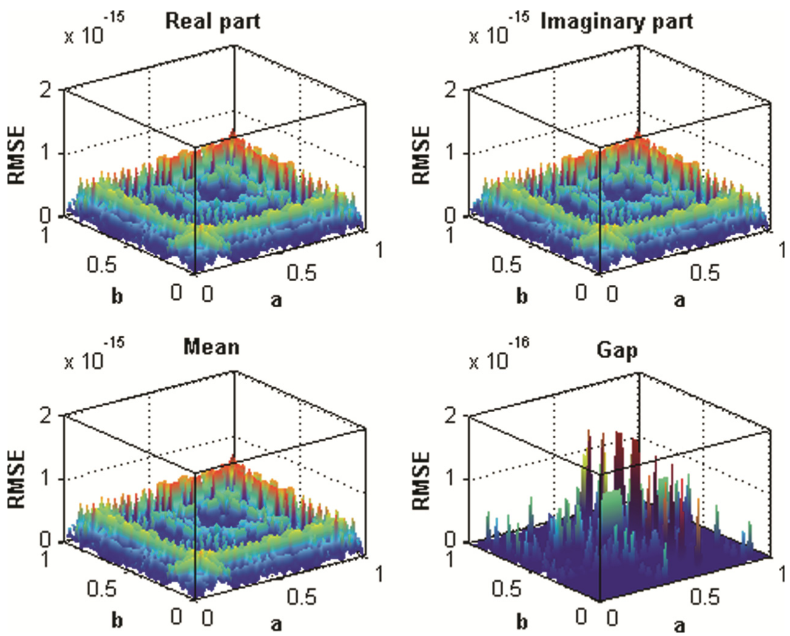

Fig. 11. RMSEs topologies for 8PSK constellation for real part, imaginary part, mean and gap view

different values in this case study. In the determination of the polyhedral edges tilts representing the matrix parameters, the tilts are not determined according to the origin but respectively from the point with highest norm in each axis. This method assures that in the absence of noise the tilts are calculated based on the origin.

Reading Fig. 11 above one can notice that the mean are adequate in certain case and the gap is negligible.

5 Conclusion

Blind channel estimation remains a challenge. This work has focused on geometric approach of channel estimation (GACE). An improved geometric approach of source separation (GASS) has been introduced. A 2×2 system with real channel and complex channel parameters have been discussed. The appropriate GACE algorithm has been derived.

References

1. Zhu, H., Zhang, S., Zhao, H.: Single channel source separation and parameter estimation of multi-component PRBCPM-SFM signal based on generalized period. Digit. Sig. Process. **40**, 224–237 (2015)
2. Acar, Y., Doğan, H., Panayırcı, E.: On channel estimation for spatial modulated systems over time-varying channels. Digit. Sig. Process. **37**, 43–52 (2015)
3. Besseghier, M., Djebbar, A.B.: New design of pilot patterns for joint semi-blind estimation of CFO and channel for OFDM systems. AEU Int. J. Electron. Commun. **69**(4), 759–764 (2015)
4. Michelusi, N., Mitra, U.: Cross-layer design of distributed sensing-estimation with quality feedback—part II: myopic schemes. IEEE Trans. Sig. Process. **63**(5), 1243–1258 (2015). https://doi.org/10.1109/TSP.2014.2388440
5. Wenbo, D., Fang, Y., Wei, D., Jian, S.: Time–frequency joint sparse channel estimation for MIMO-OFDM systems. IEEE Commun. Lett. **19**(1), 58–61 (2015). https://doi.org/10.1109/LCOMM.2014.2372006
6. Du, J., Yuan, C., Zhang, J.: Semi-blind parallel factor based receiver for joint symbol and channel estimation in amplify-and-forward multiple-input multiple-output relay systems. IET Commun. **9**(6), 735–744 (2014). https://doi.org/10.1049/iet-com.2014.0553
7. Frederico, B., et al.: Multiple-antenna techniques in LTE-advanced. IEEE Commun. Mag. **50**(3), 114 (2012)
8. Comon, P., Jutten, C.: Handbook of Blind Source Separation: Independent Component Analysis and Applications. Academic Press, Cambridge (2010)
9. Gao, F., Zeng, Y., Nallanathan, A., Ng, T.-S.: Robust subspace blind channel estimation for cyclic prefixed MIMO ODFM systems: algorithm, identifiability and performance analysis. IEEE J. Sel. Areas Commun. **26**(2), 378–388 (2008)
10. Shin, C., Heath, R.W., Powers, E.J.: Blind channel estimation for MIMO-OFDM systems. IEEE TVT **56**(2), 670–685 (2007)
11. Abed-meraim, K., Cardoso, J., Gorokhov, A., Loubaton, P., Mouliness, E.: On subspace methods for blind identification of single input multiple output FIR systems. IEEE Trans. Signal Process. **45**(1), 42–55 (1997)

12. Wang, H., Lin, Y., Chen, B.: Data – efficient blind OFDM channel identification using receiver diversity. IEEE Trans. Signal Process. **51**(10), 2613–2622 (2003)
13. Kora, A.D., Cances, J.P., Meghdadi, V., Vianou, A.: Blind MIMO OFDM channel estimation based on receiver diversity. Mediterr. J. Electron. Commun. **3**(1), 31–39 (2007)
14. Mansour, A.: Contribution à la séparation aveugle de sources: Ph.D. Dissertation. At Institut National Polytechnique de Grenoble, pp. 41–46 (1992)
15. Puntonet, C.G., Prieto, A., Jutten, C., Rodriguez-Alvarez, M., Ortega, J.: Separation of sources: a geometry based procedure for reconstruction of n-valued signal. Sig. Process. **46**(3), 267–284 (1995)
16. Puntonet, C.G., Mansour, A., Jutten, C.: Geometrical algorithm for blind separation of sources. In: Actes du XVeme colloque GRETSI, Juan-Les-Pins, France, pp. 273–276 (1995)
17. Ahossi, A.B., Kora, A.D., Faye, R.M.: MIMO blind channel estimation based on geometric approach of source separation. In: ICEER 2013, pp. 63–68 (2013)