Abstract—Independent Vector Extraction (IVE) is a modification of Independent Vector Analysis (IVA) for Blind Source Extraction (BSE) to a setup in which only one source of interest (SOI) should be separated from a mixture of signals observed by microphones. The fundamental assumption is that the SOI is independent of the other signals. IVE shows reasonable results; however, its basic variant is limited to static sources. To extract a moving source, IVE has recently been extended by considering the Constant Separating Vector (CSV) mixing model. It enables us to estimate a separating filter that extracts the SOI from a wider spatial area through which the source has moved. However, only slow gradient-based algorithms were proposed in the pioneering papers on IVE and CSV. In this paper, we experimentally verify the applicability of the CSV mixing model and propose new IVE methods derived by modifying the auxiliary function-based algorithm for IVA. Piloted Variants are proposed as well for the methods with partially controllable global convergence. The methods are verified under reverberant and noisy conditions using model-based as well as real-world acoustic impulse responses. They are also verified within the CHiME-4 speech separation and recognition challenge. The experiments corroborate the applicability of the CSV mixing model for the blind moving source extraction as well as the improved convergence of the proposed algorithms.

I. INTRODUCTION

A. Standard Independence-based BSS

The goal of Blind Source Separation (BSS) is to separate individual signals from their mixture that is observed through several sensors [1]. The standard linear instantaneous mixing model considered in BSS is given by

$$\mathbf{x} = \mathbf{A}\mathbf{s},$$

where \(\mathbf{x}\) is an \(r \times 1\) vector representing \(r\) observed (mixed) signals, \(\mathbf{s}\) is a \(d \times 1\) vector of original source signals, and \(\mathbf{A}\) is a \(r \times d\) mixing matrix. Let the number of available samples of the observed data be \(N\). In this paper, we will consider complex-valued signals and parameters, which is a setup necessary for applications in audio source separation in the time-frequency domain.

When \(r = d\) or \(r < d\), the model is referred to as determined and underdetermined, respectively. The advantage of a determined problem compared to an underdetermined one is that the inverse matrix of \(\mathbf{A}\) exists provided that \(\mathbf{A}\) is nonsingular. The BSS problem can then be solved through finding a \(d \times d\) square de-mixing matrix \(\mathbf{W}\) such that \(\mathbf{y} = \mathbf{Wx}\) correspond to the original signals \(\mathbf{s}\) up to their order and scaling factors, which cannot be determined without additional information. The rows of the de-mixing matrix and the columns of the mixing matrix will be referred to as separating and mixing vectors, respectively.

Independent Component Analysis (ICA) [2], [3] has been a popular BSS method based on the assumption that the original signals \(\mathbf{s}\) are statistically independent. Later, the idea was extended in Independent Vector Analysis (IVA) to the joint BSS problem (jBSS) where \(K > 1\) standard linear instantaneous mixtures \((k\) corresponds to the \(k\)th frequency bin in the frequency-domain BSS [4])

$$\mathbf{x}_k = \mathbf{A}_k\mathbf{s}_k, \quad k = 1, \ldots, K,$$

are separated jointly. Here, the source signals in \(\mathbf{s}_k\) are assumed to be statistically independent for every \(k\), as in ICA. In addition, the elements of the \(i\)th vector component, defined as \(\mathbf{s} = [s_1^T, \ldots, s_d^T]^T\), \(i = 1, \ldots, d\), are allowed to be mutually dependent. This dependence is used for separating the original sources so that their order is the same in all mixtures, which helps us solve the permutation problem (a different order of separated components for each \(k\)) [5]. Independent Low Rank Matrix Analysis (ILRMA) is a recent extension of IVA where samples of vector components are assumed to obey a low-rank model. For example, ILRMA combines the IVA and Nonnegative Matrix Factorization (NMF) in [6], [7].

Independence-based BSS methods can be classified according to the statistical model of signals. Basically, ICA, IVA and ILRMA assume that the original signals have independently distributed samples drawn from non-Gaussian distributions. Here, the independence of separated signals is measured through contrast functions that involve higher-order statistics [8], [9]. In IVA, it is additionally assumed that signals from different mixtures (the elements of vector components) are uncorrelated but dependent and that their dependence can be presented through higher-order statistics [9]. Another class of BSS methods, which we do not consider here, is based on Gaussian statistical models of signals that exploit only second-order statistics of signals; see, e.g., [10]–[16].
B. Mixing models for dynamic conditions

The standard mixing models (1) and (2) are not suitable for describing dynamic situations; for example, when a source is moving and the mixing matrix is varying in time. There have been few time-varying mixing models considered in the previous BSS literature; see, e.g., [17], [18] for BSS models with a linearly changing mixing matrix. Recently, Piecewise Determined Mixing models (PDM) assume that the mixture is determined and locally obeys the standard mixing model within specified time intervals [19]. The mixing matrix can be changing from interval to interval, which approximates the dynamic mixing. In PDM, the 4th sample or interval of the mixture is described by

\[ x_t = A_t s_t, \quad t \in T, \]

where \( T \) is the set of possible indices, and \( A_t \) is square (\( r = d \)). For a set of dynamic mixtures, we introduce the joint Piecewise Determined Mixing model (jPDM) described by

\[ x_{k,t} = A_{k,t} s_{k,t}, \quad k = 1, \ldots, K, \quad t \in T. \]

Here the mixing matrices \( A_{k,t} \) are also square.

The dimensions in the joint mixing models (2) and (4) can be dependent on \( k \). Nevertheless, for the practical purposes of this paper, we will consider only the same dimension \( d \) for all mixtures. When \( T \) contains only one possible value of \( t \), the PDM models coincide with the standard ones, (1) and (2).

The general PDM models correspond to a sequential application of the standard mixing model to short intervals (or even samples) of data, which is a straightforward approach used to cope with dynamic mixing conditions, e.g., in either online or batch-online implementations of BSS algorithms [20]. In this paper, we will consider a special case of the jPDM model that involves a reduced number of parameters. The model is, however, formulated for the Blind Source Extraction (BSE) problem.

C. Blind Source Extraction

BSE aims at the blind extraction of one particular source of interest (SOI) and could be seen as a subtask of BSS. Indeed, some ICA and IVA algorithms, such as FastICA, actually perform sequential or parallel BSE; see, e.g., [21]–[23]. BSE within the framework of ICA and IVA has recently been revised in [24]. Here, the problem to extract the SOI based on its independence from the remaining signals, called background, is referred to as Independent Component/Vector Extraction (ICE/IVE).

In ICE/IVE, the mixing matrix is assumed to have a special parameterization involving only the mixing and separating vectors corresponding to the SOI. It was shown that this structure is sufficient for the BSE task under the standard mixing models without bringing any limitation in terms of the achievable accuracy given by the Cramér-Rao bound [25].

The formal descriptions of the mixing models (3) and (2) coincide. Therefore, we will accept a convention that \( t \) denotes the index of a time instant or interval, while \( k \) stands for the index of the mixture.

D. Contribution

The structured mixing matrix parameterization can straightforwardly be applied within the (j)PDM models. However, the number of parameters can further be reduced, e.g., by assuming that some parameters are constant over the intervals of data. This way, Constant Mixing/Seperating Vector (CMV/CSV) models have been considered in [19].

The methods designed with CSV and CMV have been shown to be capable of extracting moving sources or static sources from a dynamic background, respectively. Usefulness of the algorithms in [19] has been shown in audio applications; however, since the gradient-based optimization is used, they suffer from slow convergence and are prone to getting stuck in local extremes of the contrast function.

In this paper, we therefore focus on the development of fast algorithms for ICE/IVE assuming that the CSV model is suitable for the blind extraction of a moving speaker. The contribution here is three-fold. First, a BSE variant of the AuxIVA algorithm is derived for the standard (static) mixing model (2) using the IVE framework; the resulting algorithm is named AuxIVA. Second, AuxIVA is extended for the CSV model, whose modification is referred to as Block AuxIVA. The third contribution is a piloted version of Block AuxIVA using the idea from [28].

It features a partially controlled convergence through relying on a pilot signal that carries information about which source should be extracted, that is, the SOI. Therefore, it is assumed to be statistically dependent on the SOI.

This article is organized as follows. In the following section, the problem of the blind extraction of a moving speaker is formulated, and its solution through IVE is described. In Section III, the AuxIVA algorithm and its variants Block AuxIVA and piloted Block AuxIVA are derived based on the original AuxIVA by Ono [29]. Section IV is devoted to experimental evaluations based on simulated as well as real-world data. The paper is concluded in Section V.

II. PROBLEM DESCRIPTION

A. Notation

Throughout this paper, we use the following notation: plain letters denote scalars, bold letters denote vectors, and bold capital letters denote matrices. Upper indices such as \( T, \cdot^H, \cdot^* \) denote, respectively, transposition, conjugate transpose, or complex conjugate. The Matlab convention for matrix/vector concatenation and indexing will be used, e.g., \( [1; \mathbf{g}] = [1, \mathbf{g}^T]^T \), \( (\mathbf{A})_{ij} \) is the \( j \)th row of \( \mathbf{A}_{k,t} \), and \( (\mathbf{a}_i)_j \) is the \( j \)th element of \( \mathbf{a} \). \( \mathbf{E}[\cdot] \) stands for the expectation operator, and \( \mathbf{E}[\cdot] \) is the average taken over all available samples of the argument.

The variant of FastICA designed for the BSE assuming an unstructured mixing matrix [21].

To the best of our knowledge, these mixing models have not yet been studied in the BSS literature; our preliminary studies in [19] and in [27] were the first.
B. Frequency-domain BSS

Audio sources propagate with delays and reflections in a typical room [4]. The mixtures observed on the microphones are therefore described by the convolutive model

$$x_i(n) = \sum_{j=1}^{d} \sum_{\tau=0}^{L-1} h_{ij}(\tau)s_j(n-\tau), \quad i = 1, \ldots, r,$$

where $x_i(n)$ is the observed signal on the $i$th microphone at time $n$, $s_1(n), \ldots, s_d(n)$ are the original signals, and $h_{ij}$ denotes the impulse response between the $j$th source and $i$th microphone of length $L$. In the Short-Time Fourier Transform (STFT) domain, the convolutive model can be approximated by the instantaneous one. Specifically, for the $k$th frequency and the $j$th frame, the STFT coefficients of the observed signals are described by

$$X_k(\ell) = A_kS_k(\ell), \quad k = 1, \ldots, K,$$

where $S_k(\ell)$ denotes the coefficient vector of the original signals. The $ij$th element of the mixing matrix $A_k$ corresponds to the $k$th Fourier coefficient of the impulse response $h_{ij}$.

Now, we can see that the joint mixing models (2) and (4) can be applied to the frequency domain signals. The data $X_k$ and de-mixing matrices, respectively, as $A_k$ and $W_k$ are described by the convolutive model

$$P_k = \frac{1}{\gamma_k}(h_k^H - I_{d-1})^{-1},$$

where $h_k$ is the mixing vector corresponding to the SOI (the first source), which is equal to the first column of $A_k$. Next, $s_k$ denotes the $k$ SOI’s component; that is, the first element of $s_k$, and $y_k$ consists of the remaining background signals: $y_k = x_k - a_k s_k$. The vector component corresponding to the SOI will be denoted by $s = [s_1, \ldots, s_K]^T$.

The IVE approach to extract the SOI is based on the assumption that $s_k$ is independent of $y_{k'}$ for every $k, k' \in \{1, \ldots, K\}$. The elements of $s$ are allowed to be dependent but uncorrelated. Next, $A_k$ is assumed to be square (the determined mixture), which also means that $y_k$ belongs to a $d - 1$ dimensional subspace. Under these assumptions, it was shown in [24] that it is sufficient to parameterize the mixing and de-mixing matrices, respectively, as

$$A_k = (a_k \quad Q_k) = \begin{pmatrix} \gamma_k & h_k^H \\ g_k & -\gamma_k I_{d-1} \end{pmatrix},$$

and

$$W_k = \begin{pmatrix} w_k^H \\ B_k \end{pmatrix} = \begin{pmatrix} \beta_k & h_k^H \\ g_k & -\gamma_k I_{d-1} \end{pmatrix},$$

where $I_d$ denotes the $d \times d$ identity matrix, $w_k$ denotes the separating vector such that $w_k^H x_k = s_k$ which is partitioned as $w_k = [\beta_k; g_k]$, and where the mixing vector $a_k$ is partitioned as $a_k = [\gamma_k; g_k]$. The vectors $a_k$ and $w_k$ are linked through so-called distortionless constraint $w_k^H a_k = 1$. $B_k$ is called blocking matrix as it satisfies that $B_k a_k = 0$. The background noise signals are defined as $z_k = B_k x_k = B_k y_k$, and it holds that $y_k = Q_k z_k$.

D. Statistical model

Let $p(s)$ denote the joint pdf of $s$ and $p_{x_k}(z_k)$ denote the pdf4 of $z_k$. The joint pdf of the observed signals reads

$$p_x(\{x_k\}_{k=1}^K) = p(\{w_k^H x_k\}_{k=1}^K) \cdot \prod_{k=1}^K p_{x_k}(B_k x_k) \cdot \det W_k^2.$$  

(11)

Hence, the corresponding log-likelihood function for one sample (frame) of the observed signals is given by

$$\mathcal{L}(\{w_k\}_{k=1}^K, a_k, \{x_k\}_{k=1}^K) = \log p(\{w_k^H x_k\}_{k=1}^K) + \sum_{k=1}^K \log p_{x_k}(B_k x_k) + \log \det W_k^2 + \text{const.}$$  

(12)

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4 We might consider a joint pdf of $z_1, \ldots, z_K$ that could possibly involve higher-order dependencies between the background components. However, since $p_{x_k}(\cdot)$ is assumed Gaussian in this paper and since signals from different mixtures (frequencies) are assumed to be uncorrelated in the standard IVA, we can directly consider $z_1, \ldots, z_K$ to be mutually independent.
In BSS and BSE, the true pdfs of the original sources are not known, so suitable model densities have to be chosen. The rule of thumb says that the mismatch between the true and model densities mainly has an influence on the separation/extraction accuracy [32]. Therefore, the aim is to select model densities that reflect the true properties of the source signals as much as possible. In BSE, it is typical to assume that the background signals are Gaussian as these are not subject to extraction [24]. The concrete choice of the model pdf for SOI will be discussed in Section III-E.

Let $f(s)$ be the model pdf, replacing $p(s)$. The background pdf will be assumed to be circular Gaussian with zero mean and (unknown) covariance matrix $C_{z_k} = E[z_k z_k^H]$, i.e., $CN(0, C_{z_k})$. Disregarding the constant terms and using $|\det W_k|^2 = |\gamma_k|^2(d-2)$, which follows from (10), the contrast function, as derived from (12) assuming N i.i.d. samples and replacing the unknown $C_{z_k}$ with its sample-based estimate $\hat{C}_{z_k} = E[z_k z_k^H]$, has the form

$$C(\{w_{k}\}_{k=1}^K, \{a_k\}_{k=1}^K) = \hat{E}[\log f(\{w_k^H x_k\}_{k=1}^K)] - \sum_{k=1}^K \hat{E}[x_k^H B_k^H C_{z_k}^{-1} B_k x_k] + (d-2) \sum_{k=1}^K \log |\gamma_k|^2.$$  (13)

**E. Orthogonally Constrained Gradient Algorithm: OGIVE$_w$**

In [24], gradient-based algorithms were proposed for estimation of the mixing and separating vectors that search for the maximum of the contrast function (13). They iterate in small steps in the direction of a constrained gradient of (13).

Specifically, the orthogonal constraint (OG) is imposed between each pair of the parameter vectors $a_k$ and $w_k$ as

$$a_k = \frac{\hat{C}_k w_k}{w_k^H \hat{C}_k w_k},$$  (14a) $$w_k = \frac{\hat{C}_k^{-1} a_k}{a_k^H \hat{C}_k^{-1} a_k},$$  (14b)

where $\hat{C}_k$ is the sample-based estimate of the covariance matrix $C_k = E[x_k x_k^H]$. The constrained gradient of (13) is the gradient taken with respect to $w_k$ or $a_k$ when the other parameter vector is dependent through (14a) or (14b), respectively. The OG must be imposed, because updating $a_k$ and $w_k$ as independent parameters (linked only through the distortionless constraint) in the directions of unconstrained gradients has been shown to be highly unstable.

The constrained gradient of (13) with respect to $w_k$ is equal to

$$\frac{\partial C}{\partial w_k} \bigg|_{w \text{ s.t. } (14a)} = a_k - \hat{E}[x_k \phi_k(\{w_k^H x_k\}_{k=1}^K)],$$  (15)

where $\phi_k(s) = -\frac{\partial}{\partial s_k} \log f(s)$ is the score function corresponding to the model pdf $f(\cdot)$. It is readily seen that, for $N \to +\infty$, the true separating vectors $\{w_k\}_{k=1}^K$ are the stationary points of the contrast function (the gradient is zero) only if $\hat{E}[w_k^H x_k \phi_k(\{w_k^H x_k\}_{k=1}^K)] = 1$. Therefore, a modified (normalized) gradient equals

$$\Delta_k = a_k - \frac{\hat{E}[x_k \phi_k(\{w_k^H x_k\}_{k=1}^K)]}{\hat{E}[w_k^H x_k \phi_k(\{w_k^H x_k\}_{k=1}^K)]},$$  (16)

and the rule for updating $w_k$, $k = 1, \ldots, K$, is

$$w_k \leftarrow w_k + \mu \Delta_k,$$  (17)

where $\mu > 0$ is a step size parameter. After each update, the scaling ambiguity can be fixed through normalizing the scale of the extracted signal or by normalizing the current mixing or separating vector (while preserving the distortionless constraint $w_k^H a_k = 1$). The resulting algorithm is referred to as OGIVE$_w$, which is an acronym of “Orthogonally-Constrained IVE” and the subscript means that the optimization proceeds in variables $\{w_k\}_{k=1}^K$.

Alternatively, the optimization can also proceed in variables $\{a_k\}_{k=1}^K$ under the constraint (14b). The corresponding algorithm is referred to as OGIVE$_a$; see [24].

**F. CSV Mixing Model**

We now consider the jPDM mixing model (4). Let the samples of the observed signals be divided into $T$ intervals; for the sake of simplicity, we assume that they have the same length $N_b = N/T$ (let this number be an integer); the intervals will be called blocks and will be indexed by $t \in T = \{1, \ldots, T\}$. The Constant Separating Vector (CSV) mixing model comes from the jPDM model (4) where the mixing matrices $A_{k,t}$ obey a structure similar to the one given by (9). In addition, the separating vectors are independent of the block index $t$ (i.e., are constant over the blocks); specifically,

$$A_{k,t} = (a_{k,t} \quad Q_{k,t}) = \begin{pmatrix} \gamma_{k,t} & \frac{1}{\gamma_{k,t}} h_k^H \\ \mathbf{I}_{d-1} & -\mathbf{I}_{d-1} \end{pmatrix},$$  (18)

and

$$W_{k,t} = (w_{k,t} \quad B_{k,t}) = \begin{pmatrix} \beta_k & h_k^H \\ -\gamma_{k,t} \mathbf{I}_{d-1} \end{pmatrix}. $$  (19)

The idea behind the CSV model is that the SOI can change its position from block to block, because the position is determined by the mixing vectors $a_{k,t}$, which in turn depend on $t$. The separating vectors do not depend on $t$, so they are forced to extract the speaker’s voice from all positions visited during its movement; see the illustration in Fig. 1. One advantage is given by the reduced number of mixing model parameters, as confirmed by the theoretical study on Cramér-Rao bounds in [27]; however, the model also brings some limitations. In theory, the mixture must obey the condition that, for each $k$, a separating vector exists such that $s_{k,t} = w_{k,t}^H x_{k,t}$ holds for every $t$; this condition seems to be quite restrictive. Nevertheless, preliminary experiments have shown that CSV is useful in practical situations [19]. An efficient BSE can be achieved through CSV; especially, when a sufficient number of microphones is used, which increases the number of the degrees of freedom. Then, the existence of the desired constant separation vectors follows from the existence of linearly constrained minimum variance (LCMV) beamformers; see [33].

The first part of our experimental study in Section IV provides practical evidence of this capability of CSV, as well as of the BSE algorithms based on it.
Its gradient computed under the OG (14a) is separately applied in each block, that is,
\[ a_{k,t} = \frac{\hat{C}_{k,t} w_k}{w^T_k C_{k,t} w_k}, \] (21)
is equal to
\[ \frac{\partial \mathcal{C}}{\partial w_k} \bigg|_{w_{k,t}}, (21) \]

Similarly to (16), the normalized gradient reads
\[ \Delta^\text{avg}_k = \frac{1}{T} \sum_{t=1}^{T} \left\{ a_{k,t} - \hat{E}[x_{k,t} \phi_k(\{w^H_k x_{k,t}\}_{k=1}^K)]/\nu_{k,t} \right\}, \] (23)
where \( \nu_{k,t} = \hat{E}[w^H_k x_{k,t} \phi_k(\{w^H_k x_{k,t}\}_{k=1}^K)] \). The rule for updating \( w_k \), \( k = 1, \ldots, K \), is, similarly to (17), given by
\[ w_k \leftarrow w_k + \mu \Delta^\text{avg}_k. \]

A detailed summary of BOGIVE\(_w\) is given in Algorithm 1, in which the method is started from the initial values of the separating vectors. After each iteration, the separating vectors are normalized so that their first elements are equal to one in order to resolve the scaling ambiguity problem. (Alternatively, the normalization of the scales of the extracted signals is possible.) It is worth noting that the normalization of mixing vectors \( a_{k,t} \) is not possible here as compared to OGIVE\(_w\), because these parameters are block-dependent. For \( T = 1 \), BOGIVE\(_w\) corresponds with OGIVE\(_w\).

**Algorithm 1: BOGIVE\(_w\): Block-wise orthogonally constrained independent vector extraction**

**Input:** \( x_{k,t}, w^\text{ini}_k \ (k,t = 1,2,\ldots,\mu, \tau, \text{tol}) \)

**Output:** \( a_{k,t}, w_k \)

1. foreach \( k = 1, \ldots, K, \ t = 1, \ldots, T \) do
   2. \( \hat{C}_{k,t} = \hat{E}[x_{k,t} x^H_{k,t}]; \)
   3. \( w_k = w^\text{ini}_k / (w^H_k w_k)^{1/2}; \)
   4. end
5. repeat
6.   foreach \( k = 1, \ldots, K, \ t = 1, \ldots, T \) do
7.     \( a_{k,t} \leftarrow (w^H_k \hat{C}_{k,t} w_k)^{-1} \hat{C}_{k,t} w_k; \)
8.     \( s_{k,t} \leftarrow w^H_k x_{k,t}; \)
9.   end
10. foreach \( k = 1, \ldots, K, \ t = 1, \ldots, T \) do
11.     \( \nu_{k,t} \leftarrow \hat{E}[s_{k,t} \phi_k(s_{1,t}, \ldots, s_{K,t})]; \)
12. end
13. foreach \( k = 1, \ldots, K \) do
14.     Compute \( \Delta^\text{avg}_k \) according to (23);
15.     \( w_k \leftarrow w_k + \mu \Delta^\text{avg}_k; \)
16.     \( w_k \leftarrow w_k / (w^H_k w_k)^{1/2}; \)
17. end
18. until \( \max(\|\Delta^\text{avg}_1\|, \ldots, \|\Delta^\text{avg}_K\|) < \text{tol}; \)

### III. Auxiliary Function-Based IVE

In [29], N. Ono derived the AuxIVA algorithm using an auxiliary function-based optimization (AFO) technique. This
method provides a much faster and more stable alternative to the natural gradient-based algorithm from [9]. In this section, we briefly describe the main principles of the optimization approach and its application within AuxIVA. Further we derive a simple modification of AuxIVA for solving the problem of IVE, which yields the AuxIVEm algorithm. Finally, Block-AuxIVEm and its piloted variant assuming the CSV mixing model are derived.

### A. Original AuxIVA

In a general optimization problem, the goal is to find an optimum point

$$\theta = \arg \min_{\theta} J(\theta),$$  \hspace{1cm} (24)

where $J(\theta)$ is a real-valued objective function. In AFO, an auxiliary function $Q(\theta, \xi)$ is assumed to be known that satisfies

$$J(\theta) = \min_{\xi} Q(\theta, \xi),$$  \hspace{1cm} (25)

where $\xi$ is called auxiliary variable. The minimum of $J(\theta)$ is then sought in two alternating steps, respectively,

$$\xi^i = \arg \min_{\xi} Q(\theta^i, \xi),$$  \hspace{1cm} (26)

$$\theta^{i+1} = \arg \min_{\theta} Q(\theta, \xi^i),$$  \hspace{1cm} (27)

where $i$ is the iteration index. In particular, AFO can be very effective when the closed-form solution of (27) is available.

In IVE, the set of fully parameterized de-mixing matrices $\{W_k\}_{k=1}^K$ plays the role of $\theta$ and the contrast function is given by [9], [29]

$$J(\{W_k\}_{k=1}^K) = -\sum_{i=1}^d \mathbb{E}[\log f(u^i)] - \sum_{k=1}^K \log |\det W_k|^2,$$  \hspace{1cm} (28)

where $u^i = [w_i^1]^H x_1, \ldots, (w_i^d)^H x_d]^T$ denotes the $i$th separated vector component; $(w_i^k)^H$ denotes the $i$th row in $W_k$. It is seen that the algebraic form of (28) mainly depends on the model density $f(\cdot)$.

In [29], Theorem 1 formulates an assumption that a scalar real-valued function $G_R(\cdot)$ exists such that $-\log f(u) = G_R(\|u\|_2^2)$ and that $G_R(\cdot)$ is continuous and differentiable in $r$ such that $G'_R(\cdot)/r$ is positive and continuous everywhere and is monotonically decreasing in the wider sense for $r \geq 0$. It is then shown that the auxiliary function can be

$$Q(\{W_k\}_{k=1}^K, r) = \frac{1}{2} \sum_{i=1}^d \sum_{k=1}^K (w_i^k)^H V_k^i w_i^k,$$

$$-\sum_{k=1}^K \log |\det W_k|^2 + R,$$  \hspace{1cm} (29)

where

$$V_k^i = \mathbb{E}[\varphi(r_i) x_k x_i^H],$$  \hspace{1cm} (30)

The problem defined by (34) has been known as Hybrid Exact-Approximate Joint Diagonalization (HEAD) [34], whose closed-form solution poses an open problem. Therefore, instead of updating (34) for all $w_i^k$ simultaneously, it is proposed in [29] to update $w_i^k$ while the other $w_i^k, (j \neq i)$ are fixed. This leads to the following problem:

$$(w_i^k)^H V_k^i w_i^k = 1,$$  \hspace{1cm} (35)

$$(w_i^k)^H V_k^i w_i^k = 0, \hspace{1cm} (j \neq i).$$  \hspace{1cm} (36)

Equations (36) determine the directions of $w_i^k$ while (35) determines their scales. Therefore, (35) can temporarily be replaced by a dummy equation $b^H V_k^i w_i^k = 1$ where $b$ is put equal to $w_i^k$ obtained in the previous iteration of AuxIVA. A simple update rule is obtained:

$$w_i^k \leftarrow (W_k V_k^i)^{-1} e_i,$$  \hspace{1cm} (37)

where $e_i$ is the $i$th column of $I_d$. The result of (37) is then re-scaled to satisfy (35).

To summarize, the complete update rules of AuxIVA for each $k$ and $i$ are as follows:

$$r_i = \sum_{k=1}^K (w_i^k)^H x_k x_i^H,$$  \hspace{1cm} (38)

$$V_k^i = \mathbb{E}[\varphi(r_i) x_k x_i^H],$$  \hspace{1cm} (39)

$$w_i^k \leftarrow (W_k V_k^i)^{-1} e_i,$$  \hspace{1cm} (40)

$$(w_i^k)^H V_k^i w_i^k = \sqrt{(w_i^k)^H V_k^i w_i^k}.$$  \hspace{1cm} (41)

For a brief overview of AuxIVA, see also [35].
B. AuxIVE

In IVE, the contrast function is given by (13), which should be maximized in variables \(w_k\) and \(a_k\). We can apply the AFO technique in a way similar to the previous subsection, because the first term in (13) corresponds to one term of the first sum in (28). Hence, following the same assumption about the model density \(f(\cdot)\) as in Theorem 1 in [29], the auxiliary function for (13) can have the form

\[
Q(\{w_k\}_{k=1}^K, \{a_k\}_{k=1}^K, r) = - \frac{1}{2} \sum_{k=1}^K (w_k^H V_k w_k - \sum_{k=1}^K \hat{E}[x_k^H B_k^H C_k^{-1} B_k x_k]) + (d-2) \sum_{k=1}^K \log |\gamma_k|^2 + R,
\]

(42)

where

\[
V_k = \hat{E}[\phi(r) x_k x_k^H],
\]

and \(r\) is the auxiliary variable, which is scalar in this case; \(R\) depends purely on \(r\). The equality between the contrast (13) and (42) holds if and only if \(r = \sqrt{\sum_{k=1}^K (w_k^H x_k)^2}\).

In a way similar to Section II-E, the OG is imposed between the pairs of vector variables \(w_k\) and \(a_k\), \(k = 1, \ldots, K\), and the optimization proceeds in \(w_k\). The constrained derivative of (42) with respect to \(w_k^H\) has the form

\[
\frac{\partial Q(\{w_k\}_{k=1}^K, r)\big|_{w.r.t. (14a)} }{\partial w_k^H} = a_k - V_k w_k.
\]

(44)

Putting the derivative equal to zero, we can derive a close-form solution:

\[
w_k = V_k^{-1} a_k.
\]

(45)

It means that the HEAD problem (34) need not be solved as compared to IVA, and the update rules for AuxIVE are

\[
r = \sqrt{\sum_{k=1}^K |w_k^H x_k|^2},
\]

(46)

\[
V_k = \hat{E}[\phi(r)x_k x_k^H],
\]

(47)

\[
a_k = C_k w_k,
\]

(48)

\[
w_k = V_k^{-1} a_k.
\]

(49)

The pseudocode of AuxIVE corresponds to Algorithm 2 when \(T = 1\).

Very recently, a similar modification of AuxIVA for the blind extraction of \(m\) sources, where \(m < d\), has been proposed in [36]; the algorithm is named OverIVA. AuxIVE could be seen as a special variant of OverIVA designed for \(m = 1\).

C. Block AuxIVE

We can now modify AuxIVE for the CSV mixing model following the results described in Section II-G. The contrast function for CSV is given by (20). Comparing (20) with (13) and using the same approach and assumptions to derive (42), we obtain the auxiliary function for the CSV model in the form

\[
Q(\{w_k, a_k, r\}_{k=1}^{1, \ldots, K}, \{r\}_{t=1}^{1, \ldots, T}) = \frac{1}{T} \sum_{t=1}^T \left\{ - \frac{1}{2} \sum_{k=1}^K w_k^H V_{k,t} w_k - \sum_{k=1}^K \hat{E}[x_k^H B_k^H C_k^{-1} B_k x_k] + (d-2) \sum_{k=1}^K \log |\gamma_k|^2 \right\} + R,
\]

(50)

where

\[
V_{k,t} = \hat{E}[\phi(r) x_k x_k^H],
\]

(51)

\(r = [r_1, \ldots, r_T]^T\), is the auxiliary variable, and \(R\) depends purely on \(r\). When \(r_t = \sqrt{\sum_{k=1}^K |w_k^H x_k|^2}\) for every \(t = 1, \ldots, T\), (50) and (20) are equal.

An OG similar to the one used in Section II-G is imposed between the pairs \(w_k\) and \(a_k\) in each block according to the relationship (21). The constrained derivative of (50) with respect to \(w_k\) then takes on the form

\[
\frac{\partial Q}{\partial w_k^H}|_{w.r.t. (21)} = \frac{1}{T} \sum_{t=1}^T \{a_k - V_{k,t} w_k\}.
\]

(52)

Putting the derivative equal to zero, we obtain the close-form solution as \(w_k = (\sum_{t=1}^T V_{k,t})^{-1} \sum_{t=1}^T a_{k,t}\). The separating vectors \(w_k\) are then normalized so that their first elements are equal to one.

To summarize, the complete update rules of Block AuxIVE are as follows:

\[
r_t = \sqrt{\sum_{k=1}^K |w_k^H x_k|^2},
\]

(53)

\[
V_{k,t} = \hat{E}[\phi(r)x_k x_k^H],
\]

(54)

\[
a_{k,t} = \frac{C_{k,t} w_k}{w_k^H C_{k,t} w_k},
\]

(55)

\[
w_k = \left(\sum_{t=1}^T V_{k,t}\right)^{-1} \sum_{t=1}^T a_{k,t}.
\]

(56)

The pseudo-code of the proposed method is described in Algorithm 2.

D. Piloted Block AuxIVE

Owing to the indeterminacy of the ordering for the original signals in BSS, it is not, in general, known which source is currently being extracted through BSE. The crucial problem is to ensure that the signal being extracted actually corresponds to the SOI. Therefore, several approaches ensuring the global convergence have been proposed, most of which are based on
Algorithm 2: Block AuxIVE: Auxiliary function based IVE for the CSV Mixing Model

**Input:** $x_{k,t}, w_k^{mi} (k, t = 1, 2, \ldots), \text{NumIter}

**Output:** $a_{k,t}, w_k$

1. **for** $k = 1, \ldots, K, t = 1, \ldots, T$ **do**
   2. $C_{k,t} = \hat{E}[x_{k,t}x_{k,t}^H]$;
   3. $w_k = w_k^{mi}/(w_k^{mi})$;
   4. **end**

5. **Iter** = 0;
6. **repeat**
7. **for** $t = 1 \ldots T$ **do**
8. $r_t = \sum_{k=1}^{K} |w_k^HX_{k,t}|^2$; **for** $k = 1 \ldots K$ **do**
9. $a_{k,t} = \frac{C_{k,t}w_k}{w_k^HC_{k,t}w_k};$
10. $\eta_{k,t} = \hat{E}[x_{k,t}x_{k,t}H];$
11. **end**
12. **end**
13. **for** $k = 1 \ldots K$ **do**
14. $w_k^H = \sum_{t=1}^{T} a_{k,t}^{-1}(\sum_{t=1}^{T} V_{k,t})^{-1}$;
15. $w_k = w_k/(w_k)$;
16. **end**
17. **Iter** = **Iter** + 1;
18. **until** **Iter** < **NumIter**;

---

additional constraints assuming prior knowledge, e.g., about the source position or a reference signal [37]–[40]. Recently, an unconstrained supervised IVA using the so-called pilot signals has been proposed in [28], where each pilot signal is dependent on the source signals, so they have a joint pdf that cannot be factorized into a product of marginal pdfs. This idea has been extended to IVE in [24], where only the pilot signal related to the SOI is needed.

Let the pilot signal dependent on the SOI (and independent of the background) be denoted by $o$, and let the joint pdf of $s$ and $o$ be $p(s, o)$. Then, the pdf of the observed data is

$$p_x(x_k^Hk=1) = p(w_k^HX_k^Hk=1, o) \prod_{k=1}^{K} p_x(B_kx_k) \det W_k^2.$$  (57)

Comparing that expression with (11) and taking into account the fact that $o$ is independent of the mixing model parameters, we can see that the Block AuxIVE admits a straightforward modification.

In particular, provided that the model pdf $f(\{w_k^Hx_k\}_k=1)$ replacing the unknown $p(\cdot)$ meets the conditions for the application of AFO as in Section III-A, the pilot algorithm has exactly the same steps as the non-piloted one with a sole difference that the non-linearity $\varphi(\cdot)$ also depends on $o$. The equality between the contrast function and the auxiliary function holds if and only if

$$r_t = \sum_{k=1}^{K} |(w_k^Hx_k)|^2 + \eta^2|o_t|^2,$$  (58)

for $t = 1, \ldots, T$, where $o_t$ stands for the pilot signal within the $t$th interval, and $\eta$ is a hyperparameter controlling the influence of the pilot signal. Finally, Piloted Block AuxIVE is obtained from Block AuxIVE by replacing the update step (53) with (58).

Finding a suitable pilot signal poses an application-dependent problem. For example, outputs of voice activity detectors were used to pilot the separation of simultaneously talking persons in [28]. Similarly, a video-based lip-movement detection was considered in [41]. A video-independent solution was proposed in [42] using spatial information about the area in which the speaker is located. All these approaches have been shown useful although the pilot signals used in them contain residual noise and interference.

**E. Choice of $f(\cdot)$**

In this paper, we choose the model pdf in the same way as it was proposed in the pioneering IVA paper [9]; namely,

$$f(s) \propto \exp\left[-\|s\|\right],$$  (59)

for which the $k$th score function is

$$\psi_k(s) = -\frac{\partial}{\partial s_k} \log f(s) = \frac{s_k}{||s||},$$  (60)

and the related nonlinearity in (30), (43) and (51) is $\phi(||s||) = \|s\|^{-1}$. This pdf satisfies the conditions for applying AFO (Theorem 1 in [29]) and is known to be suitable for speech signals that are typically super-Gaussian. It is also suitable for Piloted Block AuxIVE when an extended vector component $\tilde{s} = [s; \nu o]$ is considered; $o$ denotes the pilot signal, and $\nu$ is a scaling parameter that controls the influence of the pilot.

It is worth noting here that more accurate modeling of the source pdf usually leads to improved performance. For example, advanced statistical models are currently studied for ILRMA [7], [43]. However, this topic goes beyond the scope of this work.

**IV. EXPERIMENTAL VALIDATION**

In this section, we present results of experiments with simulated as well as real-world recordings of moving speakers. Our goal is to show the usefulness of the CSV mixing model and compare the performance characteristics of the proposed algorithms with other state-of-the-art methods.

**A. Simulated room**

In this example, we inspect de-mixing filters obtained by the blind algorithms when extracting a moving speaker in a room simulated by the image method [44]. The room has dimensions $4 \times 4 \times 2.5$ (width $\times$ length $\times$ height) metres and $T_{60} = 100$ ms. A linear array of five omnidirectional microphones is located so that its center is at the position $(1.8, 2.1, 1)$ m, and the array axis is parallel with the room width. The spacing between microphones is 5 cm.

The target signal is a 10 s long female utterance from TIMIT. During that speech, the speaker is moving at a constant speed on a $38^\circ$ arc at a one-meter distance from the center of the array; the situation is illustrated in Fig. 2a. The starting
and ending positions are \((1.8, 3, 1)\) m and \((1.82, 2.78, 1)\) m, respectively. The movement is simulated by 20 equidistantly spaced RIRs on the path, which correspond to half-second intervals of speech, whose overlap was smoothed by windowing. Next, a directional source emitting a white Gaussian noise is located at the position \((2.8, 2, 1)\) m; that is, at a one-meter distance to the right from the array.

The mixture of speech and noise has been processed by the methods described in this paper in order to extract the speech signal. Namely, we compare OGIVE, Block OGIVE, AuxIVE, and Block AuxIVE when operating in the STFT domain with the FFT length of 512 samples and 128 samples hop-size; the sampling frequency is \(f_s = 16\) kHz. Each method has been initialized by the direction of arrival of the speaker signal at the beginning of the sequence. The other parameters of the methods are listed in Table I.

In order to visualize the performance of the extracting filters, a \(2 \times 2\) cm-spaced regular grid of positions spanning the whole room is considered. Microphone responses (images) of the white noise signal emitted from each position on the grid have been simulated. The extracting filter of a given algorithm is applied to the responses, and the output power is measured. The average ratio between the output power and the power of the input signals reflects the attenuation of the white noise signal played from the given position.

The attenuation maps of the compared methods are shown in Figures 2b through 2f. Table II shows the attenuation for specific points in the room. In particular, the first five columns in the table correspond to the speaker’s positions on the movement path corresponding to angles \(0^\circ\) through \(32^\circ\). The last column corresponds to the position of the interferer.

Fig. 2d shows the map of the initial filter corresponding to the delay-and-sum (DS) beamformer steered towards the initial position of the speaker. The beamformer yields a gentle gain in the initial direction with no attenuation in the direction of the interferer.

By contrast, all the compared blind methods steer a spatial null towards the interferer and try to increase the gain of the target signal. The spatial beam steered by Block AuxIVE towards the speaker spans the whole angular range where the speaker has appeared during the movement. Block OGIVEw performs similarly. However, its performance is poorer, perhaps due to its slower convergence or proneness to getting stuck in a local extreme. AuxIVE and OGIVEw tend to focus on only a narrow angular range (probably the most significant part of the speech). The nulls steered towards the interferer are more intense by AuxIVE and Block AuxIVE than by the gradient methods. In conclusion, these results corroborate the validity of the CSV mixing model and show the better convergence properties of AuxIVE and Block AuxIVE.

### Table I: Parameter setup for the tested methods in the simulated room

| Method    | # iterations | step size \(\mu\) | block size \(N_b\) |
|-----------|--------------|-------------------|-------------------|
| OGIVE     | 1000         | 0.2               | n/a               |
| Block OGIVE | 1000     | 0.2               | 250 frames        |
| AuxIVE  | 100          | n/a               | n/a               |
| Block AuxIVE | 100       | n/a               | 250 frames        |

### Table II: The attenuation in selected points on the source path and in the position of the interferer

| Source Path | 0°  | 8°  | 16° | 24° | 32° | Interferer |
|-------------|-----|-----|-----|-----|-----|------------|
| OGIVE       | -1.09 | -1.36 | -2.02 | -4.56 | -5.08 | -15.81 |
| Block OGIVE | -1.20 | -2.14 | -1.69 | -3.12 | -3.87 | -15.86 |
| AuxIVE     | -5.85 | -3.99 | -3.08 | -4.39 | -5.12 | -23.73 |
| Block AuxIVE | -3.22 | -1.74 | -1.27 | -2.09 | -2.67 | -18.51 |

### B. Real-world scenario using the MIRaGe database

The experiment here is designed to provide an exhaustive test of the compared methods in challenging noisy situations where the target speaker is performing small movements within a confined area. Recordings are simulated using real-world room impulse responses (RIRs) taken from the MIRaGe database [45].

MIRaGe provides measured RIRs between microphones and a source whose possible positions form a dense grid within a \(46 \times 36 \times 32\) cm volume. MIRaGe is thus suitable for our experiment, as it enables us to simulate small speaker movements in a real environment.

The database setup is situated in an acoustic laboratory which is a \(6 \times 6 \times 2.4\) m rectangular room with variable reverberation time. Three reverberation levels with \(T_{60}\) equal to 100, 300, and 600 ms are provided. The speaker’s area involves 4104 positions which form the cube-shaped grid with spacings of 2-by-2 cm over the x and y axes and 4 cm over the z axis. Also, MIRaGe contains a complementary set of measurements that provide information about the positions placed around the room perimeter with spacing of \(\approx 1\) m, at a distance of 1 m from the wall. These positions are referred to as the out-of-grid positions (OOG). All measurements were recorded by six static linear microphone arrays (5 mics per array with the inter-microphone spacing of \(-13, -5, 0, +5\) and \(+13\) cm relative to the central microphone); for more details about the database, see [45].

In the present experiment, we use Array 1, which is at a distance of 1 m from the center of the grid, and the \(T_{60}\) settings with 100 and 300 ms, respectively. For each setting, 3840 noisy observations of a moving speaker were synthesized as follows: each mixture consists of the moving SOI, one static interfering speaker, and the noise. The SOI is moving randomly over the grid positions. The movement is simulated so that the position is changed every second. The new position is randomly selected from all positions whose maximum distance from the current position is \(4\) in both the x and y axes. The transition between positions is smoothed using the Hamming window of a length of \(f_s/16\) with one-half overlaps. The interferer is located in a random OOG position between 13 through 24, while the noise signal is equal to a sum of signals that are located in the remaining OOG positions (out of 13 through 24).

As the SOI and interferer signal, clean utterances of 4 male and 4 female speakers from CHiME-4 [46] database were selected; there are 20 different utterances, each having 10 s in length per speaker. The noise signals correspond to random parts of the CHiME-4 cafeteria noise recording. The signals are convolved with the RIRs to match the desired positions, and the obtained spatial images of the signals on microphones.
(a) Setup of the simulated room conditions. The position of interference is marked by the red circle, the microphones by black circles and the path of the source is marked by a blue line.

(b) Attenuation in dB achieved by Block AuxIVE

(c) Attenuation in dB achieved by AuxIVE

(d) Attenuation in dB achieved by Delay and sum Beamformer

(e) Attenuation in dB achieved by Block OGIVE

(f) Attenuation in dB achieved by OGIVE

Fig. 2: Setup of the simulated room and the attenuation in dB achieved by DOA, OGIVE, Block OGIVE, AuxIVE and Block AuxIVE from the experiment in section IV-A

are summed up so that the interferer/noise power ratio, as well as the power ratio between the SOI and interference plus noise, is 0 dB.

The methods and their parameters are compared as follows: OGIVE, Block OGIVE, AuxIVE, Block AuxIVE, Piloted AuxIVE and Piloted Block AuxIVE. The number of iterations for the AuxIVE-based methods is set to 150 and, for the gradient-based method, to 2,000. The block size for the block methods is set to 350 frames. The gradient step-length for OGIVE and Block OGIVE is set to $\mu = 0.2$. The initial separating vector $w_k$ is initialized by the DS pointing in front of the microphone array. In the Piloted version of the methods, the piloting signals are equal to the output of an MPDR beamformer where the steering vector corresponds to the ground true DOA of the SOI. All these methods operate in the STFT domain with the FFT length of 512 and a hop-size of 128; the sampling frequency is 16 kHz.

The SOI is blindly extracted from each mixture, and the result is evaluated through the improvement of the Signal-to-Interference-and-Noise ratio (iSINR) and Signal-to-Distortion ratio (iSDR) defined as in [47] (SDR is computed after compensating for the global delay). The averaged values of the criteria are summarized in Table III together with the average time to process one mixture. The averages show small but still significant differences between the methods. Nevertheless, for a deeper understanding to the results, we need to analyze the histograms of iSINR shown in Fig. 3.

Fig. 3a shows the histograms for the entire set of mixtures in the experiment, while Fig. 3b is evaluated on a subset of mixtures in which the SOI has not moved away from the starting position by more than 5 cm; there are 288 mixtures of this kind. Now, we can observe two phenomenons. First, it is seen that the non-block variants of AuxIVE yield more results between 0 and 5 dB in Fig. 3a than in Fig. 3b and, on the contrary, they show a higher percentage of very successful extractions ($i\text{SINR} \geq 10$ dB) in Fig. 3b than in Fig. 3a. That means that they perform better for the subset of mixtures where the SOI is almost static. The performance of the block-based variants seem to be similar for the full set and the subset. On the other hand, they seem to yield a fewer number of trials where $i\text{SINR} < 10$ dB than the non-block methods. To summarize, the block methods yield a more stable performance than the non-block methods when the SOI is moving. The non-block methods can yield higher iSINR when the SOI is static.

Second, the piloted variants of AuxIVE yield $i\text{SINR} < -5$ dB in a much lower number of trials than the non-piloted methods, as confirmed by the additional criterion in Table III. This proves that the piloted algorithms have improved global convergence. Simultaneously, the main peaks in the histograms of the piloted methods seem to correspond to a lower $i\text{SINR}$
than those of the non-piloted versions. We conjecture that the performance bias is caused by the fact that the pilot signal used in this experiment does not contain clean SOI and is thus also slightly dependent on the other signals in the mixture.

C. Speech enhancement/recognition on CHiME-4 datasets

We have verified the proposed methods also in the noisy speech recognition task defined within the CHiME-4 challenge considering the six-channel track [46]. This dataset contains simulated (SIMU) and real-world⁸ (REAL) utterances of speakers in multi-source noisy environments. The recording device is a tablet with multiple microphones, which is held by a speaker. Since some recordings involve microphone failures, the method from [48] is used to detect these failures. If detected, the malfunctioning channels are excluded from further processing of the given recording.

The experiment is evaluated in terms of Word Error Rate (WER) as follows: The compared methods are used to extract speech from the noisy recordings. Then, the enhanced signals are forwarded to the baseline speech recognizer from [46]. The WER achieved by the proposed methods is compared with the results obtained on unprocessed input signals (Channel 5) and with the techniques listed below.

BeamformIt [49] is a front-end algorithm used within the CHiME-4 baseline system. It is a weighted delay-and-sum beamformer requiring two passes over the processed recording in order to optimize its inner parameters. We use the original implementation of the technique available at [50].

The Generalized Eigenvalue Beamformer (GEV) is a front-end solution proposed in [51], [52]. It represents the most successful enhancers for CHiME-4 that rely on deep networks trained for the CHiME-4 data. In the implementation used here, a re-trained Voice-Activity-Detector (VAD) is used where the training procedure was kindly provided by the authors of [51]. We utilize the feed-forward topology of the VAD and train the network using the training part of the CHiME-4 data. GEV utilizes the Blind Analytic Normalization (BAN) postfilter for obtaining its final enhanced output signal.

All systems/algorithms operate in the STFT domain with the FFT length of 512 and hop-size of 128 using the Hamming window; the sampling frequency is 16 kHz. Block OGIVEw is applied with \( N_b = 170 \) which corresponds to the block length of 1.4 s. Block AuxIVEn is applied with \( N_b = 250 \approx 2 \) s. These values have been tuned up to optimize the performance of these methods. All the proposed methods are initialized by the Relative Transfer Function (RTF) estimator from [53]; Channel 5 of the data is selected as the target one (the spatial image of the speech signal of this channel is being estimated).

The results shown in Table IV indicate that all methods are able to improve the WER compared to the unprocessed case. The GEV beamformer endowed with the pretrained VAD achieves the best results. Comparable rates are also achieved by the proposed unsupervised techniques; the WER of Block AuxIVEn is higher by a mere \( 0-1.5\% \).

In general, the block-wise methods achieve lower WER than their counterparts based on the standard mixing model; the WER of Block OGIVEw is comparable with Block AuxIVEn. A significant advantage of the latter method is the faster convergence and, consequently, much lower computational burden. The total duration of the 5920 files in the CHiME dataset is 10 hours and 5 minutes. The results presented for Block OGIVEw have been achieved after 100 iterations on each file, which translates into 7 hours and 45 minutes⁹ of processing for the whole dataset. Block AuxIVEn is able to converge in 5 iterations; the whole enhancement has been finished in 57 minutes.

An example of the enhancement yielded by the proposed methods on one of the CHiME-4 recordings is shown in Fig. 4. Within this particular recording, in the interval 1.75 – 3 s, the target speaker was moved out of its initial position. The AuxIVEn algorithm focused on this initial direction only, resulting in the vanishing voice during the movement interval. Consequently, the automatic transcription is erroneous. In contrast, Block AuxIVEn is able to focus on both positions of the speaker and recovers the signal of interest correctly.

| System         | Development | Test |
|----------------|-------------|------|
| Unprocessed    | REAL        | REAL |
| BeamformIt     | 7.77        | 11.52|
| GEV (VAD)      | 4.61        | 8.10 |
| OGIVEw         | 5.59        | 9.51 |
| Block OGIVEw   | 5.64        | 8.98 |
| AuxIVEn        | 5.97        | 10.43|
| Block AuxIVEn | 5.53        | 9.65 |

V. CONCLUSIONS

We have proposed new IVE algorithms for BSE based on the auxiliary function-based optimization. The algorithms are

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⁸Microphone 2 is not used in the case of the real-world recordings as, here, it is oriented away from the speaker.

⁹The computations run on a workstation endowed with Intel i7-2600K@3.4GHz processor with 16GB RAM.
Fig. 4: Comparison of enhanced signals yielded from a recording of a moving speaker by AuxIVE and Block AuxIVE.

shown to be faster in convergence than their gradient-based counterparts. The block-based algorithms enable us to extract a moving source by estimating a separating filter that passes signals from the entire area of the source presence. This way, the moving source can be extracted efficiently without tracking in an on-line fashion. The experiments show that these methods need not necessarily be more accurate (achieve higher SINR) than standard methods, especially, when the source is almost static. However, they are particularly robust with respect to small source movements. For the future, they provide us with alternatives to the conventional approaches that adapt to the source movements through application of static mixing models on short time-intervals.

Furthermore, we have proposed the semi-supervised variants of (Block) AuxIVE utilizing pilot signals. The experiments confirm that such algorithms yield stable global convergence to the SOI even when the pilot signal is only a roughly pre-

extracted SOI containing a considerable residual of noise and interference.

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