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An overview of maximum-likelihood based algorithms for estimating multipath parameters

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Abstract

Recently the European research trend has shown an increased interest on the use of maximum-likelihood based algorithms, e.g. the Space-Alternating Generalised Expectation-maximisation (SAGE) algorithm, to estimate multipath parameters from raw measurement data. This process can require considerable processing time and resources, especially when dealing with vast multi-dimensional measurement databases. With the aim of achieving significant timesaving, and reducing both the memory utilisation and processing power of computing resources, different versions of maximum-likelihood based algorithms have been developed. This paper provides a general overview of these algorithms based on different implementation methodologies that can achieve the above objectives successfully, subject to some prerequisites. A number of results based on numerical simulations and real measurement data is also presented.

I. Introduction

Channel models now play an important role in wireless communications research that a rigorous understanding of multipath propagation mechanisms in different operational environments is essential. With the advances in different wireless signal processing algorithms (e.g. space-time coding) and modulation techniques, a realistic channel model is required as long as computer simulation is concerned. Such model requires a sensible statistical distribution of several channel parameters and an efficient way of obtaining such information is by performing channel sounding. When post-processing the raw measurement data, a reliable high resolution multipath parameters estimation algorithm will normally be used. To date, there are a number of efficient and recommended algorithms that a user can choose from, e.g. MUltiple Signal Classification (MUSIC) [1], Estimation of Signal Parameters via Rotational Invariance Technique (ESPRIT) [2], Expectation-Maximisation (EM) [3], and Space-Alternating Generalised Expectation-maximisation (SAGE) [4] algorithms.

Recently the European research trend has shown an increased interest on the use of maximum-likelihood based algorithms, e.g. SAGE algorithm, to estimate multipath parameters from raw measurement data. This is due to the high degree of flexibility and robustness of such algorithms especially when dealing with circular array geometries (which is the preferred choice of array at present). Although both EM and SAGE algorithms belong to the same family of maximum-likelihood estimators, the convergence rate of the SAGE algorithm is significantly faster than the EM algorithm due to different complexity levels when implementing the algorithms. However, multipath parameters estimation with the SAGE algorithm still requires a large amount of time and efforts especially when dealing with vast multi-dimensional measurement databases (due to the iterative nature of the algorithm). With the aim of achieving further timesaving, and reducing both the memory consumption and processing power of computing resources, different versions of the maximum-likelihood based algorithms (with more emphasis on SAGE) have been developed as further explained below.

This paper gives a general overview of these algorithms based on different implementation methodologies that can achieve the above objectives but subject to some prerequisites. Note that the full implementation of these algorithms will not be addressed here but is referred to the previously published papers. The fundamental properties of the algorithms are highlighted, and some important issues directly related to their estimation accuracy and reliability are discussed. In addition, a few recommendations based on the experience of authors are also given. A number of sample results based on numerical simulations and real measurement data is presented. Note that although the algorithms described herein are developed specifically for use with the Medav RUSK BRI channel sounder [5], the concept and implementation philosophy can also be applied elsewhere.

II. Data model revisited

This section briefly describes the data model that is used throughout all the proposed algorithms. Due to the nature of the Medav RUSK sounder [5], the channel is most conveniently modelled in the frequency domain. The R-dimensional (R-D) sounding snapshot data can be represented by an R-D data array in frequency domain, $\mathbf{H}$, whereby its element is given by:

$$H_{k_1,k_2,\cdots,k_R} = \sum_{l=1}^{L}\left(\gamma_l \prod_{r=1}^{R} g_{k_r}\left(\mu_l^{(r)}\right)\cdot e^{-jk_r\mu_l^{(r)}}\right) + N_{k_1,k_2,\cdots,k_R} \tag{1}$$

where $k_r \in [0, K_r - 1]$ denotes the entry of the R-D array, K_r is the number of elements in the r-th dimension array, $\mu_l^{(r)}$ represents the normalised l-th path's r-th dimension harmonic (i.e. parameter to be estimated, which is related to the physical multipath parameter by a certain unique projection), $g_{k_r}\left(\mu_l^{(r)}\right)$ is the response of the k_r-th element with respect to argument $\mu_l^{(r)}$, γ is the path weight, L is the number of multipath components, and N is complex Additive White Gaussian Noise (AWGN). Effectively, (1) represents an R-D data model consisting of superposition by L undamped exponential modes and the parameters estimation process is equivalent to an R-D harmonic retrieval problem. This model utilises the fact that the response from one element to the next across an r-th dimension array (in spatial, temporal, or frequency domain) can be represented by a certain phase shift value. The narrowband plane wave assumption must hold for direction-of-arrival / departure (DoA/DoD) estimation. In addition, the condition of $\Re\left\{\mu_l^{(r)}\right\} \in [0, 2\pi]$ must be fulfilled to avoid any estimation ambiguity (following from Shannon's sampling theorem), whereby $\Re\{\ \cdot\ \}$ denotes the range space of the argument. This suggests the importance of array element spacing setting in a particular dimension in order to support parameter estimation in which its range encompasses a certain minimum and maximum value without any ambiguity.

Note that the model given in (1) is the classical point-source model that has been widely used in various parameter estimation algorithms [1-4], in which the sources are normally assumed to be separated reasonably far apart (at least in one dimension) such that they are resolvable. However, it is very likely that a number of multipaths originate from a same spatial-temporal region, i.e. a cluster, such that all multipaths within a cluster are closely spaced together in all dimensions. Hence, with a slight modification, (1) can be expanded to represent a channel in a distributed-source environment in order to take the clustering phenomena into account. Without loss of generality, the distributed-source channel can be modelled as:

$$H_{k_1,k_2,\cdots,k_R} = \sum_{c=1}^{C}\sum_{l=1}^{L_c}\left(\gamma_{c,l} \prod_{r=1}^{R} g_{k_r}\left(\mu_{c,l}^{(r)}\right)\cdot e^{-jk_r\mu_{c,l}^{(r)}}\right) + N_{k_1,k_2,\cdots,k_R} \tag{2}$$

$$\mu_{c,l}^{(r)} = \mu_c^{(r)} + \delta\mu_{c,l}^{(r)} \tag{3}$$

where C is the number of clusters, L_c is the number of multipath components within a cluster (i.e. distributed sources), $\mu_c^{(r)}$ is the r-th dimension nominal parameter (i.e. centroid) of the c-th cluster, and $\delta\mu_{c,l}^{(r)}$ is the r-th dimension parameter deviation from $\mu_c^{(r)}$ for the l-th path within the c-th cluster. It is reasonable to assume that the sources within a cluster are coherent and complex-weighted replicas of each other. The distribution of $\mu_{c,l}^{(r)}$ can be modelled according to some standard distribution function, e.g. Gaussian, uniform, exponential, etc. For simplicity, we assume that the clusters do not overlap with each other.

Note that in a distributed-source environment, it is impossible for any existing high-resolution estimation algorithm to fully resolve all the $\sum_{c=1}^{C} L_c$ waves. This is due to the fundamental resolution limit of the measurement system which is mainly determined by the effective aperture size in any dimension, i.e. the number of elements on the array (with proper element spacing). However, it is likely that the estimation algorithm is able to estimate the nominal parameter values of each cluster, since the multipath parameters of very closely spaced coherent paths degenerate into a single value (usually the centroid of the cluster) within the estimation process.

III. Beamspace processing

Traditionally, the estimation algorithms are implemented in the element-space (ES) domain, whereby the full dimensionality of input data size is used throughout the estimation process. In [6], a newly developed beamspace (BS) SAGE algorithm that is able to reduce the overall dimensionality of the input data size is proposed. Although [6] presents the full implementation of BS processing with respect to the SAGE algorithm, it is also equally possible to apply this method to the EM algorithm. Note that the proposed implementation is only applicable to linear array that exhibits Vandermonde structure in its steering vector. Proper full system calibration prior to measurement is also necessary in order to fully exploit the advantages of BS processing.

In BS processing, the original raw data in the ES domain is first transformed into the BS domain with a certain scaled DFT beamforming matrix $\mathbf{W}_m^{(r)}$:

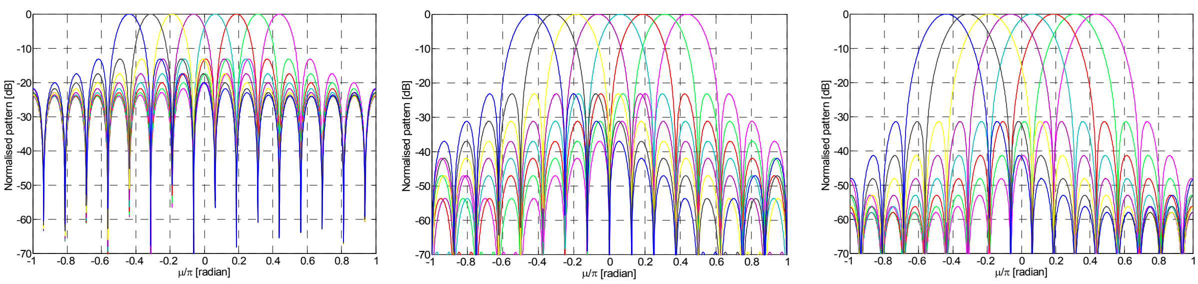
$$\mathbf{W}_m^{(r)} = \left[\mathbf{w}^{(r)}\left(m\frac{2}{K_r} \right) \vdots \; \mathbf{w}^{(r)}\left([m+1]\frac{2}{K_r} \right) \vdots \; \cdots\cdots \; \vdots \; \mathbf{w}^{(r)}\left([m+B_r-1]\frac{2}{K_r} \right) \right] \tag{4}$$

$$\mathbf{w}^{(r)}(\beta) = e^{-j\frac{K_r-1}{2}\pi\beta} \left[1, e^{j\pi\beta}, e^{j2\pi\beta}, \ldots\ldots, e^{j(K_r-1)\pi\beta} \right]^T \tag{5}$$

where m is a parameter that determines the position of all B_r beams across the array aperture, and the superscript T denotes vector transposition. The transformation maps the r-th dimension ES data of size K_r into the BS domain of size B_r, where B_r is the number of consecutive orthogonal beams in the r-th dimension. Reduction of data size is achieved when $B_r \leq K_r$, and subsequent processing can be concentrated in the region encompassed by the beams .

With a reduction in resultant input data size, BS processing manages to reduce the computational burden, memory consumption, and overall processing time of the algorithm (since the processing is focused on the region enclosed by the beams). A major advantage of the BS processing is its ability for mapping onto parallel processors. Different R-D subbands can be formed with different R-D BS transformation matrices. This procedure sectorises the original data into different regions of smaller size and all sectors can then be processed in parallel in the BS domain. This feature is beneficial if the estimation algorithm were to be implemented in digital hardware. A lower computational complexity and lesser memory consumption enable BS processing to be implemented in real time.

However, BS processing is only advantageous in the presence of a priori channel information, such that beams can be formed in regions where multipaths exist. If the beamforming process does not encompass the entire region where multipaths exist, the estimation of signals within the in-band sector might be affected by the interference of strong signals lying in the out-of-band sector (due to high sidelobe level in out-of-band region). Hence, in the absence of any a priori channel information, the influence of out-of-band components must be minimised so that the estimation within the in-band region is not subject to any significant interference from the out-of-band components. This can be achieved by applying a suitable windowing function (only for BS processing) to de-emphasise all out-of-band components whilst processing is concentrated in the subband of interest. Figure 1 shows the effect of beamforming process with different windowing functions. The influence of any out-of-band components is minimised with a reduced sidelobe level. However, this is achieved with a penalty of reduced resolution due to the broadening of main beams when windowing is applied. The resolution is reduced by 50% with a cosine window, and 100% with a hanning window.



a – no windowing   b – with cosine windowing   c – with hanning windowing

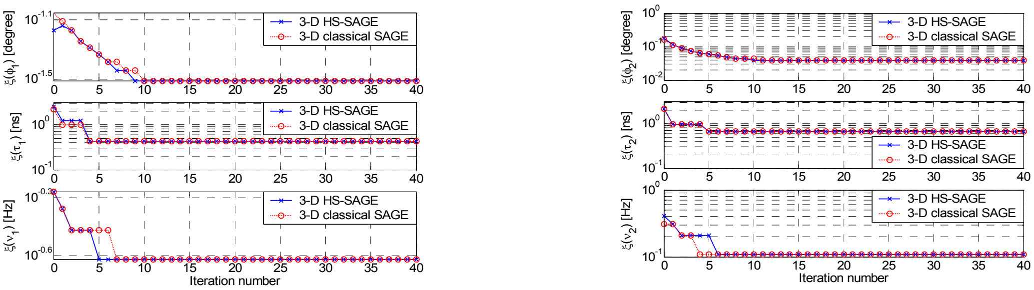
Figure 1: Illustration of different windowing effects in beamforming process (centred at 0 rad)

IV. Hybrid-space processing

Despite the advantages offered by BS processing, most researchers still prefer to process their data in the ES domain due to its implementation simplicity. Moreover, not all arrays are suitable for BS processing. A good example for this is a circular array, which has received considerable attentions around Europe in recent years due to its ability to provide full spatial view of the channel. As far as a circular array is concerned, it is recommended to process the data associated with the spatial domain in classical ES domain. Hence, in order to combine the advantages of both BS and ES processing, a new implementation of the SAGE algorithm has been proposed in [7]. The algorithm processes the data in joint ES and BS domains, namely the hybrid-space (HS) domain. Similarly, its implementation philosophy can also be applied to the EM algorithm.

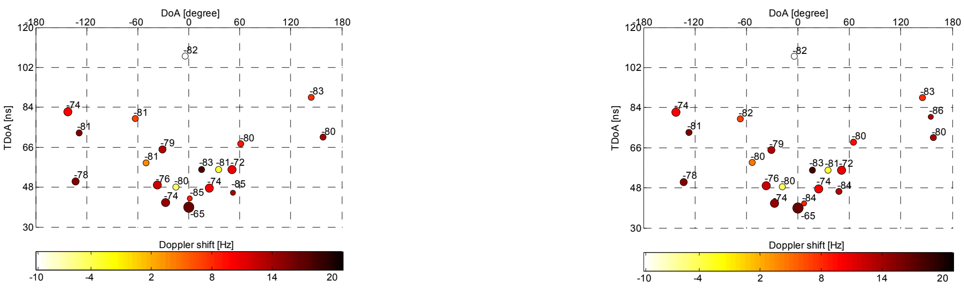
One can exploit the benefits of HS processing when at least one of the arrays (in multi-dimensional processing) has large number of elements (say more than 50). We can estimate the parameters in a particular dimension corresponding to the array with small number of elements in normal ES processing, and apply BS processing simultaneously in another dimension with large number of elements. Thus, a reduction in overall computational complexity and effective processing time is achieved. Furthermore, the automatic pairing procedure of the estimated parameters in all dimensions can still be performed in the standard manner within HS processing. Note that the array data size in BS domain cannot be reduced too much (more than 50%, say, compared to that of ES domain). This is due to the decreased degrees of freedom in resolving multipath components in BS domain with a reduction of data size (i.e. reduction of number of array elements in BS domain). In addition, the multipath components must lie well within the region encompassed by the beams.

In [7], a synthetic simulation environment is set up to evaluate the estimation error, $\xi(\cdot)$, of nominal parameters in each iteration in a 2-cluster distributed-source environment. A circular array is used in the spatial domain. Three nominal parameters are considered: DoA (ϕ), time-delay-of-arrival (TDoA-τ), and Doppler shift (ν). The nominal DoA is estimated in the ES domain, while the nominal TDoA and Doppler shift are estimated in the BS domain (without windowing). Figure 2 displays the estimation errors of both 3-D HS-SAGE and classical SAGE algorithms. It can be appreciated that both algorithms exhibit similar convergence rate and estimation errors. However, the relative processing time of the HS-SAGE algorithm is shorter due to its reduced input data size and complexity. In addition, the HS-SAGE algorithm has also been applied to real measurement data [7] and its estimation result is shown in Figure 3 together with that of the classical SAGE algorithm. It can be seen that its result is also very similar to that of the classical SAGE algorithm, but with a reduction in overall computational burden (≈0.6 processing time ratio with respect to that of the classical SAGE algorithm).



a – 1st cluster b – 2nd cluster

Figure 2: Estimation error of the nominal parameters in each iteration in a 2-cluster distributed-source environment



a – 3-D HS-SAGE algorithm b – 3-D classical SAGE algorithm

Figure 3: Estimated results from real measurement data [7], path weight [dB] is printed on figures

V. Unitary transformation

By exploiting the special centro-Hermitian property of the measurement data with a linear array (or array with column conjugate symmetric steering vector), the Unitary-SAGE (U-SAGE) [8] algorithm has been developed. Part of its implementation is similar to the Unitary ESPRIT [9] algorithm, whereby the unitary matrices are used at the beginning of the algorithm. The original data in the ES domain is first transformed into its '*unitary-space*' counterpart with the following unitary matrix of even order (left) or odd order (right):

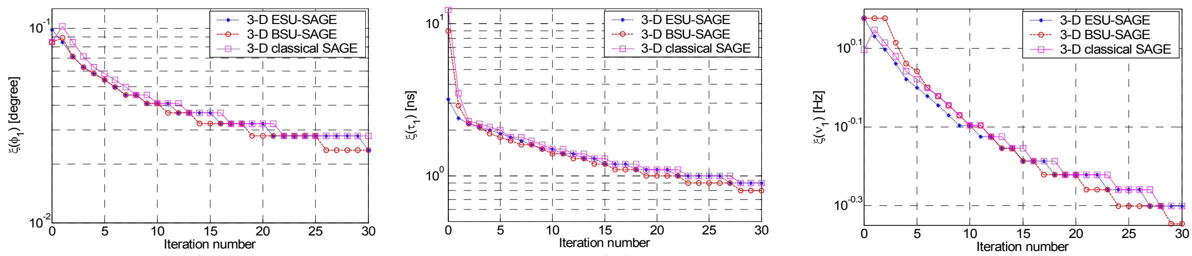
$$\mathbf{Q}_{2n} = \frac{1}{\sqrt{2}}\begin{bmatrix} \mathbf{I}_n & j\mathbf{I}_n \\ \mathbf{\Pi}_n & -j\mathbf{\Pi}_n \end{bmatrix} \qquad \mathbf{Q}_{2n+1} = \frac{1}{\sqrt{2}}\begin{bmatrix} \mathbf{I}_n & \mathbf{0} & j\mathbf{I}_n \\ \mathbf{0}^T & \sqrt{2} & \mathbf{0}^T \\ \mathbf{\Pi}_n & \mathbf{0} & -j\mathbf{\Pi}_n \end{bmatrix} \tag{6}$$

where $\mathbf{I}_n$ is the n x n identity matrix, $\mathbf{\Pi}_n$ is the n x n exchange matrix with 1's on its anti-diagonal and 0's elsewhere, and $\mathbf{0}$ is the n x 1 column vector of 0's.

Note that these unitary matrices are sparse (virtually no memory consumption) and column conjugate symmetric (also known as left Π-real and conjugate centro-symmetric [9]). Since the algorithm is restricted to centro-symmetric array (also with column conjugate symmetric steering vector), the entire maximisation step (M-step) can be implemented in the real-valued domain (refer to [8] for its full implementation). This can significantly boost up the effective processing speed of the algorithm since the computation within the M-step is no longer implemented in the complex-valued domain. Recall that one complex-valued multiplication involves four real-valued multiplications and two real-valued additions. Similarly, the U-SAGE algorithm can also be implemented in the ES or BS domain, or a combination of both as in HS processing. In addition, the restriction imposed on this implementation method implies that a proper system calibration routine in all dimensions (space, frequency, temporal) must be performed.

On the other hand, although a circular array is not suitable for the U-SAGE algorithm due to its structure (nonlinear), special treatment (to a certain extent) can be made in order to apply the U-SAGE algorithm with a circular array. The circular array structure (nonlinear) can be mapped to a linear structure of a virtual array by means of phase-mode excitation technique [10]. However, this mapping is just an approximation and is only suitable for circular array with large number of elements (say >30, in order to reduce the overall mapping error). The overall accuracy and resolution of the system is also reduced due to the unavoidable mapping error with discrete phase-mode transformation. Therefore, it is recommended that the U-SAGE algorithm should only be applied with the linear arrays.

A 3-D 2-path synthetic environment has been set up in [8] to compare the performance of the ESU-SAGE, BSU-SAGE (40% data size reduction, without windowing), and classical SAGE algorithms. The simulation is implemented using a same computer with a same set of synthesised data and the overall processing time of each algorithm is recorded. Three parameters are considered (ϕ, τ, ν) and the estimation errors, $\xi(\cdot)$, in each iteration is shown in Figure 4. It can be seen that the U-SAGE algorithm exhibits a similar performance (in terms of accuracy and convergence characteristics) as the classical SAGE algorithm. However, there are significant differences in their total processing time (T – see figure's caption). The main reason for timesaving is that the entire M-step in every iteration is implemented in the real-valued domain, which is the main advantage of using the unitary transformation, subject to the prerequisites stated above. Note that strictly speaking, the unitary matrix is not used in the BSU-SAGE algorithm. But since the BS transformation matrix is also column conjugate symmetric, real-valued implementation is feasible and the authors have used a similar name for the same implementation.



a – $\xi(\phi_1)$ b – $\xi(\tau_1)$ c – $\xi(\nu_1)$

Figure 4: Estimation errors of the algorithms, $T_{\text{ESU}} : T_{\text{BSU}} : T_{\text{classical}} = 0.41 : 0.22 : 1.00$

VI. Coping with distributed-source environments

In a real environment, it is very likely that clusters of rays (i.e. distributed sources) exist that the point-source assumption is inappropriate to represent the data model used in the estimation algorithms. The spatial-temporal spread of the multipaths within a cluster violates the point-source assumption and has been identified to be the main reason for performance degradation of the estimation algorithms [11]. Sources within a cluster are very closely separated (within very small fraction of the Rayleigh resolution) that none of the existing estimation algorithms can fully resolve them successfully. The distributed sources result in the model-mismatch problem within the estimation algorithms. More specifically, the model-mismatch effect increases the probability of estimating phantom paths (non-existent paths), especially for maximum-likelihood algorithms based on successive interference cancellation (SIC) technique. This is due to the imperfect signal cancellation effect using a point-source model in the *Expectation-step* (E-step). To overcome the problem, recent research has been directed towards the investigation of distributed-source modelling and here one of the possible solutions that have been examined [12] is presented.

For brevity, we consider a 2-D scenario that involves DoA (with uniform linear array) and TDoA estimation. We adopt the distributed-source modelling approach in [13] and expand it into a multi-dimensional case in the frequency domain. Referring to (2), the 2-D model considered here can be represented by:

$$H(f,s)=\sum_{c=1}^{C}\sum_{l=1}^{L_c}\gamma_{c,l}\cdot g_s\left(\theta_{c,l}\right)e^{-j2\pi(s-1)\frac{\Delta s}{\lambda}\sin\theta_{c,l}}\cdot g_f\left(\tau_{c,l}\right)e^{-j2\pi(f-1)\Delta f\tau_{c,l}}+N(f,s) \tag{7}$$

where f and s is respectively the data index in the frequency and spatial domain, Δf and Δs is respectively the array element spacing in the frequency and spatial domain, $\theta_{c,l}$ and $\tau_{c,l}$ is respectively the DoA (from array boresight) and TDoA of the l-th path in c-th cluster, and λ is the carrier wavelength. We assume the spread in each dimension within each cluster is small when compared with the 3 dB beamwidth of the respective array. According to [13] (for 1-D case), the model in (7) can be simplified to (8) based on first-order Taylor's series approximation:

$$H(f,s)\approx\widetilde{H}(f,s)=\sum_{c=1}^{C}\gamma_c\cdot g_s(\theta_c)e^{-j2\pi(s-1)\frac{\Delta s}{\lambda}\sin(\theta_c+j\Delta\theta_c)}\cdot g_f(\tau_c)e^{-j2\pi(f-1)\Delta f(\tau_c+j\Delta\tau_c)}+N(f,s) \tag{8}$$

where $\gamma_c=\sum_{l=1}^{L_c}\gamma_{c,l}$ is the resultant path weight of the c-th cluster, while $\Delta\theta_c$ and $\Delta\tau_c$ is respectively the DoA spread and TDoA spread of the c-th cluster.

Based on the approximated model in (8), the Enhanced-SAGE (E-SAGE) algorithm [12] has been developed. It only estimates the nominal parameters of the cluster and its spreads. The parameters for each of the multipath components within a cluster cannot be estimated due to the limited fundamental resolution of the algorithm (since the spread of the cluster is assumed small, i.e. < 3 dB beamwidth of the respective array). The implementation of the algorithm is similar to the classical manner, except that the approximated distributed-source model in (8) is used instead of the point-source model in (1), and the cluster spread parameters ($\Delta\theta_c$ and $\Delta\tau_c$) are included in the M-step within the iterations as one of the parameters to be updated.

The main advantage of using the approximated model in estimation is the ability to reduce the probability of estimating phantom paths. This is possible since the approximated model takes the spread of each cluster into account when implementing the E-step. This enables better signals cancellation, thus increasing the relative power difference between the strongest path and the phantom paths (a good condition for model order determination based on SIC technique). The accuracy of the estimated spread parameters increases as the spread of the cluster decreases, since the model error in the approximated distributed-source model (8) decreases as the spread of the cluster decreases.

A 2-cluster simulation environment has been set up to evaluate the performance of the E-SAGE algorithm using the approximated model [12], and compared with that of the classical SAGE algorithm using the point-source model. Ideally, the algorithms should estimate only 2 nominal parameters corresponding to 2 centroids of the clusters. Any path that is weaker (relative to the strongest path) more than a certain threshold level will be rejected as noise (based on the SIC technique). Figure 5 shows the cumulative distribution function (CDF) of path loss (relative to the strongest path) of the estimated 3rd and 4th paths (i.e. the 1st and 2nd phantom paths) with the SIC technique. It can be appreciated that the probability of estimating phantom paths with the E-SAGE algorithm is much lesser than the classical SAGE algorithm since the relative path loss of phantom paths with the E-SAGE algorithm is much larger than the classical SAGE algorithm. The main reason for this is that the E-SAGE algorithm is able to perform the E-step better than the classical SAGE algorithm in a distributed-source environment, thus better *complete data* estimation and greater phantom paths discrimination. In addition, the E-SAGE algorithm produces lower estimation errors than the classical SAGE algorithm, as indicated by the root-mean-squared error (RMSE) of the estimated nominal parameters in Figure 6 (across different realisations).

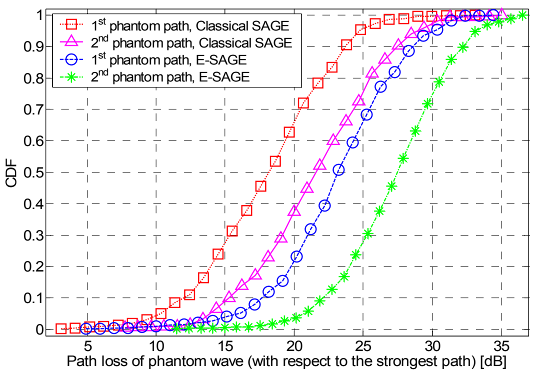


Figure 5: CDF of relative path loss of estimated phantom paths

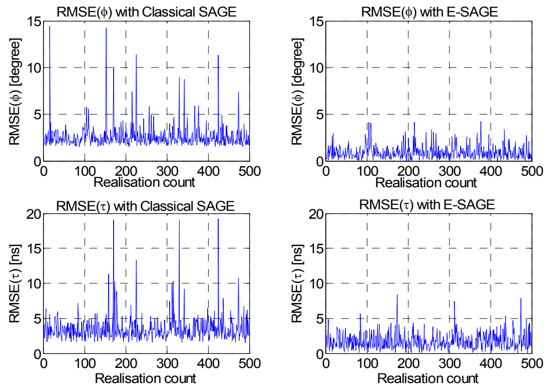


Figure 6: RMSE of estimated nominal DoA and TDoA

VII. Concluding remarks

This paper has presented an overview of various maximum-likelihood based algorithms with different implementation methodologies to estimate multipath parameters. The paper does not intend to focus on technical issues (implementation procedure) and the reader is referred to the reference papers for more details. The main motivation behind this work is to address some of the common problems that might be encountered by different researchers in this field. Due to the iterative nature of the algorithms, and with the requirement of estimating multi-dimensional multipath parameters from vast measurement database, a number of simplified solutions has been proposed. The key benefits of these algorithms include reduced computational complexity, memory consumption, and computing resources. This is due to a reduction in resultant input data size with BS processing, and reduced arithmetic operations in real-valued computations with appropriate unitary transformation. Note that the overall processing time for these algorithms is subject to the total available memory, speed of the computing processor, efficiency in implementing the algorithm, and settings of the algorithm (e.g. correlation grid size in the M-steps, total number of iterations, total number of estimated paths, etc).

A number of conditions must be met before implementing the algorithms. For BS and unitary processing, the arrays must be properly calibrated in all dimensions. The array structure also plays an important role in determining the overall performance of the algorithm. In the spatial domain, a circular array might not be suitable for BS and unitary processing and it is not recommended to employ circular array (or any nonlinear array) with these transformations. As an alternative solution for timesaving, the circular array can be applied with HS processing where the spatial domain is processed in the ES domain. The parameter settings of the algorithms must be carefully chosen in order to retain the overall accuracy of the estimated multipath parameters, e.g. the beams must concentrate in multipaths region and the reduction of data size in any domain should not be greater than 50%.

Here the performance of the proposed algorithms is compared with that of the classical SAGE algorithm. Since the performance of the classical SAGE algorithm has been evaluated in [4], its performance is used as a benchmark to other algorithms. The estimation error presented in this paper does not necessarily represent the ultimate performance of the algorithms. Note that the final estimation error depends on the size of the correlation grid step used in the M-step, total number of iterations implemented, degree of accuracy in determining total number of dominant multipath components (i.e. model order determination), effective signal-to-noise ratio of the system, means of recording the channel response data, degree of correlation between the multipath components, effective separation distance of the multipaths, and availability of precise response knowledge of the measurement system. Also, it is expected that the estimated results with different algorithms are not exactly the same since each algorithm processes the data in different domains. However, observe that their differences are much smaller than the intrinsic Rayleigh resolution of the system.

An initial solution to cope with distributed-source scenarios has been proposed. The solution employs an approximated model (based on Taylor's series expansion for distributed-source modelling) throughout the estimation and has successfully produced promising results, as long as the spreads (in space, time, and frequency) of the clusters is small compared with the 3 dB beamwidth of the arrays. To a certain extent, the enhanced method can also estimate the spread parameters within a cluster. Future work will be focused on this issue. Finally, Table 1 provides an overall summary of the material presented in this paper.

Implementation	Emphasis
Beamspace processing	Applicable to arrays that exhibit Vandermonde structure in steering vectors, beamforming must concentrate on multipath region, data size reduction should not be more than 50%, apply windowing function to suppress out-of-band interference in case of 'blind beamforming', avoid windowing if possible (when a prior channel knowledge is available) to retain ultimate resolution, calibration routine must be performed *Key advantage: data size reduction*
Hybrid-space processing	Applicable when not all arrays (in all dimensions) are suitable for BS processing (e.g. circular array), beamforming criteria are similar to BS processing *Key advantage: data size reduction, extra flexibility compared to BS processing*
Unitary transformation	Applicable to arrays with column conjugate symmetric steering vectors, calibration routine must be performed *Key advantage: full real-valued computations in M-step*
Approximated model in (8)	Applicable when the spreads of the clusters are smaller than 3 dB beamwidth of the respective arrays (ideally) *Key advantage: better phantom path discrimination, increased accuracy in estimating nominal parameters and spread parameters (for clusters)*

Table 1: Overall summary of the algorithms

Acknowledgement

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